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REVIEW

Adaptive irrigation measures in response to extreme weather events: empirical evidence from the North China plain

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Abstract
Growing evidence indicates that climate change will exacerbate the intensity and frequency of extreme weather events, particularly drought. The North China plain is an important agricultural production region that is subject to a significant shortage of water and is often hit by extreme weather events, particularly drought. Therefore, this study aims to examine how farmers in the North China plain take adaptive irrigation measures in response to drought, the determinants, and the effectiveness of their responses. The results show that, when confronted by severe drought, farmers change their irrigation practices by enhancing the intensity and increasing the efficiency of the irrigation to mitigate the negative effects of such drought. Factors such as the local irrigation infrastructure; provision of physical, financial, and technical policy support; and early-warning information services are of significant help to farmers in taking adaptive measures. Further analysis shows that such adaptive response significantly mitigates yield loss and reduces the risk of crop failure. The paper concludes with some policy implications.

Keywords Adaptive irrigation measures · Determinants · Drought · Effectiveness · North China plain

Introduction

Growing evidence indicates that climate change will exacerbate the intensity and frequency of extreme weather events, particularly drought. The total global area subject to drought will expand by 15 to 44% from now until the end of the twenty-first century (Intergovernmental Panel on Climate Change 2012). In China, the proportion of severely damaged land (yield loss of at least 30%) to drought-hit land (yield loss of at least 10%) increased from 34% in the 1950s to 46% in the 1990s and 58% in the first 10 years of this century. As one of the most important agricultural production regions in China, the North China plain (NCP) is subject to a significant shortage of water and is often hit by extreme weather events, particularly drought (Shiau et al. 2007; Yang et al. 2016). In 2015, 75% of China's wheat, 32% of its maize, and 19% of its rice were supplied by the farmlands of the NCP (National Bureau of Statistics of the People's Republic of China 2016). Water availability in the NCP is only 1/7 of the national average per capita, but their agricultural production mainly depends on irrigation (Ministry of Water Resources of the People's Republic of China 2016). Moreover, both surface and groundwater supply in the NCP has declined significantly over the past 50 years, with climate change expected to further strain the water supply in the future (Wang et al. 2013). In view of such conditions, it is not surprising that the NCP is often subject to periods of drought. Over the past three decades (1980–2015), approximately 7.4 million ha of the crop areas in the NCP on average annually (approximately 20% of the crop areas per year) have been subject to severe droughts (Ministry of Water Resources of the People's Republic of China 2016).

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In recent years, adaptation to climate change has captured the attention of numerous scholars. As farmers are the direct stakeholders subject to the consequences of climate change as well as the practitioners making adaptation decisions, analyzing farmers' adaptive behavior is crucial in designing adaptation policies (Lansigan et al. 2007). Currently, this analysis mainly focuses on three issues: the adoption status of adaptation measures, determinants of adopting adaptation measures, and effectiveness of adaptation measures in mitigating the effects. A growing body of literature indicates that scholars have started to conduct empirical studies to examine the adoption status and determinants of adaptation measures (Chen et al. 2014; Deressa et al. 2009; Di Falco et al. 2011; Wang et al. 2015; Burnham and Ma 2016). However, empirical studies seldom assess the effectiveness of such measures, and, notably, integrated empirical analyses of the determinants and effectiveness of adaptation measures are even scarcer (Di Falco et al. 2011; Huang et al. 2015). Furthermore, most existing studies on assessing the effectiveness of adaptation measures are based on simulation models that contain various assumptions on the key parameters (Wu et al. 2014; Tao et al. 2009; Xiong et al. 2004). In an attempt to sustain the development of agricultural production and mitigate the effects of climate change in the NCP, answers need to be found to various questions. These are the following: how do farmers adjust their irrigation behavior to counteract the risk of drought? What are the main factors in the irrigation behavior of farmers? How effective is adjusting irrigation behavior to improve crop productivity and reduce climate risks? In other words, to what extent can the adaptive measures reduce the risk of yield loss and yield variability in the areas suffering from drought? Obtaining valid answers to these questions is crucial to providing empirical evidence for policymakers in the formulation of adaptation plans related to extreme weather events.

The overall aim of this paper is to answer the research questions, examine in what way farmers have made adaptive irrigation responses to drought, and identify the determinants and evaluate the effectiveness of such a response in the NCP. To realize this goal, the following objectives were specified: (i) examine the occurrence of severe drought in the NCP and the farmers' adaptive irrigation responses, (ii) identify the major factors influencing the farmers' decisions on adaptive responses, and (iii) assess the effectiveness of the adaptive irrigation measures to lower the risk of yield loss and yield variability. As wheat is a major crop in China, and as 75% of the wheat is produced in the NCP, wheat farmers are chosen as the focus of our analysis.

The rest of this paper is organized as follows. The next section briefly introduces the data and sampling methods used in this study. In "Extreme drought events and adaptive irrigation measures"section, we discuss the occurrence of severe drought and the farmers' adaptive irrigation measures. In "Determinants and effectiveness of adaptive irrigation measures against drought" section, by employing the descriptive statistical analysis approach, we analyze the main factors in irrigation adaptation and their effectiveness in lowering the risk of yield loss. In "Econometric models and estimation results" section, we apply econometric models to further explore the determinants and effectiveness of adaptive irrigation measures. The policy implications of our findings are presented in "Estimation results of the econometric model" section.

Data and sampling method

The data used in this study were based on the results of a large-scale survey of households and villages that was conducted in nine provinces of China from the end of 2012 to early 2013. These nine provinces include Hebei, Henan, Shandong, Jiangsu, Anhui, and Jilin in northern China, and Jiangxi, Guangdong, and Yunnan in southern China. Of these nine provinces, five provinces (Hebei, Henan, Shandong, Jiangsu, and Anhui) are located in the NCP, and the relevant data were employed in this study (Fig. 1). The NCP also includes Beijing and Tianjin; however, the above-mentioned five provinces produced 99% of the wheat in the NCP and 75% of the total wheat production in China in 2012 (National Bureau of Statistics of the People's Republic of China 2016).

The following strategies were used during the survey for the sample design and selection in each province. First, in view of the socioeconomic losses from disasters (droughts or floods) and based on interviews with local officials (officials from the meteorological, water, and agricultural bureaus), we divided the years into three types: severe disaster, moderate disaster, and normal years (including slight disaster or absolute normal years).[1] Second, three counties in each province were selected randomly from those counties that had experienced a disaster year with severe droughts or flooding and a normal year without severe or moderate disasters over the past 3 years (2010–2012). In this way, by collecting the data for a year with extreme weather events and for a normal year, we could identify the effects of extreme weather as well as any adaptation differences between these 2 years. The selection of these counties was possible because there were approximately 100 counties in each province and at least 20% of these had experienced a severe drought or flood during the past 3 years.

Subsequently, stratified random sampling was used to select three townships from each selected county and three villages from each selected township. The townships were

[1] According to China's national standard for natural disasters (CMA 2004), the severity of a drought or flood has four categories: most severe, severe, moderate, and small. In our survey, the term "normal year" is relative and describes an average year with no more than moderate (natural disaster level 3) weather events; the term "severe drought year" refers to a most severe or severe drought (natural disaster levels 1 and 2).

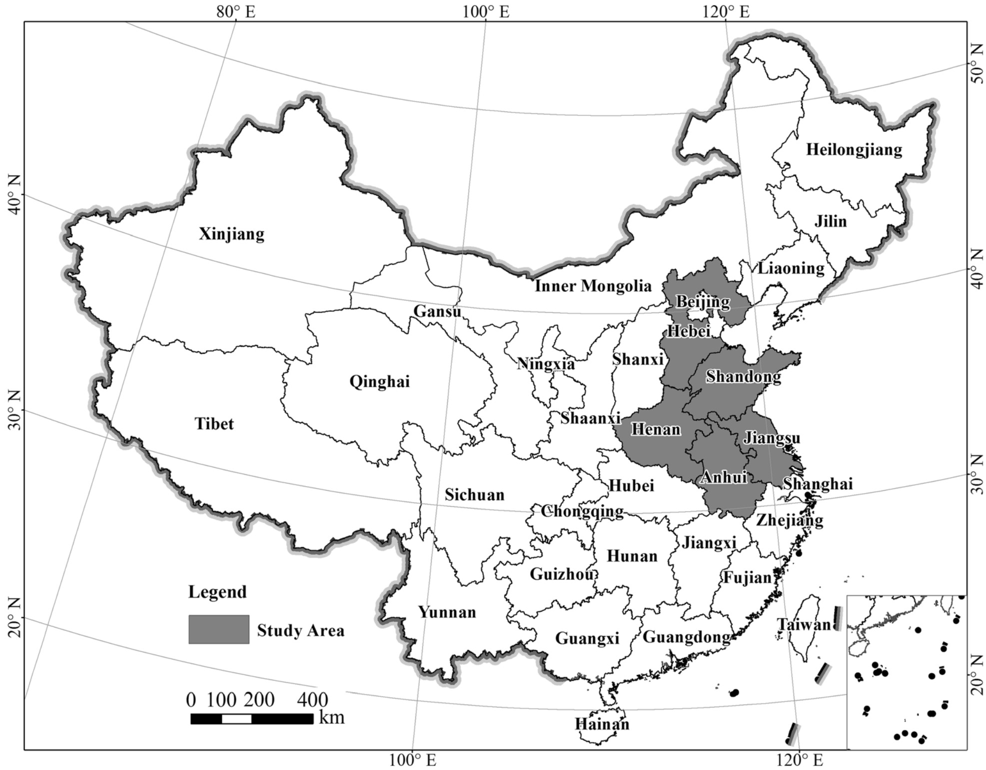

Fig. 1 Location of five provinces in the North China plain (NCP) in China

classified into three groups according to their rural water infrastructure: above average, average, and below average. Subsequently, one township from each of these three groups was randomly selected. The same approach was used to select three villages from each of these selected townships. Finally, ten farming households were randomly selected from each village, and two plots of major crops were chosen from each farming household for the survey. In total, the samples in the five selected provinces included 2700 plots, 1350 households, and 135 villages in 15 counties. Since our research focused on how the planting practices of farmers helped wheat to adapt to drought, we disregarded the samples from the flooded counties and households that did not plant wheat during the past 3 years. The final samples in our analysis included 1663 plots and 889 households in 90 villages and 10 counties. The collected data for each plot included data for a normal year (the normal year in the 10 counties was 2012) and a year of severe drought (the year of severe drought in the 10 counties was 2011). Accordingly, we collected 3326 plot samples.

Whereas the surveys at the village, household, and plot levels cover a wide range of issues, our analysis only used the data relevant to this study. For the village survey, we used the following data relevant to the irrigation infrastructure and adaptation policies, namely, the tubewell density (number/100 ha); whether surface water resources were available; whether physical, financial, or technical policy support to combat drought had been received; whether early-warning information stations were available; distance to the nearest township or upper level road; distance to the nearest farm produce market; and whether a shop selling agricultural production materials was available. As regards the household survey, we used the following data relevant to the household characteristics: the plot numbers, household assets, farm size, household labor, age and education of the household head, and the number of relatives within three generations. With respect to the plot-level survey, we used the following data relevant to plot characteristics: irrigation frequency, adoption of water-saving technologies, wheat yield, production inputs (fertilizer, labor, machinery, and other material costs), soil type (loam, clay, or sandy soil), and the salinity and topographical characteristics of the land. The descriptions of these variables are included in the Appendix.

Extreme drought events and adaptive irrigation measures

As the NCP is an ecologically vulnerable region characterized by frequent droughts, almost no absolutely normal year is experienced in this region. Based on our survey, even in the normal year, 45% of wheat plots were subject to drought (Table 1, column 1). In the year of severe drought, the percentage of plots subject to drought was obviously even higher, increasing by 29% (from 45% in the normal year to 74% in the

Table 1 Drought occurrence, wheat yield, and farmers' adaptive irrigation measures in the NCP

	Normal year	Severe drought year	Average
Plots affected by drought (%)	45	74	60
Wheat yield (kg/ha)	6454	6330	6392
Irrigation frequency (time)	1.5	1.8	1.7
Plots adopting surface pipes (%)	75	71	73

Source: Authors' survey

severe drought year) (Table 1, column 2). As expected, the occurrence of drought resulted in yield losses. The results indicated that the wheat yield was 6454 kg/ha in the normal year; however, in the year of severe drought, the wheat yield was 6330 kg/ha, i.e., 2% lower than that of the normal year (Table 1, row 2).

Consequently, farmers in the NCP have to apply adaptive irrigation measures to cope with drought conditions in both the normal and severe drought years. As the decisions on these adaptation measures are made by the farmers, they can be termed autonomous adaptations. The first important measure is to provide irrigation to the field from groundwater or surface water resources. Historically (such as during the 1950s), groundwater was used for only 5% of the total irrigated land in the NCP (Wang et al. 2006). However, since the 1970s, groundwater exploration has significantly increased, and, currently, groundwater is the main source of irrigation. For example, in our sample, groundwater was used for 74% of the irrigated land, with 62% of the irrigated land depending on groundwater only (Fig. 2).[2] Accordingly, determining the irrigation frequency has become a major decision for farmers. Our results showed that, both in the normal and severe drought years, on average, 21% of the wheat plots were not irrigated and 79% were irrigated. Notably, the irrigation frequency differed by plot, ranging from one to six times per year, with most (69%) being irrigated one to three times per year (Fig. 3).

As the region is subject to severe water shortages and in view of the importance of irrigation, increasing irrigation efficiency by applying water-saving technology is a significant topic. The surface pipe is an important water-saving method used in the NCP that can reduce water-delivery losses significantly (Zuo 1997). The surface pipe consists of a coil of hose that transports the irrigation water from the tubewells to the farming fields. Using surface pipe irrigation is common in the NCP and other water-shortage regions in China (Blanke et al. 2007), as it is relatively cheap and easy to operate by individual farmers. In our sample sites, 73% of the wheat plots used this type of irrigation (Table 1, column 3).

[2] According to our survey, 71% of the tubewells were invested in and managed by the village collective committee, and 29% of the tubewells were invested in and managed by the individual farmers. However, the investment and management patterns vary by province; for example, in Hebei Province, more than 96% of the tubewells were in the hands of individual farmers.

In particular, we were interested in learning how farmers changed or improved their irrigation measures to mitigate the potential negative effects of severe droughts. Our results indicated that, when confronted by severe droughts, the farmers *did* indeed change their irrigation measures and make adaptive responses to mitigate the effects of such droughts. Their responses included increasing irrigation frequency and adopting more water-saving technologies (Table 1, columns 1 and 2); in other words, relative to the normal year, the irrigation frequency increased by 20% during the year of severe drought (1.8 times vs 1.5 times). In addition, the percentage of wheat plots adopting surface pipe irrigation increased from 71 to 75%. Accordingly, enhancing irrigation in the field and adopting water-saving technologies are two important adaptive measures for farmers to mitigate the negative effects of drought.

Determinants and effectiveness of adaptive irrigation measures against drought

Major factors in the adoption of adaptive irrigation measures

The descriptive statistical analysis indicated that there was a positive relationship between the tubewell density and irrigation frequency. When the tubewell density was less than 11 per 100 ha, the farmers irrigated 1.2 times for wheat (Table 2, row 1); however, when the tubewell density was more than 11 or even more than 19 per 100 ha, the irrigation frequency for wheat could increase to 1.8 or even 2.1 times (Table 2, rows 2 and 3). Therefore, having more tubewells in the village facilitated an increase in irrigation frequency. Obviously, a lack of tubewells in the villages would result in the farmers not having the capacity to increase the irrigation frequency.

In addition to tubewells, access to surface water resources allowed farmers to increase their irrigation frequency. For example, as regards villages with no surface water resources, the average irrigation frequency for wheat was 1.5 times (Table 2, row 4). However, for those villages with surface water resources, the irrigation frequency could increase by 1.9 times, an increase of 30% (Table 2, row 5). Therefore, if the farmers in the NCP had access to surface water resources, the possibility of increasing irrigation frequency to ensure crop productivity would increase.

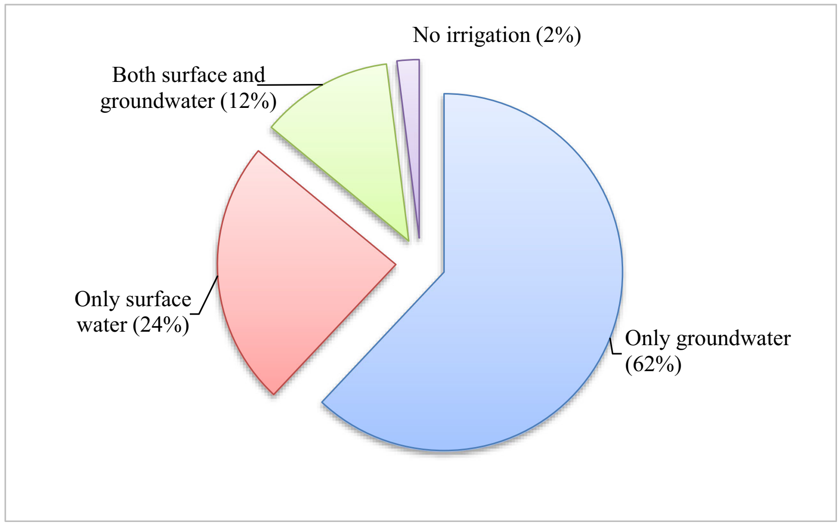

Fig. 2 Water resources for irrigation in the North China plain (NCP) in China

Further analysis indicated that the farmer's decision about whether to adopt the surface pipe method was positively related to the tubewell density but negatively related to surface water sources. For example, when the tubewell density was less than 11 per 100 ha, the proportion of plots adopting surface pipe irrigation was 56% (Table 3, row 1). However, when the tubewell density was higher than 11 per ha, more than 80% of plots adopted this method (Table 3, rows 2 and 3). This implied that, when groundwater was overexploited, leading to detrimental environmental effects such as the decline of the groundwater table, it became crucial to adopt water-saving technologies (Wang et al. 2006). As surface pipes were used mainly to deliver groundwater from tubewells to the fields, it was not surprising to find that, in the absence of any surface water resources, the proportion of plots adopting this solution was higher compared with those having access to surface water (68%) (Table 3, rows 4 and 5).

Finally, we found that adaptation policies could possibly influence irrigation frequency and the adoption of the surface pipe method. Studies had revealed that providing early-warning information influenced the adaptive behavior of farmers (Chen et al. 2014; Wang et al. 2015). Our results also indicated that irrigation frequency was higher (2.3 times vs 1.6 times) and adoption of the surface pipe method was more prevalent in villages with early-warning information stations compared with the other villages (83% vs 72%) (Table 2, rows 6 and 7 and Table 3, rows 6 and 7). Another crucial adaptation policy is to provide physical, financial, and technical support to farmers to combat the effects of drought. Physical support implied providing farmers with various production materials (such as drought-resistant seeds, film, and other materials or production facilities), financial support implied providing funds and subsidized loans, and technical support implied sending agricultural extension staff to villages to advise farmers on adopting farm management and other technical measures to deal with drought. As revealed by Chen et al.

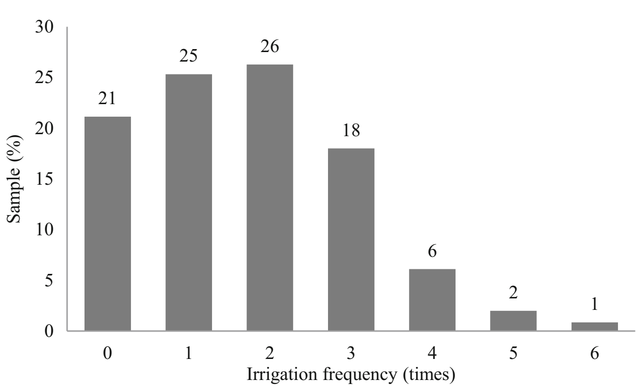

Fig. 3 Irrigation frequency for wheat during 2010–2012 in the North China plain (NCP) in China

Table 2 Relationship between tubewell density, surface water resources, and irrigation frequency in the NCP

	Irrigation frequency (time)
Tubewell density (number/100 ha)[a]	
0–11	1.2
11–19	1.8
19–98	2.1
Surface water resources	
Yes	1.9
No	1.5
Village-level early-warning information stations	
Yes	2.3
No	1.6
Policy support against drought	
Yes	1.3
No	1.7

Source: Authors' survey

[a] We divided the samples into three groups according to tubewell density, with each group having similar sample numbers

Table 3 The effect of the irrigation conditions and adaptation policy on adopting the surface pipe method in the NCP

	Proportion of plots adopting surface pipe method (%)
Tubewell density (number/100 ha)[a]	
0–11	56
11–19	82
19–98	80
Surface water resource irrigation	
Yes	68
No	80
Village-level early-warning information stations	
Yes	83
No	72
Policy support against drought	
Yes	80
No	72

Source: Authors' survey

[a] We divided the samples into three groups according to tubewell density

(2014), policy support could help to relax the constraints on farmers and help them adopt relevant adaptive measures. The results show that more farmers adopted the surface pipe method (80% vs 72%) in the villages that received policy support (Table 3, rows 8 and 9). On the contrary, when receiving policy support, the irrigation frequency will be lower (Table 2, rows 8 and 9). It is possible that, under such policy support, farmers tend to adopt other adaptation measures instead of increasing the irrigation frequency.

Effectiveness of adaptive irrigation measures for reducing yield loss

The descriptive statistical analysis indicated that increasing the irrigation frequency could possibly reduce the loss of wheat yield resulting from drought. The analysis results showed that the relationship between irrigation frequency and wheat yield was positive in both the normal and severe drought years (Table 4). For example, in the normal year and with no irrigation, the wheat yield was 6392 kg/ha; however, with irrigation three to six times per year, the yield increased to 6513 kg/ha, i.e., an increase of 2% (Table 4, column 1). The relationship between irrigation frequency and wheat yield was more obvious in the severe drought year. Compared with no irrigation, irrigating three to six times per year increased the wheat yield by 5%, an increase from 6160 to 6468 kg/ha (Table 4, column 2). Therefore, increasing the irrigation frequency was proven essential to improving agricultural productivity.

Similar to irrigation frequency, adopting the surface pipe method could facilitate a higher wheat yield. The results showed that, with surface pipe irrigation, the wheat yield was

Table 4 Relationship between farmers' adaptive irrigation measures and wheat yield in the NCP

	Normal year	Severe drought year	Average
Irrigation frequency (times)			
0	6392	6160	6276
1–2	6458	6364	6411
3–6	6513	6468	6491
Surface pipe adoption			
Yes	6469	6416	6443
No	6439	6244	6342

Data sources: Authors' survey

6469 kg/ha, 0.5% higher than without this method (6439 kg/ha; Table 4, column 1). In the severe drought year, the difference in wheat yield between the farmers who employed surface pipe irrigation and those who did not was 3% (6416 kg/ha vs 6244 kg/ha) (Table 4, column 2). Accordingly, adopting surface pipes not only improved the supply of irrigation water but also reduced the crop loss resulting from drought.

Econometric models and estimation results

Specification of econometric models

To control the effects of other factors, we applied the econometric model in our further exploration of the determinants of adaptive irrigation measures and their effectiveness in reducing the risk of yield loss. First, we constructed two econometric models to analyze the determinants of adaptive irrigation measures. These were the irrigation frequency (model 1) and the adoption of the surface pipe method (model 2):

$$I_{ijk} = \alpha_1 + \beta_1 D_k + \beta_2 F_k + \beta_3 P_k + \beta_4 V_k + \beta_5 H_{jk} + \beta_6 L_{ijk} + \beta_7 R_p + \varepsilon_{ijk}, \quad (1)$$

$$S_{ijk} = \alpha_2 + \gamma_1 D_k + \gamma_2 F_k + \gamma_3 P_k + \gamma_4 V_k + \gamma_5 H_{jk} + \gamma_6 L_{ijk} + \gamma_7 R_p + \mu_{ijk}. \quad (2)$$

In model (1), the dependent variable I_{ijk} represents the irrigation frequency (irrigation times for wheat per growing season) of plot i in household j in village k. The independent variables include the following: (i) D_k is a dummy variable measuring whether the severe drought had occurred (1 = yes, 0 = no); (ii) F_k represents the irrigation infrastructure in the village, measured by two variables, namely, tubewell density (number/100 ha) and whether surface water resources were available (1 = yes, 0 = no); (iii) P_k represents a set of adaptation policy variables, measured by two types of variables: whether the villages had established early-warning information stations (1 = yes, 0 = no) and whether the villages received physical, financial, or technical policy support to combat drought (1 = yes, 0 = no);(iv) V_k represents the village characteristics, namely, distance to the nearest township or upper level road (km), distance to the nearest farm produce market (km), and whether an agricultural production material shop was available (1 = yes, 0 = no); (v) H_{jk} represents the household characteristics, measured by plot numbers, per capita household assets (10,000 yuan), farm size (ha), ratio of household labor, age (year) and education (year) of the household head, and the number of relatives within three generations (person); and (vi) L_{ijk} represents the plot characteristics measured by soil type, loam (1 = yes, 0 = other) or clay soil (1 = yes, 0 = other), salinity of the land (1 = yes, 0 = no), and the land topography (1 = plain, 0 = mountain). We also included provincial dummy variables (R_p) to control the factors that do not change over time.

With respect to model (2), the dependent variable S_{ijk} represents the adoption of the surface pipe of plot i in household j in village k (1 = yes, 0 = no). The implications of the independent variables (D_k, F_k, P_k, V_k, H_{jk}, L_{ijk}, R_p) are similar to those in model (1). In models (1) and (2), α_1, α_2, $\beta_1-\beta_7$, and $\gamma_1-\gamma_7$ are the parameters to be estimated, whereas ε_{ijk} and μ_{ijk} are the random error terms assumed to be subject to independent identical distribution.

To estimate the effect of adaptive irrigation measures (irrigation frequency and adopting surface pipe irrigation) on reducing the risk of yield loss (mean and variance of yield), we followed the approach of the frontier production function (Just and Pope 1978) and specified the following econometric models (similar to Huang et al. 2015; Di Falco and Chavas 2009):

$$y_{ijk} = \alpha_3 + \delta_1 I_{ijk} + \delta_2 D_k + \delta_3 G_{ijk} + \delta_4 X_{ijk} + \delta_5 V_k + \delta_6 H_{jk} + \delta_7 L_{ijk} + \delta_8 R_p + \pi_{ijk}, \quad (3)$$

$$V_{ijk} = \alpha_4 + \varphi_1 I_{ijk} + \varphi_2 D_k + \varphi_3 G_{ijk} + \varphi_4 X_{ijk} + \varphi_5 V_k + \varphi_6 H_{jk} + \varphi_7 L_{ijk} + \varphi_8 R_p + \epsilon_{ijk}, \quad (4)$$

$$y_{ijk} = \alpha_5 + \delta_1 S_{ijk} + \delta_2 D_k + \delta_3 J_{ijk} + \delta_4 X_{ijk} + \delta_5 V_k + \delta_6 H_{jk} + \delta_7 L_{ijk} + \delta_8 R_p + \tau_{ijk}, \quad (5)$$

$$V_{ijk} = \alpha_6 + \omega_1 S_{ijk} + \omega_2 D_k + \omega_3 J_{ijk} + \omega_4 X_{ijk} + \omega_5 V_k + \omega_6 H_{jk} + \omega_7 L_{ijk} + \omega_8 R_p + \rho_{ijk}. \quad (6)$$

In the above models, the dependent variable y_{ijk} represents the mean of wheat yield (kg/ha), and the dependent variable V_{ijk} represents the variance of wheat yield. Just and Pope (1978) proposed the following frontier production function: $y = f(X, \beta) + h(X, \alpha)^{0.5}\varepsilon$, where y is the crop yield, $f(X, \beta)$ is an average production function, X is a set of independent variables, and α and β are the unknown parameters to be estimated. In addition, $h(X, \alpha)$is a function accounting for explicit variable-dependent heteroskedasticity, allowing yield variability as a function of observed covariates, and $h(X, \alpha) = y - f(X, \beta)$. $h^2(X, \alpha)$ is the yield variance. Models (3) and (4) are meant to analyze the effects of irrigation frequency (I_{ijk}) on the mean and variance of wheat yield, respectively, and models (5) and (6) are meant to analyze the effects of adopting the surface pipe method (S_{ijk}) on the mean and variance of wheat yield, respectively.[3]

In addition to adaptive irrigation measures (I_{ijk} or S_{ijk}), models (3) to (6) include other independent variables (D_k, V_k, H_{jk}, L_{ijk}, and R_p) that are similar to those in models (1) and (2). However, different from models (1) and (2), models (3) to (6) include two sets of new variables. The first set is G_{ijk} in models (3) and (4) and J_{ijk} in models (5) and (6). The G_{ijk} is the interaction variable between irrigation frequency and the severe drought year ($I_{ijk} * D_k$), and J_{ijk} is the interaction variable between the adoption of surface pipe irrigation and the severe drought year ($S_{ijk} * D_k$). The second set of new variables are the production input variables (X_{ijk}), including fertilizer use (kg/ha), labor (day/ha), machinery (yuan/ha), and other material inputs (yuan/ha). In models (3) to (6), $\alpha_3-\alpha_6$, $\delta_1-\delta_8$, $\varphi_1-\varphi_8$, and $\omega_1-\omega_8$ are the parameters to be estimated. The error terms are represented by π_{ijk}, ϵ_{ijk}, τ_{ijk}, and ρ_{ijk} that are assumed to be subject to independent identical distribution. During the estimation, we adopted the linear-log form and transferred the dependent variables (y_{ijk} and V_{ijk}) and one independent variable (the production input variable, X_{ijk}, into the log form). We followed the maximum likelihood approach to estimate models (3) to (6).

From the above description, the adaptive irrigation measures (I_{ijk} or S_{ijk}) were obviously endogenous in models (3) to (6). Therefore, to reduce the estimation biases, we adopted the 2SLS (two-stage least squares) approach to resolve the issue. That is, after applying model (1), we obtained the predicted value of irrigation frequency ($\hat{I}_{ijk}$) and replaced the original value of irrigation frequency (I_{ijk}) in models (3) and (4) with the predicted value. Similarly, after applying model (2), we obtained the predicted value of the surface pipe method ($\hat{S}_{ijk}$) and incorporated the predicted value into models (5) and (6) to replace the original value (S_{ijk}).

In both models (1) and (2), we included instrumental variables, namely, F_k and P_k, to resolve the endogenous issues of adaptive irrigation measures. These two types of variables were assumed to be uncorrelated with the error terms of models (3) to (6). That is, these two variables did not influence crop yield or variance directly but only influenced the adaptive irrigation measures. As these instrumental variables were measured at the village level, their influence on crop yield was mainly attributed to the changing adaptation behavior of the farmers. In

[3] The correlation coefficient between irrigation frequency and surface pipe irrigation is 0.50. In addition, the VIFs of these variables are larger than 10 (107.21 for irrigation frequency and 24 for surface pipes). Considering the serious multicollinearity problem, we have not included irrigation frequency and surface pipe irrigation in the same regression.

the following section, we would test further the validity of these variables by conducting a statistical test.

Estimation results of the econometric model

The estimation results of the determinants of irrigation frequency and its effectiveness and the determinants of adopting surface pipe irrigation and its effectiveness are presented in Tables 5 and 6, respectively. All models performed well, with higher F test values. The coefficients of most variables were statistically significant and were consistent with our expectations and the descriptive statistical analysis in the previous section. Notably, the instrumental variables included in models (1) and (2) were statistically significant and passed the conventional strength tests ($F >$ 10). For example, the F statistical test for model (1) was 15.8, and for model (2), it was 11.9. This implied that the instrumental variables were not weak, and we rejected the null hypothesis, which excluded the instruments being irrelevant for either model (1) or model (2). Therefore, the instrumental variables were considered valid, and the estimation results of the effectiveness of adaptive irrigation measures were considered not biased.

The estimation results showed that the occurrence of severe drought was a key factor prompting farmers to take adaptation measures. As shown in Table 5 (column 1), the coefficient of the severe drought year in the determinant model was positive and statistically significant. This implied that, compared with the normal year, the irrigation frequency would increase by 0.34 times in the severe drought year. Similarly, the coefficient of the severe drought year was positive and statistically significant in the determinant model for adopting surface pipe irrigation. The results showed that, after keeping the other factors constant in the severe drought year, the possibility for farmers adopting the surface pipe method increased by 4.4% (vs the normal year) (Table 6, column 1). These results implied that farmers indeed made adaptive responses to severe drought. Our results were consistent with the findings of Huang et al. (2015) relevant to rice farmers in China.

Increasing the frequency of irrigation was highly correlated with the local irrigation infrastructure and the adaptation policy. The coefficient of the tubewell density was positive and statistically significant at 1% (Table 5, column 1). This implied that, after keeping other factors constant, if villages had higher tubewell densities or superior groundwater irrigation facilities, farmers were more likely to increase irrigation frequency to improve agricultural productivity. In addition, the coefficient of surface water resources was positive and statistically significant at 1%. Therefore, if farmers had access to surface water resources, the irrigation frequency would significantly increase. Moreover, establishing early-warning information stations could increase the irrigation frequency by 0.30 times.

The adoption of the surface pipe method was also significantly related to the local irrigation infrastructure and the adaptation policy. The results showed that, in the determinant model of surface pipe irrigation, the coefficient of tubewell density was positive and statistically significant at 1%, but the coefficient for surface water was not statistically significant (Table 6, column 1). Therefore, the adoption of the surface pipe method was mainly influenced by the condition of the groundwater infrastructure, as surface pipe irrigation transports groundwater and not surface water. Consistent with descriptive statistical analysis, the coefficients of the two adaptation policy variables were positive and statistically significant. Therefore, if villages obtained physical, financial, or technical policy support or had early-warning information stations, farmers were more likely to adopt the surface pipe method. Policy support to combat drought could increase this possibility by 10.6%, and establishing early-warning information stations could increase the possibility by 5.2%.

In addition, various village, household, and plot characteristics were significantly related to the farmers' adaptive responses. For example, as shown in Table 5, the irrigation frequency was higher if the villages were located far from main roads or farm produce markets. Richer farmers and the farmers of larger farms were more likely to increase their irrigation frequency. However, older farmers were less likely to increase the irrigation frequency (Table 5, column 1) and adopt the surface pipe method (Table 6, column 1). In addition, farmers whose lands were loam soil, saline, and located in the plains areas were more likely to increase the irrigation frequency (Table 5, column 1). As regards adopting the surface pipe method in saline land, the possibility would statistically increase (Table 6, column 1). Finally, adopting the surface pipe method was significantly related to the farmers' social capital, as the coefficient of the number of relatives within three generations was positive and statistically significant. This implied that having superior social capital could help farmers obtain more information and adopt water-saving technologies.

Notably, increasing the irrigation frequency could significantly mitigate the loss of wheat yield. As shown in Table 5, the coefficient of irrigation frequency was positive and statistically significant at 1% in the mean yield function, and its interaction variable with the severe drought year was also positive and statistically significant at 1% (Table 5, column 2). This implied that, after keeping all other factors constant, increasing the irrigation frequency in the severe drought year could mitigate the loss of the wheat yield significantly. Moreover, if farmers added one instance of irrigation, their wheat yield could increase by 12.8% (10.1% + 2.7%) in the severe drought year. In addition, the coefficient of irrigation frequency was negative and statistically significant in the yield variance function, but not significant for its interaction term with the severe drought year (Table 5, column 3). Therefore, increasing irrigation frequency could also reduce yield loss risk by reducing its variability but not in the severe drought year.

Table 5 Regression results of the determinants of irrigation frequency and its effects on the mean and variance of wheat yield

	Irrigation frequency	Wheat yield	
		Mean	Variance
Irrigation frequency (time)		0.101***	− 0.548**
		(4.277)	(2.011)
Irrigation frequency* severe drought year		0.027***	− 0.014
		(3.314)	(0.147)
Serious drought year (1 = yes, 0 = no)	0.340***	− 0.097***	0.366*
	(9.403)	(5.620)	(1.828)
Instrument variable			
Tubewell density (number/100 ha)	0.009***		
	(6.287)		
Surface water resources (1 = yes, 0 = no)	0.121***		
	(2.792)		
Early-warning information stations (1 = yes, 0 = no)	0.298***		
	(4.975)		
Policy support against drought (1 = yes, 0 = no)	− 0.037		
	(0.558)		
Inputs			
Fertilizer (kg/ha) (log)		0.037***	− 0.250***
		(4.536)	(2.617)
Labor (day/ha) (log)		0.021***	0.042
		(3.481)	(0.615)
Machinery (yuan/ha) (log)		0.023***	− 0.178**
		(3.703)	(2.519)
Other material inputs (yuan/ha) (log)		0.011	0.066
		(1.143)	(0.578)
Village characteristics			
Distance to the nearest township or upper level road (km)	0.130***	− 0.009**	0.007
	(10.73)	(2.400)	(0.171)
Distance to the nearest farm produce market (km)	0.030***	− 0.002*	0.025*
	(6.459)	(1.798)	(1.879)
Agricultural production material shop (1 = yes, 0 = no)	0.063	0.023***	− 0.017
	(1.463)	(2.843)	(0.182)
Household characteristics			
Plot number	− 0.049***	0.007***	− 0.029
	(5.579)	(3.512)	(1.220)
Per capita household asset (10,000 yuan)	0.021***	− 0.002	0.034**
	(3.435)	(1.479)	(2.421)
Farm size (ha)	0.290***	− 0.030***	0.256**
	(8.364)	(3.244)	(2.371)
Ratio of household labor	− 0.050	− 0.009	0.047
	(0.484)	(0.483)	(0.216)
Age of household head (years)	− 0.008***	0.002***	− 0.001
	(4.161)	(3.870)	(0.254)
Education of household head (years)	− 0.013**	0.007***	0.004
	(2.133)	(5.919)	(0.293)
Number of relatives (three generations)	− 0.002	− 0.000	0.005
	(0.495)	(0.0614)	(0.733)
Plot characteristics			

Table 5 (continued)

	Irrigation frequency	Wheat yield	
		Mean	Variance
Loam soil (1 = loam, 0 = other)	0.081*	− 0.013	− 0.059
	(1.664)	(1.405)	(0.536)
Clay soil (1 = clay, 0 = other)	− 0.043	0.000	− 0.218**
	(0.866)	(0.0518)	(2.052)
Saline land (1 = yes, 0 = no)	0.130**	− 0.062***	0.240*
	(2.204)	(5.494)	(1.825)
Land topography (1 = plain, 0 = mountain)	0.556***	0.028	− 0.589*
	(3.816)	(0.984)	(1.760)
Province dummies	Not reported	Not reported	Not reported
Constant	1.196***	7.897***	− 1.030
	(5.535)	(80.82)	(0.910)
F values	96.690	9.650	3.590
Adjusted R^2	0.377	0.061	0.019
Observations	3326	3326	3326

Note. Absolute *t* values in parentheses. *, **, and *** indicate the statistical significance at 10%, 5%, and 1%, respectively

Furthermore, adopting the surface pipe method could lower the loss of the wheat yield significantly and contribute to limiting yield variability. In Table 6, the coefficient of the surface pipe method is shown as positive and statistically significant at 1% in the mean of the yield function, with its interaction variable with the severe drought year also being positive and statistically significant (Table 6, column 2). Therefore, after keeping all the other factors constant, adopting the surface pipe method could significantly increase the wheat yield. Moreover, if farmers adopted the surface pipe method in the severe drought year, their wheat yield could increase by 14.5% (11.5% + 3%). In addition, the coefficient of the surface pipe method was negative in the yield variance function and statistically significant at 1%, but the coefficient of interaction term between the surface pipe and severe drought year is not significant (Table 6, column 3). This implied that, because of the adoption of this method, the yield variability of wheat could be significantly reduced. In other words, the yield loss risk could be significantly reduced. However, such an effect is not significant in the severe drought year.

Finally, wheat yield and variability were significantly influenced by drought and various production inputs. The coefficient of the severe drought year was negative and statistically significant in the mean of the wheat function, relevant to both the irrigation frequency and the surface pipe model (Table 5, column 2 and Table 6, column 2). This implied that, after keeping all other factors constant, even if farmers adopted various adaptation measures, the wheat yield would be reduced because of the severe drought. In addition, the coefficient of the severe drought year was positive and statistically significant in the variance of the wheat function for both the irrigation frequency and the surface pipe model (Table 5, column 3 and Table 6, column 3). This implies that severe drought had significantly increased the wheat yield risk.

Concluding remarks

This study identified how farmers in the NCP made adaptive irrigation responses to drought, as well as the determinants and effectiveness of these responses. Our results had the following policy implications:

First, understanding of the potential benefits of irrigation measures to manage the effects of extreme drought should be improved. Our results indicated that, after keeping all other factors constant, increasing the frequency of irrigation by one instance on average could increase the wheat yield by 10.1%. In the severe drought year, increasing the irrigation could increase the yield further by 2.7%. This indicated that increasing the irrigation frequency in the severe drought year by one instance could increase the wheat yield by 12.8%. This offset the negative effects of drought risk significantly. If no irrigation took place, the wheat yield loss would rise to 9.7% in the severe drought year. Although we had no data available on the volume of irrigation applied in the fields, on estimate, based on our observations, the volume per irrigation event was less in the drought year compared with the normal year. This implied that irrigation efficiency in the drought year was higher compared with the normal year.

Second, to improve the adaptive capacity of farmers to reduce the risk of extreme drought, it would be necessary to enhance the local irrigation infrastructure further by investing

Table 6 Regression results of the determinants of the surface pipe method and its effects on the mean and variance of wheat yield

	Surface pipe	Wheat yield	
		Mean	Variance
Surface pipe (1 = yes, 0 = no)		0.115***	− 0.752***
		(6.814)	(3.782)
Surface pipe* severe drought year		0.030***	− 0.066
		(3.153)	(0.596)
Serious drought year (1 = yes, 0 = no)	0.044***	− 0.056***	0.297***
	(2.793)	(5.729)	(2.599)
Instrument variable			
Tubewell density (number/100 ha)	0.003***		
	(4.742)		
Surface water resources (1 = yes, 0 = no)	− 0.030		
	(1.551)		
Early-warning information stations (1 = yes, 0 = no)	0. 052 **		
	(2.039)		
Policy support against drought (1 = yes, 0 = no)	0.106***		
	(4.143)		
Inputs			
Fertilizer (kg/ha) (log)		0.037***	− 0.188*
		(4.472)	(1.948)
Labor (day/ha) (log)		0.021***	− 0.004
		(3.519)	(0.0645)
Machinery (yuan/ha) (log)		0.019***	− 0.172**
		(3.092)	(2.415)
Other material inputs (yuan/ha) (log)		0.013	− 0.055
		(1.324)	(0.470)
Village characteristics			
Distance to the nearest township or upper level road (km)	0.007	0.005**	− 0.053**
	(1.412)	(2.374)	(2.067)
Distance to the nearest farm produce market (km)	0.016***	− 0.005***	0.048***
	(4.984)	(3.963)	(3.500)
Agricultural production material shop (1 = yes, 0 = no)	− 0.033*	0.047***	− 0.145
	(1.759)	(5.809)	(1.520)
Household characteristics			
Plot number	0.003	0.000	− 0.014
	(0.767)	(0.114)	(0.757)
Per capita household asset (10,000 yuan)	0.003	− 0.001	0.017
	(1.189)	(1.308)	(1.255)
Farm size (ha)	− 0.018	0.009	0.102
	(1.114)	(1.418)	(1.361)
Ratio of household labor	− 0.042	0.000	− 0.049
	(0.926)	(0.0207)	(0.220)
Age of household head (years)	− 0.002***	0.001***	− 0.003
	(2.593)	(4.088)	(0.726)
Education of household head (years)	− 0.003	0.006***	− 0.002
	(1.070)	(5.915)	(0.146)
Number of relatives (three generations)	0.004***	− 0.002***	0.014*
	(2.759)	(2.691)	(1.732)
Plot characteristics			

Table 6 (continued)

	Surface pipe	Wheat yield	
		Mean	Variance
Loam soil (1 = loam, 0 = other)	− 0.028	0.011	− 0.310***
	(1.262)	(1.235)	(2.843)
Clay soil (1 = clay, 0 = other)	− 0.002	0.001	− 0.266**
	(0.107)	(0.0993)	(2.481)
Saline land (1 = yes, 0 = no)	0.049*	− 0.068***	0.177
	(1.913)	(6.126)	(1.357)
Land topography (1 = plain, 0 = mountain)	0.013	0.084***	− 0.611**
	(0.205)	(3.183)	(1.979)
Province dummies	Not reported	Not reported	Not reported
Constant		7.969***	− 0.826
		(88.35)	(0.778)
LR chi-squared	651.720	–	–
F values	–	10.49	3.630
Pseudo R^2	0.169	–	–
Adjusted R^2	–	0.066	0.019
Observations	3326	3326	3326

Note. The value in parentheses in column 1 indicates the absolute *z* values, and the values in columns 2 and 3 in parentheses are *t* values. *, **, and *** represent the statistical significance at 10%, 5%, and 1%, respectively

in or maintaining the tubewell and constructed facilities that provide access to surface water resources. However, considering the decline of the groundwater table and other related negative environmental effects from the overexploitation of groundwater resources, the local government would need to address the issue of proper use of surface water resources. In addition to exploring for new water sources in the NCP (such as pumping water from the south), technologies to harvest rainfall should be investigated. Furthermore, the government should create an environment in which incentives were offered to farmers to save water, such as implementing water pricing policies and establishing water rights institutions.

Third, to encourage farmers to adopt water-saving technologies, it was necessary to provide physical, financial, and technical policy support and to establish early-warning information systems. Currently, there was considerable room for expanding these adaptive policies. In our sample sites, only 8% of the villages had obtained policy support to combat drought, and only 13% had established early-warning information stations.

Fourth, there was room for farmers to improve their irrigation measures to combat the effects of drought. Currently, the average irrigation frequency for wheat was less than two incidences. Improving irrigation infrastructure could facilitate an increase in irrigation frequency. However, whether the irrigation intensity could be enhanced depended on the water resources available. Considering the constraints of water endowment, determining a method to encourage farmers to adopt water-saving technologies could be an important policy measure to reduce the negative effects of drought.

Fifth, enhancing the adaptive capabilities of poorer farmers in response to extreme drought events should be prioritized for policy interventions. The positive influence of household assets on adaptation decisions suggested that poorer farmers, who generally lacked sufficient capital or labor, were more vulnerable to the effects of extreme climate events. Therefore, policy support from the government (e.g., to combat drought) should be made accessible particularly to poorer farmers to boost their adaptation of reliable farm management measures.

Finally, as our results showed that farm size was a significant factor in adopting adaptation measures, developing larger family farms in China was a crucial factor to enhance the adaptive capacity of farmers. In regard to the farmers who have adopted such measures, our results appear to indicate that the scale management of agriculture helped to decrease the wheat production risks posed by extreme drought events. Policymakers should therefore promote the broad acceptance of the factor of scale management in the modernization of agriculture. Accordingly, policymakers might have to intervene to encourage land transfer in order to support the emerging rental market in the rural areas of China.

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Appendix

Table 7 Descriptive statistics of major variables in North China plain

	Mean	Standard deviation
Wheat yield (kg/ha)	6392	1113
Irrigation frequency (time)	1.711	1.307
Adopting surface pipes (1 = yes, 0 = no)	0.735	0.442
Severe drought year (1 = yes, 0 = no)	0.500	0.500
Tube well density (number/100 ha)	18	15
Surface water resources (1 = yes, 0 = no)	0.580	0.494
Early-warning information stations in the village (1 = yes, 0 = no)	0.133	0.340
Policy support against drought (1 = yes, 0 = no)	0.088	0.283
Fertilizer (kg/ha)	587.1	244.2
Labour (day/ha)	32.4	24.5
Machinery (yuan/ha)	1593.4	546.6
Other material inputs (yuan/ha)	1301.1	519.7
Distance to the nearest township or upper level road (km)	1.410	1.616
Distance to the nearest farm produce market (km)	3.562	4.190
Presence of agricultural production material shop (1 = yes,0 = no)	0.745	0.436
Plot number	4	3
Per capita household asset (10,000 yuan)	2.994	2.977
Farm size (ha)	0.555	0.637
Ratio of household labor	0.815	0.177
Age of household head (years)	54	10
Education of household head (years)	7.004	3.158
Number of relatives (three generations)	13	5
Loam soil (1 = loam, 0 = other)	0.365	0.482
Clay soil (1 = clay, 0 = other)	0.375	0.484
Saline land (1 = yes, 0 = no)	0.106	0.308
Land topography (1 = plain, 0 = mountain)	0.984	0.124

Note. Number of observations = 3326

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