INTERNATIONAL JOURNAL OF WATER RESOURCES DEVELOPMENT
https://doi.org/10.1080/07900627.2023.2197080

Mechanization in land preparation and irrigation water productivity: insights from rice production

Junpeng Li[a], Wanglin Ma[b], Julio Cesar Botero-R[b] and Phong Quoc Luu[c]

[a]School of Economics & Management, Jiangsu Collaborative Innovation Center of Regional Modern Agriculture & Environmental Protection, Huaiyin Normal University, Huaian, China; [b]Department of Global Value Chains and Trade, Faculty of Agribusiness and Commerce, Lincoln University, Christchurch, New Zealand; [c]Department of Financial and Business Systems, Faculty of Agribusiness and Commerce, Lincoln University, Christchurch, New Zealand

ABSTRACT

This study investigates how and to what extent mechanization in land preparation (MLP) can help improve irrigation water productivity (IWP) (measured as rice yield per unit volume of irrigation water). We employed an endogenous treatment regression model to estimate the 2021 China Land Economic Survey (CLES) data collected from Jiangsu province, China. The results reveal that MLP adoption increases IWP significantly; a higher IWP is determined by whether or not farmers adopt MLP rather than through which channel they access their farm machines; the effects of MLP adoption on IWP are monotonically increasing across the selected quantiles.

ARTICLE HISTORY

Received 6 February 2023
Accepted 25 March 2023

KEYWORDS

Climate change; food security; irrigation water; productivity; mechanization

Introduction

Food insecurity is widely recognized as a primary threat to humankind. The United Nations Development Programme (UNDP) reports that approximately 821 million people worldwide are chronically undernourished, and over 90 million children under five are still severely underweight (UNDP, 2022). Thus, continuously enhancing food production, especially crop production, is one of humankind's primary goals (Chen et al., 2021; Huang, Tao et al., 2021). However, driven by drastic climate changes, irrigation water scarcity hampers food production (Gupta et al., 2020; Pakmehr et al., 2021).

Climate change, such as global warming and frequent weather variability, has played havoc with the hydrological cycle, soil water balance, and runoff characteristics, leading to severe irrigation water shortages and threatens crop production (Carpena, 2019; Elliott et al., 2014; Pakmehr et al., 2021). In particular, water shortages obstruct the growth of crops from emergence to tasselling, which reduces crop yield (Brar & Vashist, 2020; Pakmehr et al., 2021). For instance, water scarcity significantly delays the leaf, tasselling and silking stages of maize, causing maize yields to vary (Brar & Vashist, 2020). As Dietz et al. (2021) pointed out,

CONTACT Wanglin Ma Wanglin.Ma@lincoln.ac.nz
Supplemental data for this article can be accessed at https://doi.org/10.1080/07900627.2023.2197080

climate change-induced water scarcity can lead to a 30% or greater loss in crop yield. Crop production loss induced by water scarcity and drought has reached US$30 billion in the past decade (Gupta et al., 2020). Clearly, water scarcity is one of the most pressing challenges to food security worldwide (Kistner et al., 2018; Wang & Hao, 2020). To improve food security, we need to adopt effective agricultural practices and technologies that help mitigate water scarcity.

Improving irrigation water-use efficiency by increasing agricultural production per unit volume of water consumption – irrigation water productivity (IWP) – could be a practical strategy to improve water sustainability (Cao et al., 2020; Carracelas et al., 2019; Çetin & Kara, 2019; Ding et al., 2021). Agricultural economists and horticultural experts have emphasized the importance of adopting multiple strategies to improve irrigation efficiency, such as water-saving farming, soil and water conservation, and drought-tolerant varieties (e.g. Carracelas et al., 2019; Jing et al., 2021; Zhang, Wang et al., 2021; Zheng, Fan et al., 2021). During crop cultivation, water scarcity manifests as a decrease in soil moisture (Jing et al., 2021; Zheng et al., 2020). In other words, water scarcity in terms of precipitation shortage, irrigation water deficit and surface runoff reduction could result in soil moisture loss (Choudhary et al., 2020; Liu et al., 2020). Hence, effective water management strategies that increase IWP would help maintain or improve soil moisture and enhance root absorption of water (Dhaliwal et al., 2022; Wang et al., 2021).

Mechanized land preparation (MLP) – practising land preparation (e.g. deep tillage, land levelling and harrowing) using machinery (e.g. cultivators and ploughs) – is supposed to have a great effect on IWP through root absorption of water and soil moisture content. On the one hand, MLP practices, such as deep tillage and harrowing, significantly increase the air permeability of the soil and accelerate the decomposition of soil organic matter (Dhaliwal et al., 2022; Li et al., 2021), contributing to fertile soil development and crop root proliferation. Consequently, crops can absorb irrigation water more efficiently. On the other hand, MLP also helps increase soil porosity and recreate microtopography, thereby retaining surface runoff and improving soil moisture content (Ding et al., 2020; Douglas, 2017; Yu et al., 2020). Consequently, MLP enables farmers to reduce water consumption and irrigation frequency during crop cultivation (Huang, Tao et al., 2021). Therefore, quantifying the effect of MLP adoption on IWP can provide practical strategies to enhance IWP for crop production and food security.

This study explores how and to what extent MLP adoption influences IWP and contributes to the literature in two ways. First, we provide a pioneering work that appraises the effect of MLP adoption on IWP. Improvement in IWP is expected to be one of the few practical pathways for addressing irrigation water sustainability and improving food security. Therefore, it is vital to explore how and to what extent MLP can serve as an effective strategy for improving IWP. Second, we address the endogeneity issues associated with MLP adoption using an endogenous treatment regression (ETR) model, which addresses both observable and unobservable endogeneity and assesses the direct effect of the treatment variable on the outcome variable (Lin et al., 2022). Our empirical results confirm that MLP adoption increases the IWP of rice cultivation significantly, thus providing a promising new avenue for enhancing food security under water scarcity conditions. Additionally, the empirical results verify the utility and efficiency of the ETR model in addressing both observed and unobserved endogenous factors and help us gain a more accurate understanding of the association between MLP adoption and the IWP of rice cultivation.

We empirically estimated data collected from rice farmers in Jiangsu province, China. Data were collected by Nanjing Agricultural University through the 2021 China Land Economic Survey (CLES). China, one of the largest agricultural countries worldwide, has successfully fed 18% of the global population using only 9% of the global arable land and 6% of the global water resources (Wang et al., 2018). This notable achievement strongly refutes Brown's (1995) famous concern about global food security when he asked: Who will feed China? Thus, China's food production has significant implications for global food security. However, owing to the intensification of climate change and increasing water demand by non-agricultural sectors, water scarcity has become a rigid constraint on China's food production (Chen et al., 2021; Huang, Yuan et al., 2021). To strengthen food production, China has intensified its efforts to equip agricultural production with machinery to address agricultural labour shortages and improve agricultural production efficiency. Currently, crop production in China urgently requires a higher level of MLP owing to the increasing population pressure (more than 1.4 billion people to feed) and severe agricultural labour shortages caused by population ageing and labour migration from rural to urban areas (Zhang, Mishra et al., 2021).

Rice is one of the largest irrigation water-consuming crops worldwide (Carracelas et al., 2019). Exacerbating water scarcity may reduce rice yields significantly and threaten China's food security. Jiangsu province is one of the leading rice-producing areas in China, accounting for approximately 10% of Chinese rice production (CESY, 2021). In 2020, Jiangsu province ranked sixth and fourth in total rice area cultivated and output, respectively, among the 31 provinces of mainland China (CESY, 2021). However, crop production in Jiangsu province is characterized by low agricultural water-use efficiency. Official data released by the Ministry of Water Resources of China (MWRC) (Figure 1) suggest that Jiangsu province ranks 12th in water productivity for crop production, even

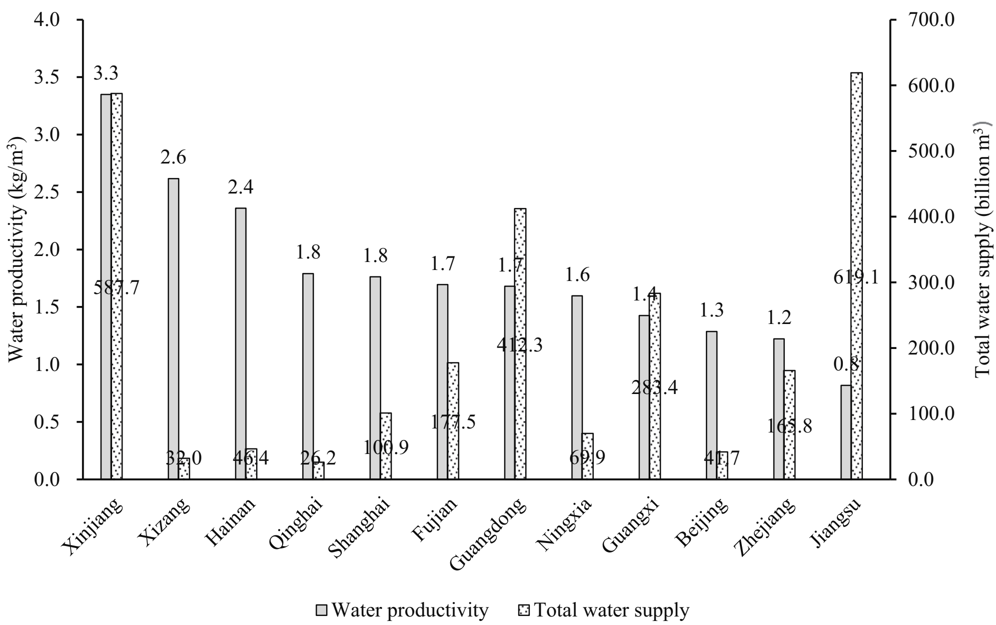

Figure 1. Top 12 water productivity provinces and their total water supply in China, 2019.

though it has the highest total water supply in China (MWRC, 2020). Given the rigid water shortage confronting China, improving agricultural water productivity in areas rich in water resources, such as Jiangsu province, is critical for relieving the water scarcity faced by the rest of China.

The remainder of this paper is structured as follows. The next section reviews the literature, followed by a discussion of the methodology in the third section. The fourth section presents and discusses the empirical results. The fifth section highlights the main conclusions and implications.

Literature review

Climate change and water scarcity

In recent years, with the advent of the resource crisis, a considerable amount of literature has investigated the factors influencing water scarcity. Generally, water scarcity is a consequence of both human activity and climate change (Huang, Yuan et al., 2021). Much of the literature has concluded that a set of human activities, such as industrial development (Huang, Liu et al., 2021), mining (Alvez et al., 2020; Rivera et al., 2016) and agricultural production (Çetin & Kara, 2019; Silalertruksa & Gheewala, 2018), have caused and deepened water scarcity globally. Most studies within the field have focused on the role of climate change because of its fundamental effect on water resource endowment. Overall, scholars have concluded that climate change is the primary factor aggravating future water scarcity (Aghapour Sabbaghi et al., 2020; Chen et al., 2021).

Global warming and frequent weather variability are the two dominant dimensions of climate change that influence water scarcity (Carracelas et al., 2019). Among them, global warming is supposed to take the leading role in exacerbating water scarcity (Carracelas et al., 2019; Hristov et al., 2021; Huang, Liu et al., 2021; Wang et al., 2021; Zheng, Fan et al., 2021). Studies conducted in China by Omer et al. (2020) and Zheng, Fan et al. (2021) concluded that increased temperatures could reduce water availability by improving evapotranspiration and hampering precipitation and river flow. This conclusion is consistent with those of Ferguson et al. (2018) for 20 river basins globally, Hristov et al. (2021) for Europe and Yin et al. (2021) for China. More urgently, a global temperature increase of 1.5°C could be reached in 2030, driving more severe water scarcity and food insecurity (Zucchinelli et al., 2021). Frequent weather variability is another water scarcity-driven phenomenon induced by climate change (Carracelas et al., 2019). Frequent weather variability changes the temporal and spatial distribution of precipitation significantly (Daghagh Yazd et al., 2020; Weligamage et al., 2014), increasing the occurrence, frequency, magnitude, and duration of droughts and waterlogging, leading to a mismatch between precipitation and water consumption (Carracelas et al., 2019; Jones & van Vliet, 2018), namely water scarcity.

Although not all related studies can be adequately summarized here, the non-negligible adverse effects of climate change on water scarcity are generally documented. Therefore, strategies that can mitigate water scarcity caused by climate change should be prioritized.

Pathways for improving agricultural water productivity

Because of the limited water resource endowment and challenges of global climate change, improving water productivity could be a reliable alternative option to cope with agricultural water scarcity (Cao et al., 2020; Carracelas et al., 2019; Çetin & Kara, 2019; Surendran et al., 2021). To this end, scholars have explored effective pathways for improving agricultural water productivity, including improved irrigation techniques (Carracelas et al., 2019; Çetin & Kara, 2019; Comas et al., 2019; Parthasarathi et al., 2018), water-saving farming practices (Huang, Tao et al., 2021; Zhang, Wang et al., 2021; Zheng, Fan et al., 2021), and improved crop varieties (Jing et al., 2021; Kukal et al., 2014; Sánchez et al., 2015). Comas et al. (2019) conducted a field experiment in Northern Colorado to investigate the effects of deficit irrigation on maize water productivity. They found that the deficit irrigation method was essential for buffering maize yield losses and improving water productivity. According to Parthasarathi et al. (2018), drip irrigation in aerobic rice production systems can increase water productivity. Zheng, Fan et al. (2021) documented that water-saving practices such as film mulching can significantly increase water productivity in crop production in China. Jing et al. (2021) suggested that water productivity can be substantially boosted by planting drought-tolerant wheat varieties.

Notwithstanding the multiple strategies discussed in the previously mentioned literature, a crucial fact is that measures to improve water productivity could always be contradictory to food security (Chen et al., 2021). In other words, some strategies such as film mulching may erode the field environment and decrease crop yield (Huang et al., 2020), even though they may improve water productivity. Accordingly, a strategy that simultaneously improves IWP and addresses the water–food nexus deserves full consideration. MLP, as discussed above, can facilitate the development of the crop root system (Zheng et al., 2020) and soil moisture (Huang, Tao et al., 2021; Yang et al., 2018), which may contribute to increasing both water productivity and crop yield. Accordingly, MLP adoption could be the strategy needed. Therefore, a deeper understanding of the association between MLP adoption and IWP is paramount for enhancing IWP and food security. Nevertheless, in our humble review, there is still a lack of literature that delves into this association, and this study addresses this gap.

Methodology

Method

Model selection

Households freely adopt or do not adopt MLP depending on various observable individual and household characteristics (e.g. age, gender, education level and asset ownership) and unobservable factors (e.g. household capacity and motivation for MLP adoption; Mano et al., 2020; Paudel et al., 2019). In other words, MLP adoption among rural Chinese households is unlikely to have resulted from random assignment. Therefore, MLP adoption is an endogenous variable and endogeneity issues should be addressed to achieve unbiased and consistent estimates of the influence of MLP adoption on IWP.

Previous studies have used different approaches to deal with endogeneity issues arising from selection biases, including the propensity score matching (PSM) model (dos Santos et al., 2023; Wen et al., 2021), augmented inverse probability-weighted

(AIPW) estimator (Kurz, 2021), inverse probability-weighted regression adjustment (IPWRA) estimator (Chigusiwa et al., 2022; Zheng & Ma, 2021), endogenous switching regression (ESR) model (Li et al., 2020; Liu et al., 2021; Suresh et al., 2021), and ETR model (Li, Vatsa et al., 2023; Ma, Nie et al., 2020; Vatsa et al., 2022). A well-known limitation of the PSM, AIPW and IPWRA approaches is that they cannot handle the selection bias caused by unobservable factors. Although the ESR model can address both observed and unobserved selection bias, it separately estimates the influence of the control variables on the outcome for the treated and untreated samples. Therefore, it cannot evaluate the treatment variable's direct effect on the outcome (Li et al., 2020). In comparison, the ETR model can address the selection bias induced by observed and unobserved factors and estimate the direct effect of MLP adoption (i.e. the coefficient of the treatment variable) on IWP (Li, Vatsa et al., 2023; Lin et al., 2022). Hence, we employed the ETR model as our primary empirical strategy.

The ETR model

The ETR model simultaneously estimates the selection and outcome equations (Zhu et al., 2020). The selection equation employs a random utility maximization framework to determine whether households choose to adopt MLP. A household's decision to adopt MLP is assumed to be a dichotomous selection based on the gap between the expected benefits (LP^*_{iA}) from adoption and expected benefits (LP^*_{iN}) from non-adoption. Under the assumptions of household risk neutrality and, *ceteris paribus*, a household typically selects to adopt MLP if LP^*_{iA} is higher than LP^*_{iN}. Let us denote MLP^*_i as the difference in the benefit between MLP adoption and non-adoption; thus, we have $MLP^*_i = LP^*_{iA} - LP^*_{iN}$. Generally, the i^{th} household decides to adopt MLP only if MLP^*_i is positive. MLP^*_i is an unobservable latent variable that can be expressed as a function of the observable components, as follows:

$$MLP^*_i = \gamma_i X_i + \delta_i IV_i + \varepsilon_i, MLP_i = \begin{cases} 1, \; if \; MLP^*_i > 0 \\ 0, \; otherwise \end{cases} \tag{1}$$

where MLP_i is the measure of household i's MLP adoption status that takes the value of 1 if the household adopts MLP in rice cultivation, and 0 otherwise; X_i denotes a vector of independent variables related to households' demographic and socio-economic characteristics that are expected to correlate to MLP adoption; IV_i refers to an instrumental variable (IV); γ_i and δ_i denote the vectors of coefficients to be estimated; and ε_i refers to a normally distributed random error term.

The outcome equation of the ETR model estimates the effects of the endogenous treatment variable (i.e. MLP adoption) and other exogenous explanatory variables on the outcome variable (i.e. IWP) using an ordinary least squares (OLS) regression model. The outcome equation is as follows:

$$IWP_i = \alpha_i MLP_i + \beta_i X_i + \mu_i \tag{2}$$

where IWP_i refers to the IWP of household i; MLP_i and X_i are defined as above; α_i and β_i are parameters to be estimated; and μ_i denotes the random error term. Within the ETR model framework, equations (1) and (2) are jointly estimated using a maximum likelihood estimator. Therefore, the random error terms of these equations (i.e. ε_i and μ_i) are supposed to have zero means. The bivariate normal distribution is specified as follows:

$$\begin{pmatrix} \varepsilon_i \\ \mu_i \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\varepsilon^2 & \rho_{\varepsilon\mu}\sigma_\varepsilon \\ \rho_{\varepsilon\mu}\sigma_\varepsilon & 1 \end{pmatrix}\right] \tag{3}$$

where $\rho_{\varepsilon\mu}$ refers to the correlation between the two error terms, ε_i and μ_i; σ_ε^2 denotes the variance of ε_i; σ_ε denotes the standard deviation (SD) of ε_i; and σ_μ^2 denotes the variance of μ_i that is normalized to 1. A significant $\rho_{\varepsilon\mu}$ reflects the existence of unobserved endogeneities of the MLP adoption (Ma, Nie et al., 2020), showing the reasonability of using the ETR model.

IV selection and validity tests

For the ETR model to be adequately specified, a valid IV included in equation (1) but excluded from equation (2) should be discreetly identified. It should be noted that IV identification is always an arduous task in empirical analysis, as it must be correlated with the endogenous treatment variable, but uncorrelated with the outcome variable. However, limited information in the 2021 CLES data makes it impossible to instrument MLP adoption directly using a specific indicator. Therefore, following previous studies (Zheng, Ma & Zhou 2021; Zhu et al., 2020), we synthesized an IV representing the proportion of people using machines for rice land preparation (excluding respondents) in the city sample. The synthesized IV is valid for two reasons. First, farmers' technology adoption tends to be influenced by their neighbours, friends, relatives and even other villagers around them (Zheng, Ma & Zhou 2021; Zhu et al., 2020). Therefore, farmers in cities with a higher proportion of people who use machines for rice land preparation are more likely to adopt MLP. Second, there are no other pathways, except MLP adoption, through which the synthesized IV can affect the IWP.

To confirm the effectiveness of the synthesized IV further, we checked its validity using falsification, under-identification and weak-identification tests. The results are presented in Table A1 in the supplemental data online. Specifically, the falsification test shows that the IV is significantly correlated with MLP adoption but is not correlated with IWP. Moreover, the statistics of the Anderson Lagrange multiplier and Cragg–Donald weak identification Wald tests in the lower panel of Table A1 online suggest that our IV is immune to the under-identification and weak-identification problems, respectively. Therefore, the IV is appropriate for mitigating endogeneity.

Data and variables

Data

In this study, data derived from the 2021 CLES were examined to assess the association between MLP adoption and IWP. The survey, sponsored by Nanjing Agricultural University (Nanjing, China), was primarily conducted in Jiangsu province. The survey collected samples in three steps using a probability proportional to size (PPS) sampling procedure. In the first step, two counties were randomly selected from each of the 13 prefecture-level cities in Jiangsu. Second, two villages or communities were randomly chosen from each county. In the final step, 40–50 rural residents from each village or community were randomly chosen and interviewed face to face, resulting in a total sample of 2420 rural households. Beyond information on household demographics and socio-economic characteristics, the 2021 CLES data pertain to detailed plot-level information on rice production, such as yield, irrigation access and agricultural inputs. This attribute makes the 2021 CLES data suitable for revealing the relationship between MLP adoption and IWP.

The data were cleaned in three steps. First, we restricted the sample to 909 rural rice growers and excluded 1511 non-rice growers. Second, 298 samples with missing values and outliers in rice yield and irrigation water consumption were removed. Third, 16 samples that reported abnormal or missing values for the control variables were deleted. Our study's dataset for the empirical analysis comprised 595 samples, of which 422 were MLP adopters.

Dependent variable

We used IWP as the dependent variable. The IWP reflects the crop yield per unit volume of irrigation water consumed (Sánchez et al., 2015; Zheng et al., 2020). In this study, IWP refers to the ratio of rice yield to the volume of irrigation water consumption, measured in kg/m^3. A higher IWP indicates that a higher level of rice yield can be generated with relatively lower irrigation water consumption, and vice versa. Compared with the water productivity measure, which only accounts for the volume of water consumption, our IWP measurement can practically reflect water-use efficiency by simultaneously considering crop yield and irrigation water consumption (Sánchez et al., 2015; Zheng et al., 2020). In addition, it parallels the path of agri-food production during water scarcity very well (Kang et al., 2017).

Treatment variable

MLP adoption is the treatment variable. Based on the empirical design in equation (1), we capture rice farmers' MLP adoption status using a dichotomous variable. Specifically, the MLP adoption variable is given a value of 1 if the respondent reports using machines for land preparation (e.g. tillage and harrowing) in rice cultivation, and 0 otherwise.

Selection of control variables

We also introduce a vector of control variables into our empirical specifications by drawing on a related set of prior studies on IWP and improved agricultural technology adoption. Specifically, following previous studies (e.g. Daghagh Yazd et al., 2020; Dhaliwal et al., 2022; Ganeshpa et al., 2018; Mano et al., 2020; Pakmehr et al., 2021; Reichert et al., 2014), we used the household head's age, gender, education, health status, household size, and elderly ratio (i.e. the proportion of household members aged more than 64 years to household size) to reflect rural households' demographic characteristics. It is worth noting that elderly farmers are rich in agricultural production experience and skills (Li et al., 2020), which helps them use irrigation water efficiently, thus promoting IWP. However, an increase in the elderly ratio may increase households' financial burden (Qiu et al., 2021), weakening farmers' affordability of irrigation facilities and technologies, and ultimately decreasing IWP. Accordingly, the elderly ratio may have a mixed effect on the IWP. Ma, Grafton et al. (2020) and Martínez-Domínguez and Mora-Rivera (2020) concluded that households in good economic conditions were more likely to adopt modern agricultural technologies. Therefore, we include asset ownership in our study to capture household economic conditions.

Experiencing adversity may erode farmers' financial conditions, which could hinder their adoption of improved agricultural practices. Therefore, we include a variable that represents negative shocks (e.g. member death and/or health deterioration) and explore how it affects IWP. Natural resource endowment is a root factor to consider when analysing MLP adoption and IWP. Following Kukal et al. (2014), He et al. (2020) and Pakmehr et al. (2021), we controlled for the effects of natural resource endowments by including variables representing farm size, soil fertility, irrigation access and natural disasters such as pest infestations. Among them, a large farm size may induce economies of scale in irrigation water consumption, on the one hand (Key, 2019), while also encouraging farmers to use flood irrigation and increase irrigation water consumption per unit area. Therefore, the effect of farm size on IWP can be either positive or negative. To capture the disparities associated with spatial attributes, we generate and include three regional dummies representing northern, central and southern Jiangsu.

Descriptive statistics

Table 1 details the descriptive statistics of our chosen variables. It shows that the average IWP is 0.60 kg/m^3. This suggests that every 1 m^3 irrigation water consumption in Jiangsu province would help increase rice yields by 0.60 kg. The IWP in our study is roughly close to the 0.80 kg/m^3 calculated by Cao et al. (2020) for China, but significantly lower than that of Carracelas et al. (2019) (i.e. 1.81 kg/m^3) for Uruguay. This finding convinces us that the IWP of rice production in Jiangsu province remains at a worrisomely low level. The

Table 1. Variable definitions and descriptive statistics.

Variables	Definitions	Mean	SD
Dependent variable			
IWP	Rice yield per unit volume of irrigation water (kg/m^3)	0.60	0.52
MLP adoption	1 if a household used machines for rice production land preparation; 0 otherwise	0.71	0.45
Control variables			
Age	Age of HH (years)	61.19	10.84
Gender	1 if the HH is male; 0 otherwise	0.75	0.43
Education	Educational level of HH (years)	6.91	3.96
Health status	1 if the HH reports him/her is in good physical condition; 0 otherwise	0.88	0.33
Household size	Number of people residing in a rural household	3.26	1.76
Elderly ratio	Ratio of the number of residents aged more than 64 years to household size	0.28	0.31
Asset ownership	1 if the rural household owns a car and/or an air purifier; 0 otherwise	0.50	0.50
Negative shock	1 if the rural household experienced negative shocks (i.e. member death and/or health deterioration); 0 otherwise	0.10	0.30
Farm size	Total area of the major plot committed to rice production (*mu*)[a]	7.74	35.69
Soil fertility	1 if the HH perceives the cultivated land is fertile; 0 otherwise	0.48	0.50
Irrigation access	1 if the major rice plot has the access to irrigation; 0 otherwise	0.98	0.13
Negative shocks	1 if the major rice plot experienced negative shocks (e.g. flood and drought) in 2020; 0 otherwise	0.26	0.44
Pest infestation	1 if the major rice plot experienced pest infestation in 2020; 0 otherwise	0.08	0.27
Traffic condition	Distance from the major rice plot to the nearest cement road (km)	0.25	0.47
Northern Jiangsu	1 if a household is located in northern Jiangsu; 0 otherwise	0.42	0.50
Central Jiangsu	1 if a household is located in central Jiangsu; 0 otherwise	0.40	0.49
Southern Jiangsu	1 if a household is located in southern Jiangsu; 0 otherwise	0.18	0.39
City-level MLP ratio (IV)	Proportion of people using machines for rice land preparation (excluding the respondent) in the same city	0.64	0.20
Sample size		595	

[a]1 *mu* = 1/15 ha.
HH, household head; SD, standard deviation.

average MLP penetration rate in our sample is 71%, which is well in line with the national rate of 76.50%. This result highlights the outstanding achievement made by the Chinese government in promoting agricultural mechanization, whereas it also implies a relatively large space for further improvement.

The statistics illustrated in Table 1 also suggest that, in general, the respondents in the sample are mainly older, male, relatively poorly educated and healthy farmers. The average household size is 3.26. On average, approximately 28% of household members are older than 64 years. The average farm size for rice production is 7.74 *mu* (1 *mu* = 1/15 ha). Approximately 10% of the sampled households experienced negative shocks (e.g. member death and/or health deterioration) in the reference year, 2020. Among the respondents, 48% perceived their major rice plots to be fertile. Moreover, the average distance from the major rice plot to the nearest cement road is 0.25 km, demonstrating that the majority of major rice plots are conveniently located.

Table 2 reports the means of the selected variables categorized as MLP adopters and non-adopters and the corresponding mean differences between the two cohorts. For the dependent variable of our primary interest, the positive but insignificant mean difference in IWP implies that MLP adopters and non-adopters are not distinguishable in IWP. Nevertheless, the insignificant mean difference in IWP between the two cohorts is far from concluding that MLP adoption is uncorrelated with the IWP of rice production as it does not control the effects of other variables. The information in Table 2 suggests that MLP adopters and non-adopters are systematically different in demographic characteristics, economic conditions, natural resource endowment, and spatial distribution. For instance, relative to non-adopters, MLP adopters are more likely to be younger, better educated, and reside in larger households with a lower elderly ratio. The significant mean differences in asset ownership, soil fertility, and natural disaster suggest MLP adopters are

Table 2. Mean differences in the variables between mechanization in land preparation (MLP) adopters and non-adopters.

	MLP			
Variables	Adopters	Non-adopters	Mean difference	t-value
IWP	0.615	0.564	0.051 (0.047)	1.073
Age	60.758	62.260	−1.502 (0.977)	−1.537*
Gender	0.756	0.728	0.028 (0.039)	0.703
Education	7.095	6.462	0.632 (0.357)	1.772**
Health status	0.886	0.855	0.031 (0.030)	1.038
Household size	3.358	3.029	0.329 (0.158)	2.081**
Elderly ratio	0.261	0.311	−0.050 (0.028)	−1.795**
Asset ownership	0.543	0.405	0.138 (0.045)	3.077***
Negative shock	0.088	0.133	−0.045 (0.027)	−1.666**
Farm size	8.372	6.182	2.190 (3.223)	0.680
Soil fertility	0.502	0.410	0.092 (0.045)	2.044**
Irrigation access	0.986	0.971	0.015 (0.012)	1.207
Negative shocks	0.301	0.150	0.151 (0.039)	3.860***
Pest infestation	0.104	0.017	0.087 (0.024)	3.603***
Traffic condition	0.257	0.215	0.043 (0.042)	1.009
Northern Jiangsu	0.393	0.497	−0.104 (0.044)	−2.332**
Central Jiangsu	0.453	0.260	0.192 (0.044)	4.422***
Southern Jiangsu	0.154	0.243	−0.089 (0.035)	−2.570***
City-level MLP ratio (IV)	0.678	0.550	0.128 (0.017)	7.375***
Observations	422	173		

Irrigation water productivity (IWP) is measured in kg/m^3; ***< 0.01, **< 0.05 and *< 0.10.

more likely to own assets (i.e. car and/or air purifier) and cultivate rice on fertile and natural disaster-stricken plots than non-adopters. Furthermore, MLP adopters tend to reside in central Jiangsu, whereas non-adopters tend to reside in northern and southern Jiangsu. In what follows, we will rely on a rigorous econometric strategy – the ETR model – to assess the effect of MLP adoption on IWP.

Empirical results

This section presents and discusses the empirical results. Table 3 presents the main results of the ETR model estimation. The coefficient of $\rho_{\varepsilon\mu}$ in the lower panel of Table 3 is statistically significant at the 1% level, confirming the presence of endogeneity issues arising from unobserved factors. This finding verifies the significance of the ETR model in identifying the correlation between MLP adoption and IWP. Meanwhile, the mean value of the variance inflation factor (VIF) is 1.35, which is much lower than the often-chosen critical value of 10 (Craney & Surles, 2002), indicating that our empirical analysis is immune to severe multicollinearity issues.

In the following subsections, as a point of departure, we first discuss the determinants of MLP adoption, followed by the discussion of the determinants of IWP. We then interpret the results of the disaggregated analysis. Finally, we present and discuss the results of the robustness check.

Table 3. Determinants of mechanization in land preparation (MLP) adoption and its impact on irrigation water productivity (IWP): endogenous treatment regression (ETR) model estimates.

Variables	MLP adoption	IWP
MLP adoption		0.247 (0.077)***
Age	−0.015 (0.008)*	0.001 (0.002)
Gender	0.100 (0.095)	0.021 (0.078)
Education	0.004 (0.020)	−0.003 (0.004)
Health status	0.150 (0.113)	0.007 (0.087)
Household size	0.048 (0.039)	−0.005 (0.009)
Elderly ratio	0.041 (0.259)	0.162 (0.078)**
Asset ownership	0.094 (0.101)	0.073 (0.034)**
Negative shock	−0.192 (0.067)***	−0.121 (0.061)**
Farm size	0.002 (0.002)	0.001 (0.000)*
Soil fertility	0.310 (0.148)**	−0.000 (0.036)
Irrigation access	0.510 (0.280)*	−0.016 (0.090)
Negative shocks	0.386 (0.206)*	−0.060 (0.052)
Pest infestation	0.780 (0.322)**	0.022 (0.080)
Traffic condition	−0.008 (0.089)	0.053 (0.066)
Northern Jiangsu	−0.058 (0.103)	0.188 (0.099)*
Central Jiangsu	0.376 (0.091)***	0.025 (0.095)
City-level MLP ratio (IV)	1.887 (0.310)***	
Constant	−1.016 (0.422)**	0.243 (0.129)*
$\rho_{\varepsilon\mu}$	−0.248 (0.076)***	
Variance inflation factor (VIF) test		Mean VIF = 1.35
Log-likelihood	−750.523	
Wald χ^2 (d.f. = 16)	51.24, p = 0.000	
Wald test of exogeneity	$\chi^2(1)$ = 9.83; Prob>χ^2 = 0.002	
Observations	595	595

IWP is measured in kg/m^3; city-level clustered standard errors are shown in parentheses; the reference region is the southern Jiangsu; ***< 0.01, **< 0.05 and *< 0.10.

Determinants of MLP adoption

Column 2 of Table 3 presents the estimated coefficients of the determinants of MLP adoption. The negative and statistically significant coefficient of the household head's age indicates that older farmers are less likely to adopt MLP. This finding echoes Brown et al. (2019), who found that older farmers are less likely to adopt new technologies in New Zealand. Compared with their younger counterparts, older farmers lack the essential human capital (e.g. knowledge and skills; Vatsa et al., 2022) and motivation (since they tend to be risk-averse; Li et al., 2020; Zheng, Ma & Li 2021) to apply new technologies, which deters them from being MLP adopters. The coefficient of the negative shock variable is negative and significant, suggesting that adversity hinders farmers from adopting MLP. This finding is understandable because negative shocks, such as member death and health deterioration, generate financial losses for farmers and reduce the affordability of MLP adoption. We find that MLP adoption is positively correlated with soil fertility. Good soil fertility can increase farmers' expected profits from rice cultivation, thereby motivating them to adopt improved agricultural practices, such as MLP. Access to irrigation has a significantly positive effect on MLP adoption. Similar to good soil fertility, irrigation access also increases expected rice yields and related income, making farmers prone to using MLP in their rice cultivation.

Both the negative shocks and pest infestation variables have positive and significant effects on MLP adoption. The findings suggest that farmers whose major rice plots experienced negative shocks (e.g. drought and flood) and pest infestation in 2020 were more likely to adopt MLP. These findings were expected. MLP adoption improves air and water permeability in soil and enhances water storage and retention capacity, thereby reducing yield losses caused by natural disasters (e.g. negative shocks and pest infestation). This finding supports the consensus that MLP is a practical risk management strategy for agricultural production (Wang et al., 2021). The estimates of our location dummies suggest that rice farmers in central Jiangsu are more likely to adopt MLP than those in southern Jiangsu. Finally, a positive and significant correlation between the city-level MLP ratio (our selected IV) and MLP adoption was observed in the empirical results. This finding demonstrates the significance of peer effects in MLP penetration, which establishes the admissibility of the IV.

Determinants of IWP

Column 3 of Table 3 presents the estimates of the IWP determinants. The estimates in this table highlight the starkly positive effect of MLP adoption on IWP. Specifically, the coefficient of MLP adoption is 0.247 and significant at the 1% level, suggesting that farmers' MLP adoption generates a 0.247 kg/m^3 increase in IWP. As discussed previously, MLP can significantly improve soil moisture and the rice root system, and increase the efficiency of irrigation water intake (Dhaliwal et al., 2022; Ding et al., 2020), leading to a considerable increase in IWP. Previous studies have focused on the role of MLP adoption in influencing agricultural intensification and efficiency (Mano et al., 2020; Reichert et al., 2014; Yu et al., 2019); this study's findings shed new light on the importance of MLP in enhancing sustainable rice production and food security via improving IWP. More importantly, compared to the application of yield-increasing inputs such as chemical fertilizers and pesticides, MLP adoption can help achieve water sustainability and food security with minimal environmental degradation. Overall, our findings have significant implications for developing countries for achieving sustainable agricultural development.

IWP is also significantly associated with the elderly ratio, asset ownership, negative shock, and farm size. Specifically, households with a high elderly ratio are more likely to have a higher IWP, which is in line with Guo et al. (2015), who find that elderly farmers who do not intend to abandon farming have a higher agricultural output than other farmers. Elderly farmers usually have rich agricultural production skills and experience (Li et al., 2020), enabling them to irrigate rice more precisely and effectively and finally gain a higher IWP. The variable for asset ownership is positively and significantly associated with IWP, suggesting that asset (i.e. car and/or air purifier) owners among rice growers tend to gain higher IWP. Asset owners are usually in good financial condition, which allows them to purchase agricultural inputs that further increase their IWP (Zou et al., 2019).

By contrast, negative shocks have a negative effect on IWP. This could be intuitive, as negative shocks may increase farmers' financial losses and directly weaken farmers' ability to afford auxiliary IWP equipment and services, consequently decreasing IWP. Farm size is another factor that drives an increase in IWP. This result parallels those of previous studies (e.g. Ganeshpa et al., 2018; Key, 2019), documenting that considerable farm size can generate considerable economies of scale. Rice farmers who cultivate large-scale farms can achieve high yields with less irrigation water consumption. As for the regional analysis, we find that rural households in northern Jiangsu are more likely to obtain a higher IWP than their counterparts in southern Jiangsu, suggesting that IWP tends to be influenced by spatial factors.

Disaggregated analysis

By machine access channels

To better understand the association between MLP adoption and IWP, we examined the dynamics of IWP by disaggregating the predictions of IWP into channels through which farm machines are accessed. Rice farmers can access farm machines through three channels: renting machines, buying machines (i.e. household-owned machines), and purchasing machinery services (i.e. outsourced machinery services; Zheng, Ma & Zhou 2021). Among these, renting machines is not common because it requires technical knowledge of machinery operations. Thus, this study considers four groups of farmers: MLP non-adopters, adopters using household-owned machines, adopters using outsourced machinery services, and adopters using both household-owned machines and outsourced machinery services.

Table 4 presents a disaggregated analysis of how MLP is accessed. The findings show that the predicted IWPs for all three categories of farmers' access to MLP are significantly higher than those for MLP non-adopters. This finding confirms the positive and significant correlation between MLP adoption and IWP from a more detailed perspective. Nevertheless, the 95% confidence intervals overlapped for the three categories of MLP access, suggesting no significant differences in the predicted IWPs within these categories. Therefore, a higher IWP is determined by whether farmers adopt MLP, rather than the channel through which they access farm machines.

Table 4. Disaggregated analysis: how the mechanization in land preparation (MLP) is accessed.

Category	Predicted IWP	95% Confidence interval
MLP non-adopters	0.436	[0.419, 0.452]
Via only household-owned machines	0.686	[0.659, 0.712]
Via only outsourcing machinery services	0.664	[0.652, 0.675]
Via both household-owned machines and outsourcing services	0.660	[0.616, 0.704]

Irrigation water productivity (IWP) is measured in kg/m^3.

By the distributions of IWP

We further explore how MLP adoption affects the distribution of the dependent variable, IWP. To achieve this goal, we use an instrumental variable-based quantile regression (IVQR) model (Kwak, 2009; Nguyen et al., 2022). Relying on a valid IV (i.e. the city-level MLP ratio in Table 1), the IVQR model addresses endogeneity issues associated with MLP adoption (Chang et al., 2018; Ma & Zheng, 2022). The IVQR model excludes the endogeneity issues derived from the correlation between MLP adoption and the rank variable (also known as disturbance; Sanglestsawai et al., 2014), thereby generating the unbiased effect of MLP adoption on IWP. The IVQR model estimates offer a more meticulous observation of the correlation between MLP adoption and IWP than the mean-based results in Table 3. For simplicity and intuitive understanding, we only graphically demonstrated the effect of MLP adoption on IWP at the 20th, 40th, 50th, 60th and 80th quantiles.

The results (Figure 2) show that the estimated coefficients are statistically significant, at least at the 10% level, across the selected quantiles (t-value > 1.7), confirming a positive relationship between MLP adoption and IWP. In addition, the effects of MLP adoption on IWP are monotonically increasing across the selected quantiles, ranging from 0.43 kg/m^3 at the lowest 20th quantile to 0.56 kg/m^3 at the highest 80th quantile. These results imply that farmers with higher IWP tend to possess good agricultural production conditions, such as high-quality inputs, improved technologies and good irrigation access, which

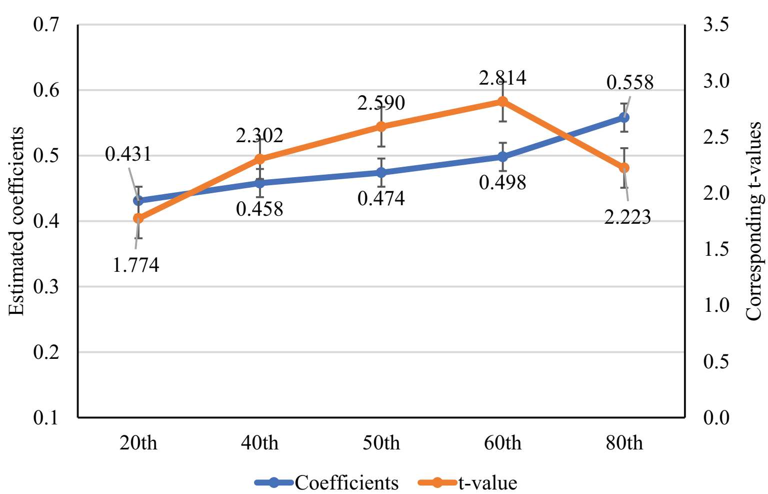

Figure 2. Impact of mechanization in land preparation (MLP) adoption on irrigation water productivity (IWP) at the selected quantiles: instrumental variable-based quantile regression (IVQR) model estimates.

complement MLP application and, therefore, amplify the effect of MLP adoption on IWP. Generally, this finding implies that the realization of positive feedback between MLP application and IWP depends predominantly on the coordinated improvement of agricultural production conditions.

Robustness check

To confirm the robustness of our main empirical results in Table 3, we follow Li et al. (2020, 2023) and Zheng and Ma (2021) to estimate the effect of MLP adoption on IWP using the AIPW and IPWRA approaches. The results are presented in Table A2 in the supplemental data online. The average treatment effects estimated using the AIPW and IPWRA approaches are positive and statistically significant at the 5% significance level. These findings suggest that MLP adoption increases the IWP of rice production significantly, supporting the robustness of the main empirical results derived from the ETR model.

Conclusions and implications

The ongoing fight to end hunger reminds us to intensify efforts to ensure food stability and security. Across the globe and in China, water scarcity exacerbates the precarious situation of food production, leaving the food supply unsafe. Therefore, practical strategies for alleviating water scarcity are urgently needed to guarantee food security and conquer hunger. This study contributed to the literature by investigating how and to what extent MLP can help improve IWP. We employed the ETR model to address the endogeneity issue of MLP adoption and estimate the data collected from rice farmers in Jiangsu province, China. In addition, we estimated the AIPW and IPWRA models for robustness check.

The empirical results of the ETR model estimates showed that MLP adoption significantly increased IWP. The estimates of the AIPW and IPWRA models verified the findings of the positive relationship between MLP adoption and IWP. We further found that rice growers' MLP adoption is positively and significantly associated with soil fertility, irrigation access, negative shocks, and pest infestation experiences, whereas it is negatively and significantly associated with the household head's age and negative shock experiences. IWP tended to be positively and significantly affected by asset ownership and farm size, whereas it was negatively and significantly influenced by negative shock experiences. Rural households usually have three ways to access machines: household-owned machines, outsourcing machinery services, and both household-owned machines and outsourcing services. The disaggregated analysis by how MLP is accessed suggested that the IWPs for all MLP access methods are significantly higher than those for MLP non-adopters, and the IWP does not vary across the MLP access channels. Moreover, the results estimated using the IVQR model indicated that the effect of MLP adoption on IWP increases monotonically across the selected quantiles.

Our findings have important policy implications. The finding that MLP significantly increases IWP highlights the importance of government efforts in supporting the adoption of MLP among smallholder farmers to help address irrigation water sustainability and improve food security. To promote MLP adoption, the government should consider providing farmers with agricultural machinery purchasing subsidies to support their adoption of MLP in crop production. Helping establish agricultural machinery cooperatives at the village level could be a practical pathway in helping link smallholder farmers to outsourced machinery services. Besides, the government, especially the MWRC, should allocate more funds to further promote the construction of irrigation infrastructure in rural areas. In consideration of the increasing water scarcity issues, the development of water-saving irrigation infrastructure, such as drip irrigation facilities and sprinkler irrigation systems, should be at the top of the agenda. Because the existing irrigation infrastructure needs necessary maintenance, rural China must establish a dedicated team composed of villagers and village committees to take over the responsibility of the maintenance tasks. Relative to Southern Jiangsu, rice farmers in Central Jiangsu are more likely to adopt MLP while those in Northern Jiangsu receive a higher IWP. Therefore, the government should consider regional differences when making investment decisions and designing policy instruments to support agricultural development sustainably.

Our study highlights the significance of MLP in enhancing the IWP in rice production. This could be particularly important for improving food security in light of water scarcity. However, our study may still suffer from limitations induced by the absence of some climate variables such as rainfall and the frequency of extreme temperatures. The 2021 CLES data provide very limited information on climate characteristics, restricting our ability to appropriately control the influence of climate change on IWP. Therefore, future efforts should be devoted to collecting climate information when exploring the factors influencing IWP. Another limitation is that our findings were developed from a cross-sectional data analysis, which could not capture the dynamic effects of MLP adoption on IWP. This is another interesting area to explore when panel data are available.

Acknowledgments

The authors gratefully acknowledge the Asian Development Bank Institute (ADBI) Virtual Conference on “Water Resource Management for Achieving Food Security in Asia Under Climate Change” held from October 26-27, 2022.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

The authors gratefully acknowledge the financial support from the National Natural Science Foundation of China [project number 72103075] and the Jiangsu Provincial Department of Education [project number 2020SJA1763].

ORCID

Junpeng Li http://orcid.org/0000-0001-8163-3376
Wanglin Ma http://orcid.org/0000-0001-7847-8459
Julio Cesar Botero-R http://orcid.org/0000-0002-0700-8748

Data availability statement

The data that support the findings of this study are available from Wanglin Ma upon reasonable request.

References

Aghapour Sabbaghi, M., Nazari, M., Araghinejad, S., & Soufizadeh, S. (2020). Economic impacts of climate change on water resources and agriculture in Zayandehroud river basin in Iran. *Agricultural Water Management*, *241*(May 2019), 106323. https://doi.org/10.1016/j.agwat.2020.106323

Alvez, A., Aitken, D., Rivera, D., Vergara, M., McIntyre, N., & Concha, F. (2020). At the crossroads: Can desalination be a suitable public policy solution to address water scarcity in Chile's mining zones? *Journal of Environmental Management*, *258*(December 2019), 110039. https://doi.org/10.1016/j.jenvman.2019.110039

Brar, H. S., & Vashist, K. K. (2020). Drip irrigation and nitrogen fertilization alter phenological development and yield of spring maize (Zea mays L.) under semi-arid conditions. *Journal of Plant Nutrition*, *43*(12), 1757–1767. https://doi.org/10.1080/01904167.2020.1744648

Brown, L. R. (1995). *Who will feed China?: Wake-up call for a small planet*. WW Norton.

Brown, P., Daigneault, A., & Dawson, J. (2019). Age, values, farming objectives, past management decisions, and future intentions in New Zealand agriculture. *Journal of Environmental Management*, *231*, 110–120. https://doi.org/10.1016/J.JENVMAN.2018.10.018

Cao, X., Zeng, W., Wu, M., Guo, X., & Wang, W. (2020). Hybrid analytical framework for regional agricultural water resource utilization and efficiency evaluation. *Agricultural Water Management*, *231*(January), 106027. https://doi.org/10.1016/j.agwat.2020.106027

Carpena, F. (2019). How do droughts impact household food consumption and nutritional intake? A study of rural India. *World Development*, *122*, 349–369. https://doi.org/10.1016/j.worlddev.2019.06.005

Carracelas, G., Hornbuckle, J., Rosas, J., & Roel, A. (2019). Irrigation management strategies to increase water productivity in Oryza sativa (rice) in Uruguay. *Agricultural Water Management*, *222*(March), 161–172. https://doi.org/10.1016/j.agwat.2019.05.049

CESY. (2021). *China energy statistical yearbook 2020*. China Statistics Press.

Çetin, O., & Kara, A. (2019). Assessment of water productivity using different drip irrigation systems for cotton. *Agricultural Water Management*, *223*(May), 105693. https://doi.org/10.1016/j.agwat.2019.105693

Chang, C.-P., Wen, J., Dong, M., & Hao, Y. (2018). Does government ideology affect environmental pollutions? New evidence from instrumental variable quantile regression estimations. *Energy Policy*, *113*, 386–400. https://doi.org/10.1016/j.enpol.2017.11.021

Chen, L., Chang, J., Wang, Y., Guo, A., Liu, Y., Wang, Q., Zhu, Y., Zhang, Y., & Xie, Z. (2021). Disclosing the future food security risk of China based on crop production and water scarcity under diverse socioeconomic and climate scenarios. *Science of the Total Environment*, *790*, 148110. https://doi.org/10.1016/j.scitotenv.2021.148110

Chigusiwa, L., Kembo, G., & Kairiza, T. (2022). Drought and social conflict in rural Zimbabwe: Does the burden fall on women and girls? *Review of Development Economics, September*. https://doi.org/10.1111/rode.12944

Choudhary, M., Panday, S. C., Meena, V. S., Singh, S., Yadav, R. P., Pattanayak, A., Mahanta, D., Bisht, J. K., & Stanley, J. (2020). Long-term tillage and irrigation management practices: Strategies to enhance crop and water productivity under rice–wheat rotation of Indian mid-Himalayan Region. *Agricultural Water Management*, *232*(May 2018), 106067. https://doi.org/10.1016/j.agwat.2020.106067

Comas, L. H., Trout, T. J., DeJonge, K. C., Zhang, H., & Gleason, S. M. (2019). Water productivity under strategic growth stage-based deficit irrigation in maize. *Agricultural Water Management*, *212*(November 2017), 433–440. https://doi.org/10.1016/j.agwat.2018.07.015

Craney, T. A., & Surles, J. G. (2002). Model-dependent variance inflation factor cutoff values. *Quality Engineering*, *14*(3), 391–403. https://doi.org/10.1081/QEN-120001878

Daghagh Yazd, S., Wheeler, S. A., & Zuo, A. (2020). Understanding the impacts of water scarcity and socio-economic demographics on farmer mental health in the Murray–Darling Basin'. *Ecological Economics*, *169*(February 2019), 106564. https://doi.org/10.1016/j.ecolecon.2019.106564

Dhaliwal, J., Kahlon, M. S., & Kukal, S. S. (2022). Deep tillage and irrigation impact on soil water balance and water productivity of maize–wheat cropping system in north-west India. *Archives of Agronomy and Soil Science*, *68*(2), 166–179. https://doi.org/10.1080/03650340.2020.1827235

Dietz, K. J., Zörb, C., & Geilfus, C. M. (2021). Drought and crop yield. *Plant Biology*, *23*(6), 881–893. https://doi.org/10.1111/plb.13304

Ding, Z., Ali, E. F., Elmahdy, A. M., Ragab, K. E., Seleiman, M. F., & Kheir, A. M. S. (2021). Modeling the combined impacts of deficit irrigation, rising temperature and compost application on wheat yield and water productivity. *Agricultural Water Management*, *244*(November 2020), 106626. https://doi.org/10.1016/j.agwat.2020.106626

Ding, J., Hu, W., Wu, J., Yang, Y., & Feng, H. (2020). Simulating the effects of conventional versus conservation tillage on soil water, nitrogen dynamics, and yield of winter wheat with RZWQM2. *Agricultural Water Management*, *230*(December 2019), 105956. https://doi.org/10.1016/j.agwat.2019.105956

dos Santos, P. S., Becker, K. L., & de Oliveira, S. V. (2023). Race-based affirmative action for higher education in Brazil: Impact assessment on performance, time, and delay in completion. *Review of Development Economics*, *27*(1), 247–267. https://doi.org/10.1111/rode.12923

Douglas, I. (2017). Ecosystems and human well-being. In *Encyclopedia of the Anthropocene* (Vol. 4, pp. 185–197). Island Press. https://doi.org/10.1016/B978-0-12-809665-9.09206-5

Elliott, J., Deryng, D., Müller, C., Frieler, K., Konzmann, M., Gerten, D., Glotter, M., Flörke, M., Wada, Y., Best, N., Eisner, S., Fekete, B. M., Folberth, C., Foster, I., Gosling, S. N., Haddeland, I., Khabarov, N., Ludwig, F., Masaki, Y., . . . Wisser, D. (2014). Constraints and potentials of future irrigation water availability on agricultural production under climate change. *Proceedings of the National Academy of Sciences*, *111*(9), 3239–3244. https://doi.org/10.1073/pnas.1222474110

Ferguson, C. R., Pan, M., & Oki, T. (2018). The effect of global warming on future water availability: CMIP5 synthesis. *Water Resources Research*, *54*(10), 7791–7819. https://doi.org/10.1029/2018WR022792

Ganeshpa, T., Kumar, A., Roy, D., & Joshi, P. K. (2018). Impact of crop diversification on rural poverty in Nepal. *Canadian Journal of Agricultural Economics*, *66*(3). https://doi.org/10.1111/cjag.12160

Guo, G., Wen, Q., & Zhu, J. (2015). The impact of aging agricultural labor population on farmland output: From the perspective of farmer preferences. *Mathematical Problems in Engineering*, *2015*, 1–7. https://doi.org/10.1155/2015/730618

Gupta, A., Rico-Medina, A., & Caño-Delgado, A. I. (2020). The physiology of plant responses to drought. *Science*, *368*(6488), 266–269. https://doi.org/10.1126/science.aaz7614

He, G., Wang, Z., & Cui, Z. (2020). Managing irrigation water for sustainable rice production in China. *Journal of Cleaner Production*, *245*, 118928. https://doi.org/10.1016/j.jclepro.2019.118928

Hristov, J., Barreiro-Hurle, J., Salputra, G., Blanco, M., & Witzke, P. (2021). Reuse of treated water in European agriculture: Potential to address water scarcity under climate change. *Agricultural Water Management*, *251*(January 2020), 106872. https://doi.org/10.1016/j.agwat.2021.106872

Huang, Y., Liu, Q., Jia, W., Yan, C., & Wang, J. (2020). Agricultural plastic mulching as a source of microplastics in the terrestrial environment. *Environmental Pollution*, *260*, 114096. https://doi.org/10.1016/j.envpol.2020.114096

Huang, Z., Liu, X., Sun, S., Tang, Y., Yuan, X., & Tang, Q. (2021). Global assessment of future sectoral water scarcity under adaptive inner-basin water allocation measures. *Science of the Total Environment*, *783*, 146973. https://doi.org/10.1016/j.scitotenv.2021.146973

Huang, Y., Tao, B., Xiaochen, Z., Yang, Y., Liang, L., Wang, L., Jacinthe, P. A., Tian, H., & Ren, W. (2021). Conservation tillage increases corn and soybean water productivity across the Ohio River Basin. *Agricultural Water Management*, *254*, 106962. https://doi.org/10.1016/j.agwat.2021.106962

Huang, Z., Yuan, X., & Liu, X. (2021). The key drivers for the changes in global water scarcity: Water withdrawal versus water availability. *Journal of Hydrology*, *601*(June), 126658. https://doi.org/10.1016/j.jhydrol.2021.126658

Jing, Q., McConkey, B., Qian, B., Smith, W., Grant, B., Shang, J., Liu, J., Bindraban, P., & Luce, M. S. (2021). Assessing water management effects on spring wheat yield in the Canadian Prairies using DSSAT wheat models. *Agricultural Water Management*, *244*(November 2020), 106591. https://doi.org/10.1016/j.agwat.2020.106591

Jones, E., & van Vliet, M. T. H. (2018). Drought impacts on river salinity in the southern US: Implications for water scarcity. *Science of the Total Environment*, *644*, 844–853. https://doi.org/10.1016/j.scitotenv.2018.06.373

Kang, S., Hao, X., Du, T., Tong, L., Su, X., Lu, H., Li, X., Huo, Z., Li, S., & Ding, R. (2017). Improving agricultural water productivity to ensure food security in China under changing environment: From research to practice. *Agricultural Water Management*, *179*, 5–17. https://doi.org/10.1016/j.agwat.2016.05.007

Key, N. (2019). Farm size and productivity growth in the United States Corn Belt. *Food Policy*, *84* (March), 186–195. https://doi.org/10.1016/j.foodpol.2018.03.017

Kistner, E., Kellner, O., Andresen, J., Todey, D., & Morton, L. W. (2018). Vulnerability of specialty crops to short-term climatic variability and adaptation strategies in the Midwestern USA. *Climatic Change*, *146*(1–2), 145–158. https://doi.org/10.1007/s10584-017-2066-1

Kukal, S. S., Yadvinder-Singh, Jat, M. L., & Sidhu, H. S. (2014). Improving water productivity of wheat-based cropping systems in South Asia for sustained productivity. In *Advances in Agronomy* (Vol. 127, pp. 157–258). Elsevier. https://doi.org/10.1016/B978-0-12-800131-8.00004-2

Kurz, C. F. (2021). Augmented inverse probability weighting and the double robustness property. *Medical Decision Making*, 1–12. https://doi.org/10.1177/0272989X211027181

Kwak, D. W. (2009). Instrumental variable quantile regression method for endogenous treatment effect. *The Stata Journal*, *401*(ii), 1–30.

Li, J., Ma, W., Renwick, A., & Zheng, H. (2020). The impact of access to irrigation on rural incomes and diversification: Evidence from China. *China Agricultural Economic Review*, *12*(4), 705–725. https://doi.org/10.1108/CAER-09-2019-0172

Li, J., Ma, W., Wang, P., & Meng, X. (2023). Farmers' willingness to transform untreated livestock manure into organic fertilizer: Does information technology adoption make a difference? *Environment, Development and Sustainability*, *0123456789*. https://doi.org/10.1007/s10668-023-02920-y

Li, H., Mei, X., Wang, J., Huang, F., Hao, W., & Li, B. (2021). Drip fertigation significantly increased crop yield, water productivity and nitrogen use efficiency with respect to traditional irrigation and fertilization practices: A meta-analysis in China. *Agricultural Water Management*, *244*(September 2020), 106534. https://doi.org/10.1016/j.agwat.2020.106534

Lin, Y., Hu, R., Zhang, C., & Chen, K. (2022). The role of public agricultural extension services in driving fertilizer use in rice production in China. *Ecological Economics*, *200*(September 2021), 107513. https://doi.org/10.1016/j.ecolecon.2022.107513

Liu, M., Min, S., Ma, W., & Liu, T. (2021). The adoption and impact of e-commerce in rural China: Application of an endogenous switching regression model. *Journal of Rural Studies*, *83*, 106–116. https://doi.org/10.1016/j.jrurstud.2021.02.021

Liu, Y., Zhang, X., Xi, L., Liao, Y., & Han, J. (2020). Ridge–furrow planting promotes wheat grain yield and water productivity in the irrigated sub-humid region of China. *Agricultural Water Management*, *231*(December 2018), 105935. https://doi.org/10.1016/j.agwat.2019.105935

Li, J., Vatsa, P., & Ma, W. (2023). Small acts with big impacts: Does garbage classification improve subjective well-being in rural China? *Applied Research in Quality of Life*, *0123456789*. https://doi.org/10.1007/s11482-022-10142-z

Ma, W., Grafton, R. Q., & Renwick, A. (2020). Smartphone use and income growth in rural China: Empirical results and policy implications. *Electronic Commerce Research*, *20*(4), 713–736. https://doi.org/10.1007/s10660-018-9323-x

Ma, W., Nie, P., Zhang, P., & Renwick, A. (2020). Impact of Internet use on economic well-being of rural households: Evidence from China. *Review of Development Economics*, *24*(2), 503–523. https://doi.org/10.1111/rode.12645

Mano, Y., Takahashi, K., & Otsuka, K. (2020). Mechanization in land preparation and agricultural intensification: The case of rice farming in the Cote d'Ivoire. *Agricultural Economics*, *51*(6), 899–908. https://doi.org/10.1111/agec.12599

Martínez-Domínguez, M., & Mora-Rivera, J. (2020). Internet adoption and usage patterns in rural Mexico. *Technology in Society*, *60*, 101226. https://doi.org/10.1016/j.techsoc.2019.101226

Ma, W., & Zheng, H. (2022). Heterogeneous impacts of information technology adoption on pesticide and fertiliser expenditures: Evidence from wheat farmers in China*. *Australian Journal of Agricultural and Resource Economics*, *66*(1), 72–92. https://doi.org/10.1111/1467-8489.12446

MWRC. (2020). *China Water Statistical Yearbook 2020*. China Water & Power Press.

Nguyen, T. T., Nguyen, T. T., & Grote, U. (2022). Internet use, natural resource extraction and poverty reduction in rural Thailand. *Ecological Economics*, *196*(February), 107417. https://doi.org/10.1016/j.ecolecon.2022.107417

Omer, A., Elagib, N. A., Zhuguo, M., Saleem, F., & Mohammed, A. (2020). Water scarcity in the Yellow River Basin under future climate change and human activities. *Science of the Total Environment*, *749*, 141446. https://doi.org/10.1016/j.scitotenv.2020.141446

Pakmehr, S., Yazdanpanah, M., & Baradaran, M. (2021). Explaining farmers' response to climate change-induced water stress through cognitive theory of stress: An Iranian perspective. *Environment, Development and Sustainability*, *23*(4), 5776–5793. https://doi.org/10.1007/s10668-020-00846-3

Parthasarathi, T., Vanitha, K., Mohandass, S., & Vered, E. (2018). Evaluation of drip irrigation system for water productivity and yield of rice. *Agronomy Journal*, *110*(6), 2378–2389. https://doi.org/10.2134/agronj2018.01.0002

Paudel, G. P., Kc, D. B., Rahut, D. B., Justice, S. E., & McDonald, A. J. (2019). Scale-appropriate mechanization impacts on productivity among smallholders: Evidence from rice systems in the mid-hills of Nepal. *Land Use Policy*, *85*(October 2018), 104–113. https://doi.org/10.1016/j.landusepol.2019.03.030

Qiu, T., He, Q., & Luo, B. (2021). Does land renting-out increase farmers' subjective well-being? Evidence from rural China. *Applied Economics*, *53*(18), 2080–2092. https://doi.org/10.1080/00036846.2020.1855315

Reichert, J. M., Bervald, C. M. P., Rodrigues, M. F., Kato, O. R., & Reinert, D. J. (2014). Mechanized land preparation in eastern Amazon in fire-free forest-based fallow systems as alternatives to slash. *Agriculture, Ecosystems and Environment*, *192*, 47–60. https://doi.org/10.1016/j.agee.2014.03.046

Rivera, D., Godoy-Faúndez, A., Lillo, M., Alvez, A., Delgado, V., Gonzalo-Martín, C., Menasalvas, E., Costumero, R., & García-Pedrero, Á. (2016). Legal disputes as a proxy for regional conflicts over water rights in Chile. *Journal of Hydrology*, *535*, 36–45. https://doi.org/10.1016/j.jhydrol.2016.01.057

Sánchez, J. A., Reca, J., & Martínez, J. (2015). Water productivity in a Mediterranean semi-arid greenhouse district. *Water Resources Management*, *29*(14), 5395–5411. https://doi.org/10.1007/s11269-015-1125-5

Sanglestsawai, S., Rejesus, R. M., & Yorobe, J. M. (2014). Do lower yielding farmers benefit from Bt cornα evidence from instrumental variable quantile regressions. *Food Policy*, *44*(January), 285–296. https://doi.org/10.1016/j.foodpol.2013.09.011

Silalertruksa, T., & Gheewala, S. H. (2018). Land–water–energy nexus of sugarcane production in Thailand. *Journal of Cleaner Production*, *182*, 521–528. https://doi.org/10.1016/j.jclepro.2018.02.085

Surendran, U., Raja, P., Jayakumar, M., & Subramoniam, S. R. (2021). Use of efficient water saving techniques for production of rice in India under climate change scenario: A critical review. *Journal of Cleaner Production*, *309*(July 2020), 127272. https://doi.org/10.1016/j.jclepro.2021.127272

Suresh, K., Khanal, U., Wilson, C., Managi, S., Quayle, A., & Santhirakumar, S. (2021). An economic analysis of agricultural adaptation to climate change impacts in Sri Lanka: An endogenous switching regression analysis. *Land Use Policy*, *109*(June), 105601. https://doi.org/10.1016/j.landusepol.2021.105601

UNDP. (2022). *The SDGs in action – Goal 2 – No hunger*. Sustainable Development Goals.

Vatsa, P., Li, J., Luu, P. Q., & Botero-R, J. C. (2022). Internet use and consumption diversity: Evidence from rural China. *Review of Development Economics, August*, 1–22. https://doi.org/10.1111/rode.12935

Wang, Y., & Hao, F. (2020). Public perception matters: Individual waste sorting in Chinese communities. *Resources, Conservation and Recycling*, *159*(April), 104860. https://doi.org/10.1016/j.resconrec.2020.104860

Wang, J., Zhang, Z., & Liu, Y. (2018). Spatial shifts in grain production increases in China and implications for food security. *Land Use Policy*, *74*, 204–213. https://doi.org/10.1016/j.landusepol.2017.11.037

Wang, C., Zhao, J., Feng, Y., Shang, M., Bo, X., Gao, Z., Chen, F., & Chu, Q. (2021). Optimizing tillage method and irrigation schedule for greenhouse gas mitigation, yield improvement, and water conservation in wheat–maize cropping systems. *Agricultural Water Management*, *248*(November 2020), 106762. https://doi.org/10.1016/j.agwat.2021.106762

Weligamage, P., Shumway, C. R., & Blatner, K. A. (2014). Water access, farm productivity, and farm household income: Sri Lanka's Kirindi Oya irrigation system. *Agricultural Economics*, *45*(5), 649–661. https://doi.org/10.1111/agec.12113

Wen, L., Paudel, K. P., Chen, Y., & He, Q. (2021). Urban segregation and consumption inequality: Does hukou conversion matter in China? *Review of Development Economics*, *25*(4), 2298–2322. https://doi.org/10.1111/rode.12805

Yang, X., Zheng, L., Yang, Q., Wang, Z., Cui, S., & Shen, Y. (2018). Modelling the effects of conservation tillage on crop water productivity, soil water dynamics and evapotranspiration of a maize–winter wheat–soybean rotation system on the Loess Plateau of China using APSIM. *Agricultural Systems*, *166*(January), 111–123. https://doi.org/10.1016/j.agsy.2018.08.005

Yin, J., Guo, S., Gentine, P., Sullivan, S. C., Gu, L., He, S., Chen, J., & Liu, P. (2021). Does the hook structure constrain future flood intensification under anthropogenic climate warming? *Water Resources Research*, *57*(2). https://doi.org/10.1029/2020WR028491

Yu, J., Long, A., Deng, X., He, X., Zhang, P., Wang, J., & Hai, Y. (2020). Incorporating the red jujube water footprint and economic water productivity into sustainable integrated management policy. *Journal of Environmental Management*, *269*(September 2019), 110828. https://doi.org/10.1016/j.jenvman.2020.110828

Yu, Y., Wei, W., Chen, L., Feng, T., & Stefani, D. (2019). Quantifying the effects of precipitation, vegetation, and land preparation techniques on runoff and soil erosion in a Loess watershed of China. *Science of the Total Environment*, *652*(18), 755–764. https://doi.org/10.1016/j.scitotenv.2018.10.255

Zhang, J., Mishra, A. K., & Zhu, P. (2021). Land rental markets and labor productivity: Evidence from rural China. *Canadian Journal of Agricultural Economics*, *69*(1), 93–115. https://doi.org/10.1111/cjag.12247

Zhang, S., Wang, H., Sun, X., Fan, J., Zhang, F., Zheng, J., & Li, Y. (2021). Effects of farming practices on yield and crop water productivity of wheat, maize and potato in China: A meta-analysis. *Agricultural Water Management*, *243*(December2019), 106444. https://doi.org/10.1016/j.agwat.2020.106444

Zheng, J., Fan, J., Zhang, F., Guo, J., Yan, S., Zhuang, Q., Cui, N., & Guo, L. (2021). Interactive effects of mulching practice and nitrogen rate on grain yield, water productivity, fertilizer use efficiency and greenhouse gas emissions of rainfed summer maize in northwest China. *Agricultural Water Management*, *248*(October 2020), 106778. https://doi.org/10.1016/j.agwat.2021.106778

Zheng, H., & Ma, W. (2021). Smartphone-based information acquisition and wheat farm performance: Insights from a doubly robust IPWRA estimator. *Electronic Commerce Research*, *0123456789*. https://doi.org/10.1007/s10660-021-09481-0

Zheng, H., Ma, W., & Li, G. (2021). Learning from neighboring farmers: Does spatial dependence affect adoption of drought-tolerant wheat varieties in China? *Canadian Journal of Agricultural Economics*, *69*(4), 519–537. https://doi.org/10.1111/cjag.12294

Zheng, H., Ma, W., & Zhou, X. (2021). Renting-in cropland, machinery use intensity, and land productivity in rural China. *Applied Economics*, *53*(47), 5503–5517. https://doi.org/10.1080/00036846.2021.1923642

Zheng, H., Shao, R., Xue, Y., Ying, H., Yin, Y., Cui, Z., & Yang, Q. H. (2020). Water productivity of irrigated maize production systems in Northern China: A meta-analysis. *Agricultural Water Management*, *234*(July 2019), 106119. https://doi.org/10.1016/j.agwat.2020.106119

Zhu, Z., Ma, W., Sousa-Poza, A., & Leng, C. (2020). The effect of internet usage on perceptions of social fairness: Evidence from rural China. *China Economic Review*, *62*(May), 101508. https://doi.org/10.1016/j.chieco.2020.101508

Zou, B., Mishra, A. K., & Luo, B. (2019). Grain subsidy, off-farm labor supply and farmland leasing: Evidence from China. *China Economic Review, May*, *2018*, 1–16. https://doi.org/10.1016/j.chieco.2019.04.001

Zucchinelli, M., Spinelli, R., Corrado, S., & Lamastra, L. (2021). Evaluation of the influence on water consumption and water scarcity of different healthy diet scenarios. *Journal of Environmental Management*, *291*(December 2020), 112687. https://doi.org/10.1016/j.jenvman.2021.112687