sustainability

MDPI

Article

Adaptation to Climate Change and its Impacts on Wheat Yield: Perspective of Farmers in Henan of China

Shuiping Quan [1,2], Yingming Li [1,2,*], Jianxin Song [3], Tao Zhang [4] and Mingyue Wang [2]

[1] Institutes of Science and Development, Chinese Academy of Sciences (CASISD), Beijing 100190, China; quanshuiping15@mails.ucas.ac.cn
[2] University of Chinese Academy of Sciences (UCAS), Beijing 100049, China; wangmingyue16@mails.ucas.ac.cn
[3] Baoshang Bank Co., Beijing 100101, China; sjxbj@163.com
[4] Infinite-Sum Modeling Inc., Beijing 100091, China; zhang.tao@infsum.com
* Correspondent: liyingming@casipm.ac.cn; Tel.: +86-010-5935-8512

Received: 26 February 2019; Accepted: 28 March 2019; Published: 1 April 2019

check for updates

Abstract: This paper explored farm households' autonomous climate change adaptation strategies and corresponding impacts on wheat yield. Based on a survey of 314 wheat farmers in rural China, results show that Chinese wheat farmers have a high rate of climate change awareness and adoption of climate change adaptation measures. Farmers' cultivated area, cognition level and information accessibility on climate change significantly affect their adaptation decisions. However, these farmers are given limited adaptation strategies, mainly including increasing irrigation, and using more chemical fertilizer and pesticides. Through employing a simultaneous equations model with endogenous switching, we find farmers' adaptation to climate change is maladaptive with negative effects on wheat yield. This study, therefore, suggests policymakers be mindful of farmers' maladaptive responses to climate change and provide effective adaptation measures, to help farmers cope with the risks of climate change and ensure farmer's livelihood security and sustainable agriculture development.

Keywords: climate change; agriculture; adaptation; Henan of China

1. Introduction

Previous research has indicated that climate change, especially the increase of extreme weather phenomena, has a profoundly adverse effect on agriculture production [1–7]. A recent study shows that depending on the severity of climate change conditions, the average yield of barley wheat could fall from 3% to 17% worldwide [8]. How to overcome the risks of climate change on agriculture has gained extensive attention from researchers all over the world [2]. There are two main adaption categories, which are actors–private adaptation and public adaptation [9]. Private adaptations are autonomous adaptation–practices made by households, and public adaptations are planned adaptation–decisions made by governments [10].

Climate change is hitting farmers the hardest of all, especially in the least developed and developing countries [1,5]. Farmers autonomously adjust their production practices in response to climate change impacts depending on their existing knowledge and technology [11,12]. Several studies have researched the determinants of farmers' adaptation decisions and measures to enhance their adaptive capacity [13–16]. Chen et al. (2014) found that, in China, farm characteristics and local governments' policies are key factors affecting farmers' climate change adaptation decisions.

In order to ensure food security, it is necessary to analyze farmers' autonomous adaptation to climate change and investigate whether such adaptations can reduce climate-induced yield loss [12]. Several studies have assessed the impact of farmers' climate change adaptation strategies on crop yields. Some studies found that farmers' climate change adaptation significantly increases crop yield [12,17–19]. However, depending on different climatic, economic, social and institutional factors, farmers adopt different adaptation strategies [15], and some adaptation practices may lead to different effects according to different countries, regions and crop species.

China is a large agricultural country, with about 270 million people engaged in agricultural activity in 2012 [20]. Crop production is still dominated by small farm households in China, and wheat is one of the two staple food crops in China. Over the past century, China's annual average temperature has risen higher than the global average; and by the end of 21st century, in most areas of China, the temperature is forecasted to rise from 1.3 °C to 5 °C [21]. It is necessary to understand farmers' actual climate change adaptation practices and its impact on wheat yield especially because China's agriculture sector is in a period of transition, facing various crises and challenges. Huang et al. (2015) analyzed wheat farmers' adaptation and its impact on yield. However, they only took into account one adaptation strategy in extreme climate events. Therefore, little is known about whether Chinese farmers' adaptation practices support farm productivity. This study investigates wheat farmers' general adaptation strategies to climate change and the corresponding impact on farmers' wheat yield.

2. Method

2.1. Study Area and Data Collection

This study focuses on Henan province due to its significance in China's cereal production. Located in central China, Henan Province is one of the thirteen major grain cultivating areas. Based on relevant statistics, Henan Province's cultivated land area and grain yield are both ranked second in the country [22]. Henan Province is located in the junction area of the subtropical and warm temperate zone, with clear climate transitional characteristics [21].

This study is based on a survey conducted on 360 farm households located within six traditional cropland zones in Henan province in January 2016. Rejecting the invalid ones, 314 questionnaires were collected with a return rate of 87.2%. The sampling procedure consisted of five steps. First, six cities (AnYang, KaiFeng, XuChang, ZhouKou, NanYang, XinYang) were selected based on geographical and climatic distribution characteristics, scattered in the east, south, west, north and central of Henan. Second, each county was randomly chosen from each city, so six counties (NeiHuang, LanKao, ChangGe, XiHua, DengZhou, Xi) were selected. Third, we randomly selected three rural towns from each county. Fourth, one sub-district division (village) was randomly selected from each town (see Figure 1). Finally, 20 farmers were randomly selected from each village from a list of farmers collected from the village committee.

In order to collect information concerning farmers' characteristics and their actual adaptation strategies, a pre-tested structured questionnaire was used. We asked each farmer the following three contingent questions to ensure that their production adjustments were actual responses to climate change not due to other pressures [12]. (1) Do you perceive any changes in the local climatic condition in the last 10 years? If yes, what changes? (2) Does climate change have an impact on wheat production? If yes, what impact? (3) Do you adopt any actions in response to climate change? If yes, what actions?

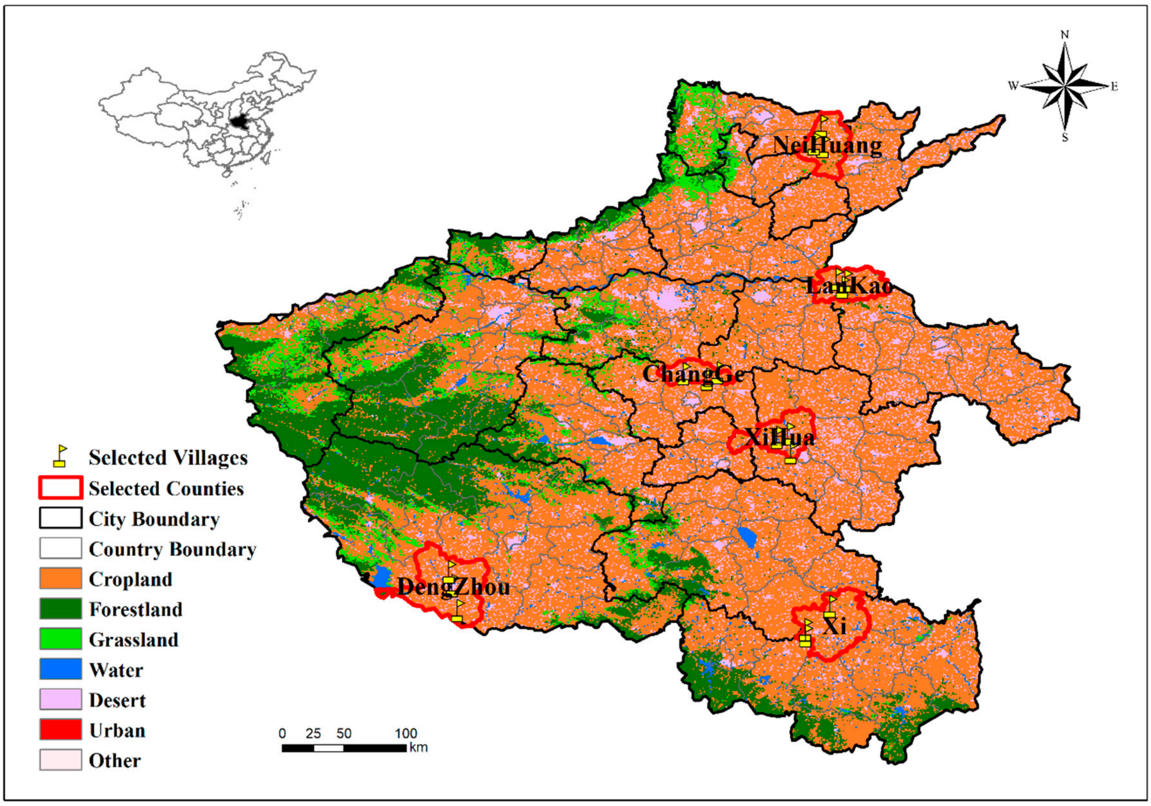

Figure 1. Location of study area.

2.2. Modelling Adaptation to Climate Change and Wheat Yield

Following Di Falco et al. (2011), a climate change adaptation decision and its effects on wheat yield can be simulated using a two-stage framework [12,19,23,24].

In the first stage, we employed a selection model for climate change adaptation decisions. It assumes that the risk-averse farmer household will implement climate change adaptation strategies if it generates net benefits, and the net benefits can be represented by a latent variable A*.

$$A_i^* = Z_i a + \eta_i \; with \; A_i = 1, \text{ if } A_i^* > 0 \; and \; 0 \; otherwise \tag{1}$$

Farm i will choose to adopt climate change adaptation strategies ($A_i = 1$) if $A_i^* > 0$, and 0 otherwise. The vector Z represents variables that influence farmers' adaptation decisions. According to empirical literature on the determinants of farmers' climate change adaptation decisions [12,15,18], this study chose farm household characteristics and climate information provided by extension agents as the dependent variables. Household characteristics include gender, age, education, labor share, the area under cultivation and climate cognition. The information from government mainly included weather warnings about frost and drought.

In the second stage, the effect of adaptation on wheat yield was modeled via the production technology. The simplest approach would have been to apply the ordinary least squares (OLS) method, taking adaptation as a dummy variable in the food productivity equation. However, assessing the impact of adaptation on wheat yield through the OLS approach may have created many potential problems. For example, adaptation may be potentially endogenous, which if true will lead to biased estimates [18]. In addition, problems such as sample selection bias and inconsistent estimates might rise and confound the results [12].

According to Di Falco et al. (2011), a simultaneous equation model of climate change adaptation and its impact on wheat yield with endogenous transformation was estimated with full information maximum likelihood. In our study, the variables regarding climate cognition and climate information were used as selection instruments. Table A1 shows that climate cognition and climate information significantly affected farmers' adaptation decision, but they have no significant impact on the wheat yield of non-adaptors. Therefore, they can be considered as valid selection instruments.

In this paper, the endogenous switching regression model was selected to estimate the impact of climate change adaptation on wheat yield. Adaptors and non-adaptors have different yield functions.

$$y_{1i} = \beta_1 x_{1i} + \varepsilon_{1i} \quad if\ \mathrm{A}_i = 1 \tag{2}$$

$$y_{0i} = \beta_0 x_{0i} + \varepsilon_{0i} \quad if\ \mathrm{A}_i = 0 \tag{3}$$

where y_{1i} and y_{0i} are the wheat quantity produced per hectare specified in log for adopters and non-adopters respectively. x_i is a vector of inputs specified in log form (e.g., seeds, fertilizers, manure, labor), β is the parameter vector to be estimated, and ε is the error term.

Following Di Falco et al. (2011), the error terms in Equations (1)–(3) are assumed to have a trivariate normal distribution, with $(\eta, \varepsilon_1, \varepsilon_0)' \sim N(0, \Sigma)$

$$\mathrm{cov}(\eta, \varepsilon_A, \varepsilon_N) = \Sigma = \begin{pmatrix} \sigma_n{}^2 & \sigma_{\eta A} & \sigma_{\eta N} \\ \sigma_{A\eta} & \sigma_A{}^2 & \sigma_{AN} \\ \alpha_{m1} & \sigma_{NA} & \sigma_N{}^2 \end{pmatrix} \tag{4}$$

Following Di Falco et al. (2011) and Khanal et al. (2018), the expected values of ε_1 and ε_0 are non-zero, given as:

$$E[\varepsilon_{1\mathrm{i}} | A_\mathrm{i} = 1] = \sigma_{1i} \frac{\varphi(Z_i\alpha)}{1 - \phi(Z_i\alpha)} = \sigma_{1\eta}\lambda_{1i} \tag{5}$$

and

$$E[\varepsilon_{0\mathrm{i}} | A_\mathrm{i} = 0] = -\sigma_{0i} \frac{\varphi(Z_i\alpha)}{1 - \phi(Z_i\alpha)} = \sigma_{0i}\lambda_{0i} \tag{6}$$

Following Di Falco et al. (2011), the endogenous switching regression model can be used to investigate four conditional expectations of wheat yield.

$$E(y_{1i} | A_1 = 0) = \beta_1 x_{1i} + \sigma_{1i}\lambda_{1i} \tag{7}$$

$$E(y_{0i} | A_1 = 0) = \beta_0 x_{0i} + \sigma_{0i}\lambda_{0i} \tag{8}$$

$$E(y_{0i} | A_1 = 1) = \beta_0 x_{1i} + \sigma_{0i}\lambda_{1i} \tag{9}$$

Equations (7) and (8) represent the actual expectations observed in the sample. Equations (9) and (10) represent the counterfactual expected outcomes. In addition, the average treatment effect on the treated (TT) can be calculated using the difference between Equations (7) and (9). Similarly, the difference between Equations (10) and (8) can be calculated as the average treatment effect on the untreated (TU) for the household that actually did not adapt. For the group of "adopters", the effect of base heterogeneity is the difference between Equations (7) and (10). Similarly, for the "non-adopters" group, the effect of base heterogeneity is measured using the difference between (9) and (8).

More details about the endogenous switching regression model can be found in Di Falco et al. (2011).

3. Results

3.1. Descriptive Statistics

Table 1 shows definitions and descriptive statistics of the surveyed farmer households. It shows that, on average, 91.7% of the farmers perceived climate changes and 82.8% of households adopted adaptation strategy in response to the changes for wheat cultivation; and 43% of households received external climate change information. Farmers adopted several measures to adapt their wheat crop to climate change. Overall, the major strategies were to increase the frequency and amount of irrigation, increase the use of chemical fertilizer and pesticides, and change crop variety. Moreover, about 63.3% of the farmers adopted more than one adaptation strategy and 2.3% of the households adopted more than three adaptation strategies. Overall, farmers were informed of the information about temperature rise and rainfall decrease at the research sites. More details about the farmer's perception of climate change, the impacts of climate change on wheat production and farmer's adaptation practices are presented in Figure A1.

Table 1. Variable names, definitions and descriptive statistics for the sample.

Variable	Description	Sample Mean	Std. Dev
Yield	Wheat output (kg/ha)	6827.579	1749.542
Area	Area under wheat in hectare	0.771	1.992
Seeds	Seeds use per hectare (RMB)	1129.651	364.152
Chemical fertilizer	Chemical fertilizers use per hectare (RMB)	2476.440	697.026
Farm manure	Farm manure use per hectare (RMB)	171.858	564.062
Pesticide	Pesticides per hectare (RMB)	542.944	296.527
Household labor	Household labor input per hectare (RMB)	2638.080	2135.371
Employment expense	Employment expense per hectare (RMB)	180.419	581.991
Machinery	Machinery cost per hectare (RMB)	1526.853	701.715
Irrigation	Irrigation cost per hectare (RMB)	463.738	459.876
Rental	Rental expense per hectare (RMB)	32.684	94.295
Male	Dummy = 1, if the head of farmer household is male, 0 otherwise	0.723	0.448
Age	Age of the household head	55.124	10.417
Education	Dummy = 1 if the household head had attained > 9 years of schooling, 0 otherwise	0.615	0.487
Labor share	The proportion of Labor force in the total household population	0.604	0.221
Climate cognition	Dummy = 1 if the respondent perceives climate change, 0 otherwise	0.917	0.276
Climate impact on wheat	Dummy = 1 if the respondent believes climate change impacts wheat production, 0 otherwise	0.857	0.351
Climate Information	Dummy = 1 if the respondent received pre-warning weather information, 0 otherwise	0.430	0.496
Adaptation	Dummy = 1 if the farming household adapted to climate change, 0 otherwise	0.828	0.378

In addition, we collected detailed production data in different production stages. Labor input was classified by household labor and employment. The household average wheat planting area was 0.771 hectare, and the average wheat yield was 6827 kg/hectare, which was above the national average at 5471 kg/h [20]. Major inputs from farmers were chemical fertilizer, household labor, and machinery, and they had low rental and employment expenses. The average age of household heads was 55 years old, and sixty percent of them received more than nine years' education.

In this study, farmers that adopted at least one adaptation action were termed "adopters" and those not adopting any strategy as "non-adopters". Table 2 shows differences in household characteristics between adopters and non-adopters. The average wheat yield for non-adopters was significantly higher than that of adopters. It is also evident that some inputs, such as the cost of employment expense and irrigation, was significantly higher for non-adopters than that of adopters. However, adopters had a higher perception of climate change and corresponding impact on wheat production, and access to climate change information.

Table 2. Farm and household characteristics of adopters and non-adopters.

Variable	Adopters		Non-Adopters		Difference
	Mean	Std. Dev.	Mean	Std. Dev.	
Adaptation	1.000	0.000	0.000	0.000	
Yield	6740.563	1831.214	7246.547	1213.885	−505.984 **
Area	0.809	2.146	0.588	0.948	0.221
Seeds	1127.578	375.437	1139.629	306.923	−12.051
Pesticide	2467.206	692.978	2520.898	721.167	−53.692
Farm manure	144.332	521.404	304.387	727.207	−160.055
Chemical fertilizers	544.795	300.001	534.028	281.712	10.767
Household labor input	2708.825	2219.873	2297.456	1644.566	411.369
Employment expense	133.105	478.036	408.226	905.401	−275.121 **
Machinery	1547.522	651.598	1427.338	906.063	120.184
Irrigation	436.741	454.060	593.72	469.75	−156.979 **
Rental	33.584	96.138	28.349	85.563	5.235
Male	0.731	0.444	0.685	0.469	0.046
Age	55.238	10.256	54.574	11.241	0.664
Education	0.612	0.488	0.63	0.487	−0.018
Labor Share	0.597	0.218	0.637	0.236	−0.040
Climate cognition	0.977	0.150	0.63	0.487	0.347 ***
Climate impact on wheat	0.977	0.150	0.278	0.452	0.699 ***
Climate Information	0.508	0.501	0.056	0.231	0.452 ***

Note: ** and *** represent the statistically significant at 5% and 1%, respectively.

3.2. Estimates of Climate Change Adaptation and Wheat Yield Equations

The endogenous switching regression model estimates adaptation decisions and yield outcome equations jointly [12]. Table 3 shows the results of endogenous switching regression.

Table 3. Endogenous switching regression results for climate change adaptation and impact on wheat yield.

Variable	Adaptation	Wheat Yield(log)	
		Adopters	Non-Adopters
Male	0.263 (1.10)	−0.003 (−0.07)	0.118 ** (2.55)
Age	−0.002 (−0.20)	0.001 (0.58)	0.000 (0.06)
Labor share	−0.616 (−1.36)	0.070 (0.98)	0.138 (1.48)
Education	−0.017 (−0.07)	0.065 * (1.91)	0.060 (1.15)
Area	0.298 * (1.85)	−0.021 ** (−2.55)	−0.073 ** (−2.17)
Seeds(log)		−0.053 (−1.28)	−0.098 (−0.85)
Farm manure(log)		−0.002 (−0.69)	0.006 * (1.78)
Chemical fertilizers		0.068 (1.26)	0.045 (0.64)
Pesticide(log)		0.042 (1.57)	0.051 (1.27)
Household labor (log)		−0.009 (−1.19)	−0.105 *** (−2.97)
Employment expense(log)		−0.007 (−1.35)	−0.001 (−0.10)

Table 3. *Cont.*

Variable	Adaptation	Wheat Yield(log)	
		Adopters	Non-Adopters
Irrigation(log)		0.012 *** (4.88)	−0.002 (−0.27)
Machinery(log)		−0.007 (−1.10)	−0.006 (−1.13)
Rental(log)		−0.009 ** (−2.26)	−0.009 (−1.39)
Rent (0/1)	0.157 (0.43)		
Climate cognition	1.877 *** (4.91)		
Climate Information	1.259 *** (4.65)		
Constant	−0.923 (−1.34)	8.189 *** (16.63)	9.613 *** (9.81)
σ_1		−1.402 *** (−29.70)	
σ_0			−1.999 *** (−10.83)
ρ_1		0.347(1.54)	
ρ_0			0.584(0.70) (0.70)

Note: *, ** and *** represent the statistically significant at 10%, 5% and 1%, respectively; t-value in parenthesis.

The second column of Table 3 presents the estimated results of the adaptation selection equation representing the determinants of adopting climate change adaptation. The coefficient of area is positive and statistically significant, suggesting that farmers with larger cultivation area were more likely to employ climate change adaptation strategies. The effects of climate cognition and climate information were both positive and statistically significant, indicating that farmers who are aware of climate change and could obtain information about climate change were more likely to adapt to climate change.

The estimates presented in the third and fourth column of Table 3 account for the endogenous switching in the wheat yield function. The estimated coefficients of the correlation coefficients ρ_0 or ρ_1 are both not significantly different from zero, indicating there may be no sample selectivity bias in the sample [18]. However, the differences in the coefficients of the wheat yield equation between the adopters and non-adopters suggest heterogeneity in the sample [6,18]. The results in Table 3 indicate that area is an important factor in explaining lower wheat yield in both adopter and non-adopter groups. However, gender, education, farm manure, household labor, irrigation, and rent appear to have differentiated impacts on the wheat yield of adopters and non-adopters. The results in the third column indicate that education and irrigation are significant and positive factors in wheat yields among adopters. However, household labor input seems to have a negative and significant effect on the wheat yield of non-adopters.

Table 4 presents the expected farmers' wheat yield under actual and counterfactual conditions and the estimated results of the average treatment effects and base heterogeneity effects. Cells (a) and (b) represent the expected wheat yield observed in the sample. Cell (c) represents the expected wheat yield of the adopters if they had decided not to adapt, and cell (d) represents the expected wheat yield of the non-adopters if they decided to adapt. Adopters would have produced about 1911 kg/ha (29%) more if they had not adapted. Similarly, non-adopters would have produced about 1039 kg/ha (14%) less if they had adapted.

Table 4. Impact of adaptation on average expected wheat yield: treatment and heterogeneity effects.

Sub-Samples	Decision Stage		Treatment Effects
	To Adapt	Not to Adapt	
Adopters	(a) 6551.72 (49.211)	(c) 8463.331 (344.042)	TT = −1911.611 *** [−5.614]
Non-adopters	(d) 6167.134 (89.356)	(b) 7206.905 (110.097)	TU = −1039.771 *** [−13.716]
Heterogeneity effects	BH1 = 384.587 *** [3.770]	BH2 = 1256.427 *** [3.478]	

Note: Standard errors in parenthesis and t-value in square brackets. *** represent the statistically significant at 1%.

In addition, the last row of Table 4 shows that adopters would have produced significantly more than the non-adopters in the counterfactual case. The significant heterogeneity effects imply that, regardless of the issue of climate change, the adopters are "better producers" than the non-adopters caused by some important sources of heterogeneity. The finding is consistent with Di Falco et al. (2011) and Khanal et al. (2018).

4. Conclusions and Discussion

This study found that over 90% of the wheat farmers are aware of climate change and over 80% of the households have autonomously adopted adaptation strategies. Farmers' cultivated area, climate change cognition and information on climate change significantly determined their adaptation decisions. However, farmers have limited adaptation strategies, mainly including increasing irrigation, and using more chemical fertilizer and pesticides. Based on this study, farmers' climate change adaptation strategies significantly decreased wheat yield, indicating that farmers' climate change adaptation actions may be maladaptive.

Some studies also found maladaptive outcomes of some agricultural adaptation actions [25–27]. In this study, why did the measures fail to reduce climate risk and have adverse consequences? The following are the possible reasons for the failure of main adaptation actions.

First, according to Liu et al. (2010), in the grain-filling stage of winter wheat, the frequency and quantity of irrigation should be reduced appropriately [28]. Therefore, the farmers' adaptation action to increase irrigation frequency and amount in response to reduced rainfall may lead to a negative effect on wheat yield, if they increase irrigation in an improper period. Second, in Ethiopia and Nepal, the input of fertilizer is a significant factor in higher food yields [12,18]. However, China has input utilizes about 52 times pesticides per hectare more than Ethiopian and Nepal; and China spent about 7 and 35 times fertilizer per hectare more than Ethiopian and Nepal respectively [29] China ranks first in the intensity of fertilizer used in agricultural production in the world, but fertilizer utilization is about 45%, far lower than the 60% utilization rate in developed countries [30]. Some empirical studies have shown that small farmers are risk-averse and would like to use a higher amount of fertilizer in order to avoid the negative impact of potential climate risks on agricultural production [31,32]. However, most farmer households have limited technical knowledge and a lack of agricultural labor force, depending on their traditional experience and habits, the phenomenon of farmer's overuse of fertilizer is widespread and serious in China [32,33]. Overuse of chemical fertilizers may decline the fertility of arable land, cause water pollution [34], and erode sustainable development of agriculture [25]. Therefore, the adaptation action of increasing fertilizer in response to the climate change risk would raise food production when the use of fertilizer is insufficient, but instead farmers increasing use of fertilizers and pesticides likely have a negative effect on wheat yield and the environment, if the fertilizer and pesticide inputs are excessive and inefficient. Third, some farmers change crop varieties to plant drought tolerant and disease-resistant wheat varieties in response to reduced rainfall and increasing pest and disease damage. However, the drought tolerant and disease-resistant wheat varieties may not be high-yield varieties and the adaptability of a new variety in complex environmental factors may lead to crop failure.

There is no doubt that adaptation is an important part of reducing the negative effects of climate change, sustaining farmers' livelihoods and ensuring agricultural sustainable development [35]. In particular, agriculture in China faces serious resource and environmental constraints, like water shortage and environmental degradation. However, small farmer's autonomous adaptation may be maladaptive and unsustainable. Therefore, the local government in Henan should help small farmers implement appropriate and effective adaptation strategies because government is in charge of agricultural infrastructure construction (irrigation and water conservancy systems, the agricultural product quality monitoring system and the agricultural information system) and agricultural science and technology progress (agricultural science and technology research, and agricultural science and technology popularization) [36,37]. Otherwise, small farmers may waste their efforts and resources without benefit, and may even experience loss if they just rely on themselves. Based on our findings, on one hand, it is urgent to implement scientific irrigation and fertilization to increase the efficient use of fertilizers and water for the interests of farmers and the sustainable development of agriculture. On the other hand, it is advisable to pay more attention to seed variety research and development to provide farmers with wheat varieties that have high yields, drought tolerance, and disease resistance, and guide them to choose suitable varieties according to local conditions.

This study investigates the phenomenon of wheat farmers' maladaptation to climate change in Henan of China. Reasons behind the phenomenon, and whether it represents a general condition across different regions or crop varieties, will be explored in further research.

Author Contributions: Conceptualization, S.Q. and Y.L.; Funding acquisition, Y.L.; Investigation, Y.L. and J.S.; Methodology, S.Q. and T.Z.; Supervision, Y.L.; Writing—original draft, S.Q.; Writing—review & editing, Y.L. and M.W.

Funding: This research was funded by the National Natural Science Foundation of China, grant number 71473241; The APC was funded by the National Natural Science Foundation of China, grant number 71473241.

Acknowledgments: Distinctive thanks to all respondents for their great support to our field research. And helpful comments from the reviewers and editors are appreciated.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

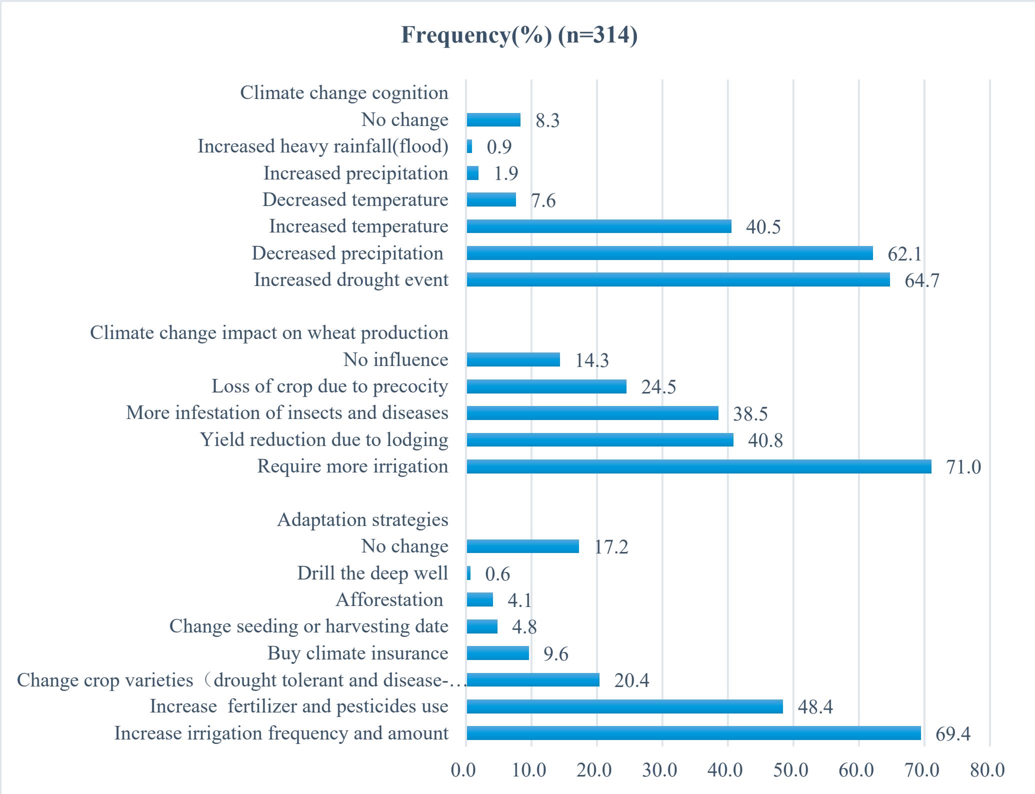

Figure A1. Percentage of farmers' perception of climate change, climate change impacts on wheat production and farmers' adaptation practices.

Table A1. Validity test of selection instruments.

	Model 1	**Model 2**
	Adaptation 1/0	**Wheat Yield per Hectare Produced by Non-Adopters**
Male	0.246(0.238)	0.116 **(2.09)
Age	−0.004(0.011)	0.000120 (0.05)
Labor share	−0.549(0.443)	0.144(1.31)
Education	0.034(0.224)	0.090(1.45)
Area	0.016(0.011)	−0.060(−1.39)
Climate cognition	1.889 ***(0.335)	0.012(0.057)
Climate Information	1.230 ***(0.273)	−0.147(0.111)
Seeds(log)		−0.031(−0.32)
Pesticide(log)		0.055(1.15)
Farm manure(log)		0.004(0.98)
Chemical fertilizers(log)		0.036(0.42)
Machinery(log)		−0.00148(−0.26)
Irrigation(log)		0.00106 (0.14)
Household labor input(log)		−0.085 *(−2.02)
Employment expense(log)		0.00375(0.62)
Rental(log)		−0.089(−1.26)
Rent (0/1)	0.147(0.345)	
Cons	−0.849(0.704)	8.916 ***(10.17)
	χ^2 = 87.67 ***	F-stat. = 1.85
Sample size	314	54

Note: Model 1: Probit model (Pseudo R^2 = 0.304); Standard errors in parenthesis. Model 2: Ordinary least squares (R^2 = 0.445). T-value in parenthesis. *, ** and *** represent the statistically significant at 10%, 5% and 1%, respectively.

References

1. Bandara, J.S.; Cai, Y. The impact of climate change on food crop productivity, food prices and food security in South Asia. *Econ. Anal. Policy* **2014**, *44*, 451–465. [CrossRef]
2. IPCC. *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Summary for Policymakers*; IPCC: Geneva, Switzerland, 2014.
3. Lobell, D.B.; Burke, M.B.; Tebaldi, C.; Mastrandrea, M.D.; Falcon, W.P.; Naylor, R.L. Prioritizing climate change adaptation needs for food security in 2030. *Science* **2008**, *319*, 607–610. [CrossRef] [PubMed]
4. Muller, C.; Cramer, W.; Hare, W.L.; Lotze-Campen, H. Climate change risks for African agriculture. *Proc. Natl. Acad. Sci. USA* **2011**, *108*, 4313–4315. [CrossRef] [PubMed]
5. Parry, M.L.; Rosenzweig, C.; Iglesias, A.; Livermore, M.; Fischer, G. Effects of climate change on global food production under SRES emissions and socio-economic scenarios. *Glob. Environ. Chang.* **2004**, *14*, 53–67. [CrossRef]
6. Piao, S.; Ciais, P.; Huang, Y.; Shen, Z.; Peng, S.; Li, J.; Zhou, L.; Liu, H.; Ma, Y.; Ding, Y.; et al. The impacts of climate change on water resources and agriculture in China. *Nature* **2010**, *467*, 43–51. [CrossRef] [PubMed]
7. Schlenker, W.; Lobell, D.B. Robust negative impacts of climate change on African agriculture. *Environ. Res. Lett.* **2010**, *5*, 014010. [CrossRef]
8. Xie, W.; Xiong, W.; Pan, J.; Ali, T.; Cui, Q.; Guan, D.; Meng, J.; Mueller, N.D.; Lin, E.; Davis, S.J. Decreases in global beer supply due to extreme drought and heat. *Nat. Plants* **2018**, *4*, 964–973. [CrossRef] [PubMed]
9. Smit, B.; Skinner, M.W. Adaptation options in agriculture to climate change: a typology. *Mitig. Adapt. Strateg. Glob. Chang.* **2002**, *7*, 85–114. [CrossRef]
10. Stage, J.; Limburg, K.; Costanza, R. Economic valuation of climate change adaptation in developing countries. *Ann. N. Y. Acad. Sci.* **2010**, *1185*, 150–163. [CrossRef] [PubMed]
11. Leclère, D.; Jayet, P.-A.; de Noblet-Ducoudré, N. Farm-level Autonomous Adaptation of European Agricultural Supply to Climate Change. *Ecol. Econ.* **2013**, *87*, 1–14. [CrossRef]
12. Khanal, U.; Wilson, C.; Hoang, V.-N.; Lee, B. Farmers' Adaptation to Climate Change, Its Determinants and Impacts on Rice Yield in Nepal. *Ecol. Econ.* **2018**, *144*, 139–147. [CrossRef]
13. Chen, H.; Wang, J.; Huang, J. Policy support, social capital, and farmers' adaptation to drought in China. *Glob. Environ. Chang.* **2014**, *24*, 193–202. [CrossRef]
14. Schlenker, W.; Lobell, B.D.; Bryan, E.; Ringler, C.; Okoba, B.; Roncoli, C.; Silvestri, S.; Herrero, M.; Nhemachena, C.; Rashid, H.; et al. Determinants of African farmers' strategies for adapting to climate change: Multinomial choice analysis. *Environ. Manag.* **2010**, *2*, 22.
15. Deressa, T.T.; Hassan, R.M.; Ringler, C.; Alemu, T.; Yesuf, M. Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Glob. Environ. Chang.* **2009**, *19*, 248–255. [CrossRef]
16. Alauddin, M.; Sarker, M.A.R. Climate change and farm-level adaptation decisions and strategies in drought-prone and groundwater-depleted areas of Bangladesh: An empirical investigation. *Ecol. Econ.* **2014**, *106*, 204–213. [CrossRef]
17. Abid, M.; Schneider, U.A.; Scheffran, J. Adaptation to climate change and its impacts on food productivity and crop income: Perspectives of farmers in rural Pakistan. *J. Rural Stud.* **2016**, *47*, 254–266. [CrossRef]
18. Di Falco, S.; Veronesi, M.; Yesuf, M. Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *Am. J. Agric. Econ.* **2011**, *93*, 829–846. [CrossRef]
19. Huang, J.; Wang, Y.; Wang, J. Farmers' Adaptation to Extreme Weather Events through Farm Management and Its Impacts on the Mean and Risk of Rice Yield in China. *Am. J. Agric. Econ.* **2015**, *97*, 602–617. [CrossRef]
20. NBSC. *China Statistical Yearbook 2018*; China Statistics Press: Beijing, China, 2018. (In Chinese)
21. WGCNARCC. *The Third National Assessment Report on Climate Change*; Science Press: Beijing, China, 2015. (In Chinese)
22. MOAC. *China Agricultural Year Book 2015*; China Agriculture Press: Beijing, China, 2015. (In Chinese)
23. Khanal, U.; Wilson, C.; Hoang, V.N.; Lee, B.L. Autonomous adaptations to climate change and rice productivity: a case study of the Tanahun district, Nepal. *Clim. Dev.* **2018**. [CrossRef]
24. Khanal, U.; Wilson, C.; Lee, B.L.; Hoang, V.N. Climate change adaptation strategies and food productivity in Nepal: a counterfactual analysis. *Clim. Chang.* **2018**, *148*, 575–590. [CrossRef]
25. Antwi-Agyei, P.; Dougill, A.J.; Stringer, L.C.; Codjoe, S.N.A. Adaptation opportunities and maladaptive outcomes in climate vulnerability hotspots of northern Ghana. *Clim. Risk Manag.* **2018**, *19*, 83–93. [CrossRef]

26. Kihupi, M.L.; Mahonge, C.; Chingonikaya, E.E. Smallholder Farmers' Adaptation Strategies to Impact of Climate Change in Semi-arid Areas of Iringa District Tanzania. *J. Biol. Agric. Healthc.* **2015**, *5*, 123–132.
27. Müller, B.; Johnson, L.; Kreuer, D. Maladaptive outcomes of climate insurance in agriculture. *Glob. Environ. Chang.* **2017**, *46*, 23–33. [CrossRef]
28. Liu, P.; Cai, H.; Wang, J. Effects of Soil Water Stress on Growth Development, Dry-matter Partition and Yield Constitution of Winter Wheat. *Res. Agric. Mod.* **2010**, *37*, 1049–1059.
29. FAO. *Food and Agriculture Data*; FAO: Rome, Italy, 2018.
30. Wu, L.; Yin, S.; Wang, J. *Introduction to 2014 China Development Report on Food Safety*; Peking University Press: Beijing, China, 2014.
31. Paudel, K.P.; Lohr, L.; Martin, N.R. Effect of risk perspective on fertilizer choice by sharecroppers. *Agric. Syst.* **2000**, *66*, 115–128. [CrossRef]
32. Huanguang Qiu, H.L. Effect of risk aversion on farmers' overuse of fertilizer. *Chin. Rural Econ.* **2014**, *3*, 85–96. (In Chinese)
33. Huang, J.; Hu, R.; Cao, J.; Rozelle, S. Training programs and in-the-field guidance to reduce China's overuse of fertilizer without hurting profitability. *J. Soil Water Conserv.* **2008**, *63*, 165A–167A. [CrossRef]
34. Tilman, D.; Fargione, J.; Wolff, B.; D'Antonio, C.; Dobson, A.; Howarth, R.; Schindler, D.; Schlesinger, W.H.; Simberloff, D.; Swackhamer, D. Forecasting agriculturally driven global environmental change. *Science* **2001**, *292*, 281–284. [CrossRef]
35. Hailegiorgis, A.; Crooks, A.; Cioffi-Revilla, C. An Agent-Based Model of Rural Households' Adaptation to Climate Change. *J. Artif. Soc. Soc. Simul.* **2018**, *21*, 4. [CrossRef]
36. Wu, C. *A Research on Rural Public Goods Supply System Development during the Transformation Period in China*; Huazhong Agricultural University: Wuhan, China, 2007. (In Chinese)
37. Cheng, X.; Wu, Q. The responsibility of the government in the rural public goods supply system. *Rural Econ.* **2009**, *2*, 54–58. (In Chinese)