AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
http://ageconsearch.umn.edu
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

Beyond quantity: the crowding-in effects of perception of climate risk on chemical use by Chinese rice farmers

L. Tang; J. Zhou; Q. Liu

Zhejiang University, Center for Agricultural and Rural Development(CARD), China

Corresponding author email: luckytlq@163.com

Abstract:

Farmers' perceptions of climate risk reflect their subjective probability weighting bias, which are the prerequisite for their adaptation decisions and thus shape their actions. As an adaptation strategy, farmers prioritized the technological measures of chemical input as the most simple and convenient for climate risks. However, this is little evidence of empirical work on the mechanism between farmers' perceptions and chemical use behavior. Based on cross-sectional data from a survey of farmers in China, this study develops a theoretical framework that considers adaptation decisions of heterogonous farmers within a perception-decision-action (PDA) analytical framework, and further estimates the effects of farmers' perceptions on chemical use behavior by utilizing endogenous switching regression model. The results indicate that under ceteris paribus, the key variables "perception of climate risk" of farmers have significant effect on their claim of increase in the quantity of chemical use. We find evidence of crowding-in of farmers' perceptions on chemical use, which in turn will have negative effect on environment and food quality. The paper concludes by offering some policy implications for the presented results.

Acknowledegment: Acknowledgements We are grateful for support from the Key Project of National Natural Science Foundation of China (No.71633002), the National Natural Science Foundation of China (No. 71273234), the Key project of the Ministry of Education (No.16JJD63007), The Key Project of National Social Science Foundation (No. 13AZD079), and The Key Soft Science Project of Science Technology Department of Zhejiang Province (No. 2017C35G2100255).

JEL Codes: Z13, R2

#1390

Beyond quantity: the crowding-in effects of perception of climate risk on chemical use by Chinese rice farmers

Abstract: Farmers' perceptions of climate risk reflect their subjective probability weighting bias, which are the prerequisite for their adaptation decisions and thus shape their actions. As an adaptation strategy, farmers prioritized the technological measures of chemical input as the most simple and convenient for climate risks. However, this is little evidence of empirical work on the mechanism between farmers' perceptions and chemical use behavior. Based on cross-sectional data from a survey of farmers in China, this study develops a theoretical framework that considers adaptation decisions of heterogonous farmers within a perception-decision-action (PDA) analytical framework, and further estimates the effects of farmers' perceptions on chemical use behavior by utilizing endogenous switching regression model. The results indicate that under *ceteris paribus*, the key variables "perception of climate risk" of farmers have significant effect on their claim of increase in the quantity of chemical use. We find evidence of crowding-in of farmers' perceptions on chemical use，which in turn will have negative effect on environment and food quality. The paper concludes by offering some policy implications for the presented results.

Key words: perception of climate risk; chemical use; rice farmer; endogenous switching regression model; China

1. Introduction

Accumulating evidence have revealed significant climate warming trends in recent decades (IPCC 2014; Shrestha and Nepal 2016;). Climate change, characterized by increasing temperature, uncertain rainfall and changing weather patterns, poses a major threat to agricultural systems (Rosenzweig and Parry 1994; Parry et al. 1999; Zhou et al. 2018). For China, the economic losses due to natural

disaster reached 13.6 billion dollars in 2015, which suffered most serious from natural disaster globally (UNISDR 2016), and the annual average crop area suffering from drought has more than doubled since the 1950s, followed by flood events (MWR 2014). Ju et al. (2007) report that the direct economic losses caused by meteorological disaster account for an estimated 3~6% of GDP each year, among of which drought is the most severe extreme events faced by China's rice producers. Rice is the main staple food in China, which produces nearly 30% of the world's total rice output (FAOSTAT 2014), but it is particularly vulnerable to climate extremes. Hence we especially shed light on rice production in this study.

A large body of literature have examined the impact of climate change on crop yield (e.g. Rosenzweig et al. 2001; Ju et al. 2007; Chen et al. 2015; Huang et al. 2015; Bobojonov et al. 2016; Zhou et al. 2018), but climate change, especially extremely high temperatures during the ripening period can lead to high risk of milky white grains, immature grains, cracked grains (Kawasaki and Uchida 2016) and accelerate the evaporation rate of chemical use (Ahmed and Stepp 2016; Zhou et al. 2017). This in fact may bring about a decline in the effectiveness of chemical use and an expanding range of pests and diseases outbreaks (Chen and McCarl 2001; Miraglia et.al 2009; Sun et al. 2012; Chen 2015; Zhou et al. 2017). As an adaptation strategy, farmers then adjust their chemical use quantity to new emerged conditions in order to mitigate potential yield loss. In China, the chemical fertilizers consumption rises from 25.90 million tons in 1990 to 59.12 million tons in 2013 (NBSC 2014). However, the chemical fertilizer use efficiency is only around 33% (MOA 2015), indicating that around two thirds of the agricultural chemicals utilized go into the environment. So China's agricultural expansion has been at the expense of environment and of sustainable development (Ali et al. 2017). Despite their positive contribution to agricultural productivity, excessive chemical use can lead to contamination of surface and groundwater, soil, and a higher risk of chemical residues via agricultural products (e.g. Rosenzweig et al. 2001; Chen and McCarl 2001; Hall et al. 2002; Zhou et al.

2017). There is substantial evidence that Chinese farmers apply too much chemical fertilizers (e.g. Li & Zhang 2013；Zhang et al. 2015; Zhou et al. 2017). As the principal microeconomic entity of agriculture production, individual and small-scale production by farmers in China is identified as the main factor affecting the agriculture environment and food quality (Gong et al. 2010; Tian et al. 2015; Zhou et al. 2017). Farmers' proper use of chemical input is an original and key link to ensure the safety of food quality, because it will be reflected in all the downward links of supply chain and sequentially affect consumers' health and safety (Henson et al. 2005; Koureas et al. 2012; Thongprakaisang et al. 2013; Zhou et al. 2017). Especially along with increasing society's concerns for sustainability and global climate warming, to reduce pesticide and fertilizer use is becoming one of the most challenging environmental policy objectives. But farmers in China are most poorly educated, 40.3% of whom are primary school level or less, 48.1% are middle school level and only 11.6% are highly educated[1]. The low-level education of farmers poses more challenges to the proper use of chemical input. Thus seeking to reduce pesticide and fertilizer use has therefore become a policy priority in China (MOA 2015).

However, climate change as objective phenomenon, farmers may observe the change on climate, but they do not necessarily perceive its change. Only farmers who have perceived climate risk can possibly form adaptation decision and then take adaptation behavior (Deressa et al. 2011; Banerjee 2015; Hou et al. 2015, 2017). The existing literature has stated that farmers' perceptions are an essential first step in the adaptation process (Gbetibouo 2009; Moser and Ekstrom 2010; Hou et al. 2015; Devkota et al. 2016). Farmers' perceptions of climate risk are prerequisite for farmer's adaptation, and farmers' adaptation behaviors can be regarded as the process of how their perceptions are be translated into decision-making in agriculture production (Below et al. 2012; Banerjee 2015). Only farmer who is aware of climate

[1] Data source: according to the survey results of *Sixth Population Census* conducted by National Bureau of Statistics of the People's Republic of China in 2010.

risk, he or she will form a decision or motivation to take actions (Gbetibouo 2009; Hou et al. 2017). But farmers who decided to do not really mean that they would translate into actions, thus it is essential to distinguish farmers' adaptation decisions from actual adaptation behaviors. Generally, farmers' adaptation behaviors exhibited a three steps of engagement pattern: observation, risk perception and action, and each of these steps occurred in sequence, whereby taking each step depended on the step that precede it (Bohensky and Brewer 2013). Thus we select the key variable of "perception of climate risk" focused on in the study as the indicator, rather than objective meteorological data, to measure the effects of climate change on farmers' rice production behaviors. However, the potential endogeneity of perceived risk may be endogenous to adaptation decisions, which might induce estimation bias (Whitehead 2006). Very few studies have so far examined the impact of farmers' perceptions of climate risk on adaptation behavior by jointly addressing the importance of psychological factors in the process of forming adaptation decisions and thus on adaptation behaviors. In this study, we argue that perception of climate risk has to be treated as endogenous to adaptation decisions in order to accurately evaluate farmers' adaption behaviors. To the extent that farmers self-select into increasing or not increasing chemical use, we use endogenous switching regression model to account for potential endogeneity and selectivity bias.

To address the gap in current literature, based on 1080 households' survey data from four leading rice producing provinces in China, we developed a Perception-Decision-Action (PDA) analytical framework and adopted an endogenous switching regression model to estimate the effects of farmers' perceptions of climate risk on their chemical use behavior, which taking farmer's psychological steps into consideration when they make adaptation decisions. Specifically, we attempt to answer the following questions: what are the perceptions of farmers on the local climate and their effects on rice, especially changes in drought and flood? How do farmers' perceptions affect their adaptation decisions, particularly with respect to

chemical use? To what extent are farmers' chemical use behavior affected by their perceptions?

Rest of the paper is organized as follows. Section 2 illustrates climate risk and rice farmers' responses in study areas. Section 3 explains the empirical strategy used to evaluate farmers' perceptions of climate risk and their effects on chemical use. Section 4 introduces the data and sampling method used in this study. Then Section 5 provides econometric estimation results. The final section concludes with policy implications.

2. Climate risk and rice farmers' responses: A PDA analytical framework

2.1. Drought and flood trends in study areas

The areas affected by drought and flood respectively account for 17.6% and 8.1% of the total grain acreage, while the proportions for each province respectively vary from 5～19% and 2～10% in China (Ju et al. 2007). Considering that drought and flood are the most severe weather events faced by Chinese rice farmers, so the scope of this study is limited to drought and flood events. According to the meteorological record dataset[2], the frequency of drought and flood has shown an increasing but widely fluctuating trend in the studied four provinces in the past four years (see Fig.1). On average, Hunan suffered drought most serious, along with higher volatility risk. In Sichuan, the average annual crop area suffering from drought increased from 0.20 million hectares in 2011 to 0.85 million hectares in 2013, with an average growth rate of 6.2% (NBSC 2014). The drought severity in Jiangsu has been relatively stable during the same period, with a declining severity of flood. Zhejiang, as an exception among the four provinces, has seen a declining severity of drought. It is worth noting that the total area affected by drought in four provinces is especially significant in 2013, indicating the occurrence of national-wide drought in China in 2013. On the

[2] Source: the meteorological record dataset are obtained from the National Meteorological Information Center of the Republic of China.

other, with respect to flood, Hunan and Sichuan have witnessed more serious flood shocks in recent years, while Jiangsu has seen a declining severity of flood.

[Insert Fig. 1 here]

2.2. Rice farmers' responses: A PDA analytical framework

Following Bohensky and Brewer's (2013) three steps of farmers' adaptation engagement pattern, we developed a Perception-Decision-Action (PDA) analytical framework to analyze farmers' perceptions on climate risk and their effects on adaptations (chemical use) both subjective dimension and objective dimension (See Fig.2). On one hand, we select the variable of 'whether to increase chemical use' as subjective dimension to measure farmers' perceived severity of climate risk on their adaptation decisions. We assume that rice farmers who perceive more severe climate risk are more likely to increase chemical use in order to mitigate the potential yield losses. On the other, from objective dimension, we select 'the quantity of chemical use' to further quantify the effects of farmers' perceptions of climate risk on chemical use behavior.

Previous studies have examined either farmers' perceptions on climate change and their adaptive measures (e.g. Seo and Mendelsohn 2008; Patt & Schröter 2008; Bryan et al. 2009; Kuruppu & Liverman 2011; Chen et al. 2014; Wang et al. 2014; Zhao 2014; Devkota and Bhattarai 2015; Bai et al. 2015; Huang et al. 2015; Hou et al. 2017; Xie et al. 2017), such as diversifying crop varieties, adopting technological measures, and adjusting chemical use such as pesticide and fertilizer, or just only focused on farmers' pesticide use behavior (Chen and McCarl 2001; Skevas and Lansink 2014; Skevas and Serra 2016) or chemical fertilizer use (e.g. Coady 1995; Croppenstedt et al. 2003; Gong et al. 2010; Ning & Wu 2011; Ning Chou et al. 2014; Tian et al. 2015). However, with more frequent and extreme weather events, especially extremely high temperatures, farmers are suffering increasing stress on the frequent outbreaks of pests and diseases, which may allow pest migration or population expansions and lead to an expanding range of pests and diseases disasters

(Chen and McCarl 2001; Kawasaki and Uchida 2016; Ahmed and Stepp 2016; Zhou et al. 2017) and thus could correspondingly induce farmers to increase chemical use in order to mitigate the potential losses (Chen and McCarl 2001; Miraglia et al. 2009; Sun et al. 2012; Zhou et al. 2017). Our survey results also indicate that 38.7% of surveyed farmers in China prioritized the technological measures of adjusting chemical input such as pesticides as the most simple and convenient adaptation strategy for climate risks (see Table 3), particularly along with the sharply increasing trend of labor cost in recent years. But the mechanism between farmers' perceptions and their effects on chemical use behavior are under-researched. Therefore, we focused on farmers' perceptions of climate risk and their possible effects on chemical use behavior in this study.

[Insert Fig. 2 here]

3. Empirical model

3.1 Base Model

For the present study, we assume that farmer's adaptation decision and adaptation behavior or action are two sequential but distinct processes. The first is a farmer's decisions on whether to take adaptation measures when they have perceived severity of climate risk on rice; the second is a farmer's decision on the extent of participation in an adaptation behavior or action. By taking farmer's adaptation behavior into consideration, in order to estimate the degree to which farmers' perceptions of climate risk on chemical use, we specify the quantity of chemical use function as:

$$\log(q) = f(D, C, X, \beta) + \mu \tag{1}$$

Where q denotes the quantity of chemical use (kg/ha); D is a dummy variable denoting the decision on whether to increase chemical use (1 for increase, and 0 otherwise). C denotes farmers' perceived severity of climate risk on rice. X is a set of explanatory variables. β is a vector of parameters to be estimated. u is the error term that captures measure errors，unobserved heterogeneities, and uncertainties, and satisfies $E(u) = 0$.

If $f(D, C, X, \beta)$ is specified as a linear function, the coefficient of D exactly measures the impact of adaptation decision (whether to increase chemical use) on the quantity of chemical use. However, farmer's adaptation decision, which is linked to farmer's perceptions of climate risk, could be endogenous. Farmers who decide to increase chemical use or not may have different functions, so that is not good to pool the two functions together. Thus it is necessary to estimate separately, and we proposed an endogenous switching regression to tackle this issue.

3.2 Endogenous Switching Regression Model

To deal with the endogeneity of farmers' adoption decision (D), we further employ an endogenous switching regression model. In the switching regression approach, farmers are partitioned into two regimes according to the farmer's decision on whether to increase chemical use or not. Formally, let Y_{1i} and Y_{2i}, i=1…, N, denote the dependent variable to be explained in each of two regimes. Let X_{1i} and X_{2i} be $1\times k_1$and $1\times k_2$ vectors of explanatory variables relevant to each regime. Let β_1 and β_2 be respectively $k_1\times 1$ and $k_2\times 1$ parameter vectors, and α be an $m\times 1$ parameter vector. Also, let A_i^* be the latent variable determining which regime applies, Z_i be a $1\times m$ vector of variables explaining the decision or selection into the regimes. Finally, let η_i u_{1i}, u_{2i} be error terms.

Theoretically, farmers typically choose to adopt adaptation strategy when there is a net benefit from doing so (Abdulai and Huffman 2014; Bai et al. 2015). We adopt a utility maximization function in the presence of climate risk to conceptualize adaptation decisions. In our case, a farmer i decides to increase chemical use if the expected utility from adoption of more chemical input (U_a) is better than the corresponding utility from non-adoption (U_{na}), i.e., $U_a - U_{na} > 0$. Farmer i's adaptation decision (whether to increase chemical use) thus can be modelled by a latent variable explanatory variable A_i^* as

(2) $$D_i^* = X_i\alpha + I_i\kappa + C_i\gamma + \eta_i$$

$$D_i = \begin{cases} 1, D_i^* > 0 \\ 0, D_i^* \leq 0 \end{cases}$$

Where the variable I_i is an instrument variable (IV) for D. It is defined as access to local weather warning service at the village level (1=yes, 0 otherwise). Furthermore, we control the level of farmer's perception of climate risk C_i on rice, which includes two dummy variables: obvious (1=yes, 0 otherwise), very obvious (1=yes, 0 otherwise) and we set the farmers who perceived *no effect* as baseline. Then,α, κ, γ denote a vector of parameters to be estimated; η is the error term and satisfies E (η) = 0 and $\sigma_\eta^2 = 1$.

According to farmer's decision on whether to increase chemical use, a separate outcome function of two regimes for farmers corrected for endogenous adoption are specified:

(3a) Regime 1: $\log(q_{1i}) = X_{1i}\beta_1 + \sigma_{1u1\mathrm{i}}\hat{\lambda}_{1i} + u_{1i} \quad if\ D_i = 1$ (To increase）

(3b) Regime 2: $\log(q_{2i}) = X_{2i}\beta_2 + \sigma_{2u2\mathrm{i}}\hat{\lambda}_{2i} + u_{2i} \quad if\ D_i = 0$ (Not to increase)

Where y_{1i} and y_{2i} are the quantity of chemical use (in logarithm) of farmer i under regime 1 (to increase) and regime 2 (not to increase). X_i is a vector of explanatory variables and the vectors β_1 and β_2 are parameters to be estimated; $\hat{\lambda}_{1i} = \frac{\phi(Z_i\hat{\alpha})}{\Phi(Z_i\hat{\alpha})}$ and $\hat{\lambda}_{2i} = \frac{\phi(Z_i\hat{\alpha})}{1-\Phi(Z_i\hat{\alpha})}$ are the inverse Mill's ratios (IMR) computed from the decision equation and are included in equations (3a) and (3b) to correct for selection bias in a two-step estimation procedure. The standard errors in equations (3a) and (3b) are bootstrapped to account for the heteroscedasticity arising from the generated regressor ($\hat{\lambda}$). $\sigma_{1u1\mathrm{i}}$ and $\sigma_{2u2\mathrm{i}}$ are the variances of the error terms from the two regimes respectively.

Together with the probit model of decision in Equation (2), the endogenous switching regression can be jointly estimated by the full information maximum likelihood (FIML) method (Lokshin and Sajaia 2004). The decision equation (2) helps identify the factors that determine farmers' adaptation decisions on chemical use. The outcome equation (3a) and (3b) quantify the effects of farmers' perceptions on

chemical use behavior. To the best of our knowledge, this study is the first to utilize an endogenous switching regression model to evaluate the effects of farmers' perceptions of climate risk on their chemical use behaviors in China.

4. Data source and sampling

Taking full consideration of regional crop production systems and climate situations, we used a stratified sampling method and selected rice farms in four major rice producing provinces with high risk of rice yield loss in order to make the samples more representative: Zhejiang and Jiangsu in the coastal area of eastern China, Sichuan in southwest China, and Hunan in central China. We then conducted a large-scale household survey regarding the impact of adaptation to climate change on rice production during the period from October 2014 to August 2015. From each of the provinces selected, six counties are randomly chosen following three standards. First, we identified counties that had experienced at least one episode of drought or flood year in the past three years (2012, 2013 or 2014). Second, we only kept those which had experienced one normal year of weather in the past three years and randomly selected 6 counties from each province. Then three towns are randomly selected from the chosen counties based on the condition of agricultural production infrastructure of 'good', 'medium' and 'poor', respectively. Finally, we randomly selected villages from these towns and 15 households were randomly selected from each chosen village for face-to-face interviews. Finally, a total of 1,080 from 72 villages in 24 counties rice farms were interviewed. Excluding the incomplete samples，the final sample used in our analysis includes 1,057 households from 68 villages in 24 counties (see Fig.3 & Table 1).

[Insert Fig. 3 and Table 1 here]

The information collected in the survey include: 1) farmers' perceptions of climate risk and their effects on chemical use. To capture the possible heterogeneity of farmers' perceptions, we control the level of farmer's perceived severity of climate risk, which contains two dummy variables: *obvious* (1=yes, 0 otherwise) and *very*

obvious (1=yes, 0 otherwise), with farmers' perceived climate risk of *no effect* as baseline; 2) household characteristics (the age, gender and education of household head) and farm characteristics (rice farm size, agricultural labor, annual family income and membership in any cooperatives); 3) whether participated in any technical training and whether perceived more stress on pests and diseases, both of which were collected in the village level survey; 4) access to local weather warning service and 5) province dummies (fixed effects at the provincial level) to control for unobserved heterogeneities for province.

In order to investigate farmers' perceptions on local climate and corresponding responses, four questions were asked in sequence to fully collect households' attitudes related to climate change (see Table 2). Overall, about 92.3% of the sample farmers reported they observed change on local climate and over 80% perceived that climate change could pose a risk to rice production. Among of them, more than 67% of farmers reported that they have suffered more pests and diseases during rice production between 2012-2014, and over 40% claimed that they would increase chemical use as a response because they prioritized chemical use as the most simple and convenient adaptation strategy for pests and diseases, especially along with the sharply rising trend of labor cost in China. Our survey results also indicate that as adaptation strategies, adjusting chemical use ranked the highest (38.7%), followed by changing dates of sowing and/or harvesting (29.5%) and diversifying crop varieties (16.9%) (see Table 3).

[Insert Table 2 &3 here]

Besides, as we can see from Table 4, under *ceteris paribus*, the key variable "perception of climate risk" of farmers has a significant effect on both the probability of increasing chemical use and the quantity of chemical use. Specifically, farmer who perceived more severity of climate risk on rice are more likely to increase chemical use as a response, 61.51% for *very obvious*, 52.12% for *obvious*, and 26.55% for *no effect*, respectively. While regarding the quantity of chemical use, farmers who

perceived *very obvious* used 442.13 kg/ha on average, 404.95 kg/ha for *obvious* and 367.62 kg/ha for *no effect,* further confirming that farmer's more severity of climate risk do induce an increase in chemical use.

[Insert Table 4 here]

5. Results and discussion

5.1. Summary statistics

Table 5 provides a description statistic for variables included in the empirical models. Of the 1057 samples, most of household heads are middle to old aged (average of 48 years old), male-dominated and less educated (middle school or below) The average of rice farm size per household is about 3.11 ha, almost five times larger than the 2009 national average arable land per household, which is less than 0.667 ha per household[3]. It is mainly due to the fact that most households in our surveyed areas are engaged in rice production and thus have relative larger farm size. The number of agricultural labor forces per household is about 2 on average, with annual family income of RMB 50,000-100,000[4] or even below, and over half of rice farms had membership with some cooperatives. However, only 18.7% of sampled farmers participated in technical training and about one-third of rice farms in our study areas can access to local weather warning at village level, suggesting that the current public services are generally low and there is still much room to improve. Of significant interest in the study is the variable of perception of climate risk on rice. Table 4 shows that 58.8% of the sampled farmers perceived that climate change has very obvious effect on rice, while 24.5% perceived obvious effect on rice. Besides, 61% of sampled farmers reported they suffered more stress on pest and diseases. As a response, 52.3% of farmers decided to increase chemical use as an adaptation strategy and the average quantity of chemical use was about 420.55 kg/ha.

[Insert Table 5 here]

---

[3] According to *the Second National Land Survey* conducted by Ministry of Land and Resources of China during 2007-2009, the national arable land per capital was 0,101 ha (1.52 mu) and the national average arable land per household was less than 0.667 ha (10 mu) at the end of 2009.

[4] RMB is the unit of Chinese currency. 1 RMB=0.1526 US$ in 2016.

5.2. Estimation Results of Decision Function

As aforementioned, we use maximum likelihood techniques to jointly estimate decision equation (2), and outcome equations (3a) and (3b), which can be simultaneously estimated by using the STATA *movestay* command, developed by Lokshin and Sajaia (2004). The second column in Table 6 reports the estimation results for the decision function (2), which is a probit model helping explain why some farmers decide to increase chemical use as adaptation strategy and others not. The third and fourth columns present, respectively, the estimated coefficients of outcome functions (3a) and (3b) respectively for farmers who claimed to increase chemical use and who did not.

[Insert Table 6 here]

In the results of decision function (2), we are particularly interested in the effects of farmers' different severity of perceived climate risk on their adaptation decision (whether to increase chemical use). Farmer's perceived more severity of climate risk was assumed to motivate for a response action. The descriptive results in Table 4 have shown that farmers who perceived higher climate risk are more likely to increase chemical use as adaptation strategy (61.51% for *very obvious*, 52.12% for *obvious*, and 26.55% for *no effect*). And the empirical results suggest that the coefficients for "*obvious*" and "*very obvious*" are 0.288 and 0.775, both statistically significant at 1% level (see the row 1-2 in the second column of Table 6), confirming that rice farmers' adaptation decisions are significantly positive correlation with their perceived severity of climate risk. It is understandable that rice farmers are more motivated to increase chemical use when they have perceived higher climate risk, which is also consistent with the findings that more farmers were found to adjust their farm management practices in severe drought and flood years than in normal years (Huang et.al 2015; Hou et al. 2017).

According to the estimation results, farmers' participation in technical training was significantly negatively correlated with their adaptation decision (whether to

increase chemical use) and its coefficient is -1.094. This may be because farmers who attended technical training may have more knowledge of the side-effects of chemical use and more likely to take some other environmentally-friendly adaptation measures to cope with climate change. Besides, farmer's membership in any cooperatives has significantly negative effect on farmers' decision in chemical use. A possible explanation is that the membership contributes to more communication with external environment and expand farmers' knowledge of technology and market information, thus strengthening farmers' commitment to cooperatives (Zhou et al. 2017). Besides, more stress on pest and disease and rice farm size raised the likelihood of a household's decision on more chemical input. It may be due to the fact chemical input such as pesticide and fertilizer, as one of the most important inputs in agriculture, are generally regarded as the most common and convenient way to cope with pest and disease and mitigate the potential yield losses (Chou et.al 2014; Liu and Huang 2013).

In addition, some household characteristics also affect farmers' decisions to take adaptations. Both the coefficients of age and education are statistically significant negative in the decision equation, implying that older and more educated farmers are less likely to increase chemical use as a response, which is consistent with our common sense that old-aged farmers are rich in farming experiences and probably take other adaptation measures in respond to climate change (Chou et al. 2014; Zhou et al. 2017) and better educated farmers prefer to have off-farm jobs or more easily to adopt more advanced technologies (e.g., De Brauw et al. 2002; Chou et al. 2014).

Finally, we take the estimated coefficient for the instrument variable (IV) — local access to weather warning service, which is a significant predictor of adaption decision. As an instrumental variable, it should be correlated with decision function, but not the error terms in the outcome function. The estimated value is 0.516 and statistically significant at the 1% level. It implies that local access to weather warning service could help increase the likelihood of farmer adoption on more chemical use.

5.3 Estimation Results of Outcome Functions

Consistent with decision function, we used a separate outcome function of two regimes (whether to increase chemical use or not) for farmers to quantify the effects of farmers' perceptions of climate risk on the quantity of chemical use..

In the estimated results of outcome equations, as expected, most of the estimated results in equation (3a) and (3b) are consistent to the estimated results in decision equation (2). On the whole, we find that farmers' perceived more severity of climate risk in general increase chemical use no matter for farmers who claimed to increase or not increase. The estimated coefficients for farmers who claimed to increase chemical use are statistically significant at the 1% level (0.08 for *obvious*, 0.128 for *very obvious*), while farmers who claimed not to increase chemical use, only the estimated coefficient for *very obvious* is statistically significant and its value is 0.063, but the estimated coefficient for *obvious* is not statistically significant and its value is only 0.003. Thus compared to farmers who claimed not to increase chemical use, the magnitudes in terms of absolute value of the estimated coefficients for farmers who claimed to increase chemical are much larger. It implies that under *ceteris paribus*, the key variable "perception of climate risk" of farmers has a significant effect on their claim of an increase in chemical use, given the same severity of climate risk. Actually, it is found that farmers who perceived high climate risk increased the quantity of chemical use by about 13% for *very obvious* and 8% for *obvious*, respectively. Thus we find evidence of crowding-in of farmers' perceptions on chemical use, confirming the opinion that farmers who perceived more climate risk do induce more chemical use.

Consistent to the findings in decision equation, other factors such as local access to weather warning service, stress on pest and disease and rice farm size in outcome equations are empirically found to be induce more chemical use by farmers, while farmer's participation in technical training, membership in any cooperatives could reduce chemical use. Surprisingly, both the age and education of household head are not statistically significant in two outcome equations, which is contrary to the

conclusions that highly educated and old-aged farmers are less likely to increase chemical use (De Brauw et al. 2002; Chou et al. 2014; Zhou et al. 2017). However, for farmers who claimed to increase chemical use, there are three other factors, including the male head of household, the number of agricultural labor and annual family income, which are significantly related with the quantity of chemical use by rice farmers. The positive impact of male head of household suggests that men tend to be more motivated to increase chemical input to minimize the yield loss caused by climate risk, consistent with the findings by Zhou et al. (2017), but contrary to that woman tend to be more motivated to adjust farm management practices related to extreme events (Huang et al., 2015). The estimated coefficient for annual family income is positive and statistically significant, confirming that the rich may be better able to withstand climate risk due to their advantages of financial capacity. It is interesting that the variable of agricultural labor force is statistically significant and implies that more agricultural labor force in rice production are more likely to increase chemical use, consistent with previous findings on intensive or excessive use of production inputs in China now (e.g., Huang et al. 2008; Holst et al. 2013). This result suggests a need for policymakers to pay particularly attention to improve farmer's productivity and efficiency of chemical use.

Finally, the third and fourth rows from the bottom of Table 6 present the covariance term *rho* in the outcome functions for two group farmers who whether to increase chemical use or not, which account for the endogenous switching in two outcome functions. The estimated results show that *rho* (its value is 0.522) has a positive sign and is statistically significant in the equation for adapters, indicating that farmers who claimed to increase chemical use do have significantly more chemical input than a random household in the sample. Although the estimated coefficients of the correlation term *rho* is not statistically significant for non-adapter, the estimated coefficients of many variables in the outcome functions between adapters and non-adapters differ (see Table 6). Therefore, the above results suggest that we would

have encountered estimation problems if we had not used the endogenous switching regression model.

6. Conclusions

This study examined the mechanism between farmers' perceptions of climate risk, adaptation decisions and adaptation behaviors. Based on 1080 households' survey data from four leading rice producing provinces in China, we developed a Perception-Decision-Action (PDA) analytical framework and adopted an endogenous switching regression model to estimate the effects of farmers' perceptions of climate risk and their effects on chemical use behavior by jointly addressing the importance of psychological factors in the process of making adaptation decisions and adaptation behaviors. To the best of our knowledge, this study is the first to utilize an endogenous switching regression model to assess farmers' perceptions of climate risk and their effects on chemical use behavior in China.

The results show that farmers' perceptions of climate risk play a critical role in their adaptation behaviors. Empirical results further indicate that under ceteris paribus, the key variable "perception of climate risk" of farmers has a significant effect on their claim of increase in the quantity of chemical use in order to mitigate the potential losses. Actually, farmers who perceived high climate risk increased the quantity of chemical use by about 13% for *very obvious* and 8% for *obvious*, respectively. We find evidence of crowding-in of farmers' perceptions on chemical use. Besides, the results reveal that farmers' participation in technical training, their membership in cooperatives, and the age and education of household heads are negatively associated with farmers' adaptation decisions, while the three factors (access to local weather warning service, stress on pests and diseases and rice farm size) could incentivize farmers to take adaptation measures.

Though chemical input such as pesticide and fertilizer can contribute to increasing production, their excessive use and long-term intensive application can not only a matter for environmental sustainability, such as non-point source pollution and

agricultural ecology degradation, but a major source for food quality (Sanders 2006; Koureas et al. 2012; Shen et al. 2012; Sun et al. 2012). This situation is severer in developing economies, since more agricultural chemicals and pesticides are used for food security concerns. These findings provide implications for the design of effective policies. First, more attention should be paid to the potential impact of climate risk on the quality of agricultural products. Our empirical results indicate that rice farmers perceived more severity of climate risk induce more chemical use, which support China's recent efforts to reduce the growth rate of chemical fertilizer and pesticide consumption to zero (MOA 2015). Second, various measures should be taken to reduce the chemical use by farmers, such as providing more technical training for farmers, investing more on education for cultivating vocational farmers, and encouraging farms to join some cooperatives. For example, our survey results indicate that over four-fifths of farmers are still not able to access to technical training, so it is prior to provide more technical training for farmers, as well as providing more agricultural public service, in order to guide farmers to use chemical scientifically and promote the sustainability development of agriculture effectively. Third, farmers with certain demographic characteristics will be the targeted group for such efforts. For example, our results show that old aged farmers are less likely to take adaptation measures. This will become an even bigger issue with the rising aging in farming. Another prioritized area for policy interventions should be to improve adaptation capacity for the farmers who are more vulnerable and enhance their adaptive capabilities comprehensively. Thus the results of this study have important implications for both China and other developing countries.

Appendix

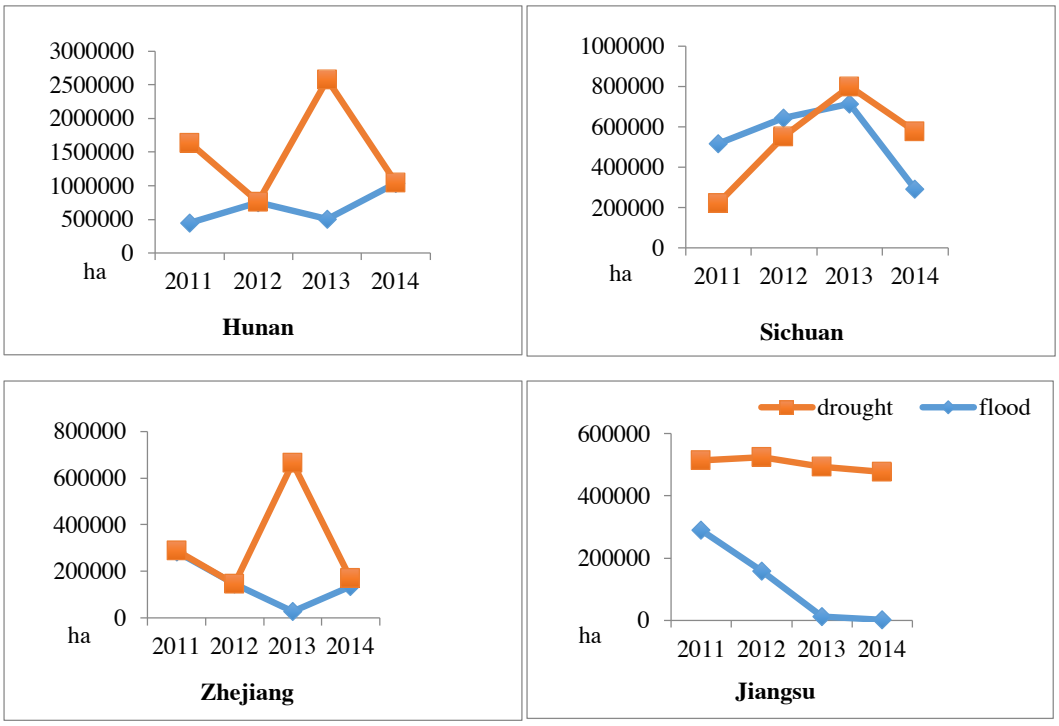

Fig.1 the total area affected by drought and flood in 4 sampled provinces[5]

[5] Source: the dataset of the total area affected by drought and flood are obtained from the National Meteorological Information Center of the Republic of China.

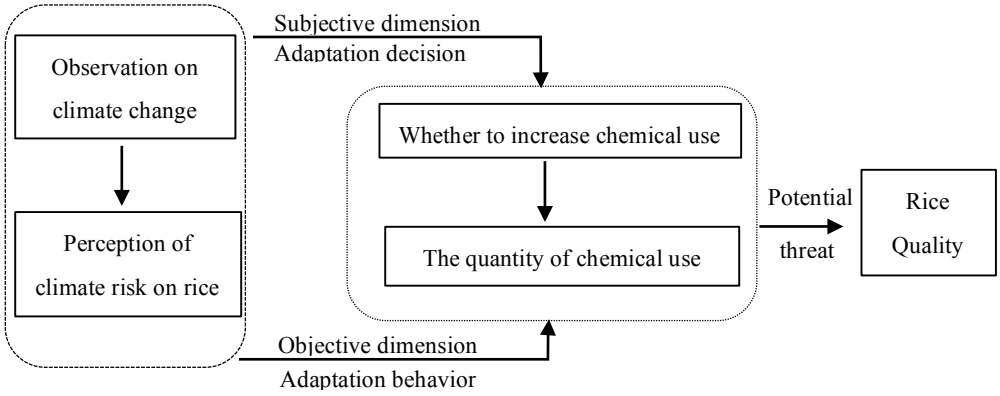

Fig. 2 “Perception-Decision-Action” (PDA) analytical framework

Fig. 3 Map of China and four sample provinces

Table 1 Distribution of surveyed rice farmers

Province	City/County	Village	Household	Province	City/County	Village	Household
Hunan	Changsha	2	30	Sichuan	Chengdu	4	70
	Yueyang	3	45		Nanchong	3	68
	Yiyang	2	35		Dazhou	3	48
	Hengyang	2	30		Mianyang	4	62
	Yongzhou	2	25		Ziyang	3	48
	Shaoyang	1	20		Yibin	4	63
Zhejiang	Hangzhou	3	50	Jiangsu	Suzhou	3	45
	Jiaxing	4	63		Taizhou	2	30
	Shaoxing	3	45		Nantong	3	45
	Huzhou	3	40		Suqian	3	45
	Jinhua	4	52		Yancheng	2	30
	Wenzhou	3	28		Lianyungang	2	30
Total					24	68	1057

Source: author's survey.

Table 2 Survey questions and possible combinations of responses by rice farmers

1. Do you observe climate change in recent ten years?	2. Whether climate change posed a risk to rice production?	3. Have you suffered more pests and diseases during 2012-2014?	4. Whether to increase chemical use as a response?	Response combination (%)
Yes	No	No	No	10.6
Yes	**Yes**	No	No	14.5
Yes	**Yes**	**Yes**	No	26.4
Yes	**Yes**	**Yes**	**Yes**	40.8
No	No	No	No	3.5
All other (11) combinations				4.2

Note: Bold shading of **Yes** responses highlights the pattern investigated in this paper, that is, a positive response to each question in this sequence is associated with a positive response to the previous question.

Table 3 Percentage of major adaptation measures adopted by rice farmers

Major adaptation measures	Percentage of farmers (%)				
	Hunan	Sichuan	Zhejiang	Jiangsu	Total
Adjusting chemical use (i.e., pesticides)	53.8	42.6	25.7	31.3	38.7
Changing dates of sowing and/or harvesting	40.3	31.8	20.6	23.5	29.5
Diversifying crop varieties	20.7	23.6	13.2	10.4	16.9
Covering with plastic sheeting	10.5	7.9	3.5	4.8	8.5
Irrigation	2.2	1.4	0.6	1.2	2.3

Note: According to our survey results, farmers could took several adaptation measures at the same time in respond to climate risk, so the aggregate percentage for five adaptation measures adopted by farmers in each province may larger than 100%.

Table 4 Rice farmers' perceptions of climate risk and corresponding chemical use

Chemical use / Perceptions of climate risk	Whether to increase chemical use （%）		The quantity of chemical use （kg/ha）
	Yes	No	Mean
No effect	26.55	73.45	367.62
Yes, obvious	52.12	47.88	404.95
Yes, very obvious	61.51	38.49	442..13

Source: authors' survey.

Table 5 Descriptive Statistics of the Sample （N=1057）

Variables	Definition/Unit	Mean	Std. Dev	Min	Max
Dependent variables					
Whether to increase chemical use	1=yes; 0=no	0.523	0.500	0	1
The quantity of chemical use	Kg/ha	420.551	85.278	283.358	667.219
Independent variables					
Perceptions of climate risk on rice					
Obvious	1=yes; 0=no	0.245	0.430	0	1
Very obvious	1=yes; 0=no	0.588	0.493	0	1
Households characteristics					
Age	Years	48.39	11.66	20	82
Gender	1=male;0=female	0.806	0.396	0	1
Education	Years	7.981	3.305	0	18
Farm characteristics					
Rice farm size	ha	3.110	8.520	0.033	80.04
Agricultural labor	No.	2.220	1.524	1	16
Annual family income (RMB)	1=below 50,000; 2=50,000-100,000; 3=100,000-150,000; 4=150,000-200,000; 5= above 200,000	1.979	1.130	1	5
Membership in any cooperatives	1=yes; 0=no	0.513	0.500	0	1
Participation in technical training	1=yes; 0=no	0.187	.0.390	0	1
Stress on pests and diseases	1=yes; 0=no	0.691	0.462	0	1
Instrument variable					
Access to weather warning service	1=yes; 0=no	0.359	0.480	0	1

Table 6 Estimation results of Endogenous switching regression model

	Decision Equation	**Outcome Equations**	
	Whether to increase chemical use	The quantity of chemical use (log)	
		To increase	Not to increase
Perceptions of climate risk on rice			
Obvious	.288**(.143)	.080***(.023)	.003(.012)
Very obvious	.775***(.130)	.128***(.024)	.063***(.012)
Households characteristics			
Age	-.010 **(.004)	.000(.001)	.000(.000)
Gender	.140(.108)	.031**(.014)	-.010(.010)
Education	-.054***(.014)	-.002(.002)	-.001(.001)
Farm characteristics			
Rice farm size	.001***(.000)	.001***(.000)	.000***(.000)
Agricultural labor	-.006 (.030)	.015***(.004)	.003(.003)
Annual family income	.034 (.041)	.013**(.005)	.004(.004)
Membership in any cooperatives	-.202**(.085)	-.003(.011)	-.029***(.009)
Participation in technical training	-1.094*** (.146)	-.125***(.037)	-.060***(.013)
Stress on pests and diseases	.416***(.097)	.086***(.016)	.062***(.009)
Instrument variable			
Access to weather warning service	.516***(.090)		
Province dummies	Yes	Yes	Yes
Constant	.020(.298)	3.079***(.048)	3.103***(.031)
sigma		.131***(.009)	.091***(.003)
rho		.522**(.178)	.197(.166)
Number of observations		1057	
Wald *chi* square		342.06***	

Notes: (1) Robust standard errors are reported in parentheses.

(2) Based on farmers' perceptions of climate risk on, we divide the sample into three groups rice (i.e., no effect, obvious, very obvious) and use the group who perceived *no effect* as the base category.

(3) *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively.

References

Abdulai, A., W. Huffman. 2014. The Adoption and Impact of Soil and Water Conservation Technology: An Endogenous Switching Regression Application. Land Economics 90 (1): 26–43.

Ahmed, S., Stepp, J. R. 2016. Beyond yields: Climate change effects on specialty crop quality and agroecological management. Elem Sci Anth, 4.

Ali, T., Huang, J., Wang, J., Xie, W.. 2017. Global footprints of water and land resources through China's food trade. *Global Food Security,* 12:139-145.

Bai, J., Xu, Z., Qiu, H., Liu, H. 2015. Optimising seed portfolios to cope ex ante with risks from bad weather: evidence from a recent maize farmer survey in China. Australian Journal of Agricultural and Resource Economics, Vol. 59(2):242-257.

Banerjee, R. R. 2015. Farmers' perception of climate change, impact and adaptation strategies: a case study of four villages in the semi-arid regions of India. Natural Hazards, 75(3), 2829-2845.

Below, T. B., Mutabazi, K. D., Kirschke, D., Franke, C., Sieber, S., Siebert, R., & Tscherning, K. 2012. Can farmers' adaptation to climate change be explained by socio-economic household-level variables? Global Environmental Change, 22(1), 223-235.

Bobojonov, I., Berg, E., Franz-Vasdeki, J., Martius, C., & Lamers, J. P. 2016. Income and irrigation water use efficiency under climate change: An application of spatial stochastic crop and water allocation model to Western Uzbekistan. Climate Risk Management, 13, 19-30.

Bohensky, E. L., Smajgl, A., Brewer, T. 2013. Patterns in household-level engagement with climate change in Indonesia. Nature Climate Change, 3(4), 348-351.

Bryan, E., Deressa, T. T., Gbetibouo, A et al.. 2009. Adaptation to climate change in Ethiopia and South Africa: Options and constraints, Environmental Science and Policy (12): 413-426.

Chen, C. C., McCarl, B. A. 2001. An investigation of the relationship between pesticide usage and climate change. Climatic Change, 50(4), 475-487.

Chen, H., J. Wang, and J. Huang. 2014. Policy Support, Social Capital and Farmers' Adaptation to Drought in Crop Production of China. Global Environmental Change 24: 193–202.

Chen, S. 2015.The impact of climate change on the wheat productivity: Evidence from HuangHuaiHai Plain. China Rural Economy (7), 4-16.

Chou, H., Luan, H., Li, J., Wang, Y., 2014. The Impact of Risk Aversion on Farmers' Excessive Fertilizer Application. China's Rural Economy, 3, 85-96.

Coady, D.P. 1995. An empirical analysis of fertilizer uses in Pakistan. Economica 62(246), 213–234.

Croppenstedt, A., Demeke, M., Meschi, M.M. 2003. Technology adoption in the presence of constraints: The case of fertilizer demand in Ethiopia. Rev. Dev. Econ. 7(1), 58–70.

De Brauw, A., Huang, J., Rozelle, S., Zhang, L., Zhang, Y.. 2002. The evolution of china's rural labor markets during the reforms. J Comp Econ 30:329–353.

Deressa, T. T., Hassan, R. M., Ringler, C. 2011. Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. The Journal of Agricultural Science, 149(1), 23.

Devkota, R. P., Bhattarai, U. 2015. Assessment of climate change impact on floods from a techno-social perspective. Journal of Flood Risk Management.

Devkota, R. P., Pandey, V. P., Bhattarai, U., Shrestha, H., Adhikari, S., & Dulal, K. N. 2016. Climate change and adaptation strategies in Budhi Gandaki River Basin, Nepal: a perception-based analysis. Climatic Change, 2(140), 195-208.

FAOSTAT. 2014. Statistics Database of Food and Agriculture Organization of the United Nations, Rome.

Gbetibouo, G. A. 2009. Understanding farmers' perceptions and adaptations to climate change and variability: The case of the Limpopo Basin, South Africa (Vol. 849). Intl Food Policy Res Inst.

Gong, Q., Mu, X., Tian, Z.. 2010. Influencing factors of farmers excessive fertilization risk perception and aversion Capability—based on 284 household survey in Jianghan Plain. *Chinese Rural Economy*, 10: 66-76.

Hall, G. V., D Souza, R. M., Kirk, M. D. 2002. Foodborne disease in the new millennium: out of the frying pan and into the fire? Medical Journal of Australia, 177(11/12), 614-619.

Henson, S., Masakure, O. and Boselie, D.. 2005. Private food safety and quality standards for fresh produce exporters: The case of hortico agrisystems, zimbabwe. Food Policy 30 (4):371-384.

Huang, J., R. Hu, J. Cao, and S. Rozelle. 2008. Training Programs and in–the–field Guidance to Reduce China's Overuse of Fertilizer without Hurting Profitability. Journal of Soil and Water Conservation 63 (5): 165–7.

Hou, L., Huang, J., Wang, J. 2015. Farmers' perceptions of climate change in China: the influence of social networks and farm assets. Climate Research, 63(3), 191-201.

Hou, L., Huang, J., Wang, J. 2017. Early warning information, farmers' perceptions of, and adaptations to drought in China. Climatic Change, 141(2), 197-212.

Holst, R., X. Yu, and C. Grun. 2013. Climate Change, Risk and Grain Yields in China. Journal of Integrative Agriculture 12 (7): 1279–91.

Huang, J., Wang, Y., Wang, J. 2015. Farmers' adaptation to extreme weather events through farm management and its impacts on the mean and risk of rice yield in China. American Journal of Agricultural Economics, 97(2), 602-617.

Intergovernmental Panel on Climate Change (IPCC). 2014. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Fifth Assessment Report of the Inter-governmental Panel on Climate Change. Cambridge, UK: Cambridge University Press.

Ju, H., Xu, Y., Xiong, W. 2007. The impacts of climate change on agriculture in China. Environment Protection (06A), 71-73.

Kawasaki, K., Uchida, S. 2016. Quality Matters more than quantity: asymmetric temperature effects on crop yield and quality grade. American Journal of Agricultural Economics, 98(4), 1195-1209.

Koureas, M., Tsakalof, A., Tsatsakis, A. and Hadjichristodoulou, C. 2012. Systematic review of biomonitoring studies to determine the association between exposure to organophosphorus and pyrethroid insecticides and human health outcomes. Toxicology Letters 210 (2):155-168.

Kuruppu, N., Liverman, D.. 2011. Mental preparation for climate adaptation: the role of cognition and culture in enhancing adaptive capacity of water management in kiribati. *Global Environmental Change*,*21*(2), 657-669.

Liu, E. M. and Huang, J. 2013. Risk Preferences and Pesticide Use by Cotton Farmers in China. Journal of Development Economics 103: 202-215.

Lokshin, M., Sajaia, Z. 2004. Maximum likelihood estimation of endogenous switching regression models. Stata Journal, 4, 282-289.

Miraglia, M., Marvin, H. J. P., Kleter, G. A., Battilani, P., Brera, C., Coni, E., Filippi, L. 2009. Climate change and food safety: an emerging issue with special focus on Europe. Food and chemical toxicology, 47(5), 1009-1021.

Ministry of Agriculture, People's Republic of China (MOA). 2015. Plan for zero growth in pesticide and chemical fertilizer use in 2020. Beijing: China Agriculture Press.

Ministry of Water Resources, People's Republic of China (MWR). 2014. Bulletin of Flood and Drought Disaster in China 2014. Beijing: China Water Power Press.

National Bureau of Statistics in China (NBSC). 2014. China Statistical Yearbook 2014. Beijing: China Statistical Press.

Ning, M., Wu, X.. 2011. Study on the relationship between agricultural training and farmers applying chemical elements behavior—an empirical analysis of Fujian Province. *Journal of Agrotechnical*, 2: 27-34.

Parry, M.L., Rosenzweig, C., Iglesias, A., Fischer, G. and Livermore, M. 1999. Climate change and world food security: a new assessment, Global Environmental Change-Human and Policy Dimensions 9, S51–S67.

Patt, A. G., Schröter, D.. 2008.Perceptions of climate risk in mozambique: implications for the success of adaptation strategies. *Global Environmental Change, 18*(3), 458-467.

Rosenzweig, C., Iglesias, A., Yang, X. B., Epstein, P. R., Chivian, E. 2001. Climate change and extreme weather events; implications for food production, plant diseases, and pests. Global change & human health, 2(2), 90-104.

Rosenzweig, C., Parry, M.L. 1994. Potential impact of climate-change on world food supply, Nature 367, 133–138.

Sanders, R. 2006. A market road to sustainable agriculture? Ecological agriculture, green food and organic agriculture in china. Development and Change 37 (1):201-226.

Seo, S.N., Mendelsohn R.. 2008. Measuring Impacts and Adaptations to Climate Change: A Structural Ricardian Model of African Livestock Management. Agricultural Economics 38(2): 151–65.

Shen, Z., Liao, Q., Hong, Q. and Gong, Y. 2012. An overview of research on agricultural non-point source pollution modelling in china. *Separation and Purification Technology* 84:104-111.

Shrestha, R.P., Nepal, N.. 2016. An assessment by subsistence farmers of the risks to food security attributable to climate change in Makwanpur, Nepal. Food Secur 8:415–425.

Skevas, T., Lansink, A. O. 2014. Reducing pesticide use and pesticide impact by productivity growth: the case of Dutch arable farming. Journal of agricultural economics, 65(1), 191-211.

Skevas, T., Serra, T.. 2016. The role of pest pressure in technical and environmental inefficiency analysis of Dutch arable farms: an event-specific data envelopment approach. Journal of Productivity Analysis, 46(2), 139-153.

Sun, B., Zhang, L., Yang, L., Zhang, F., Norse, D., Zhu, Z. 2012. Agricultural non-point source pollution in China: causes and mitigation measures. Ambio, 41(4), 370-379.

Thongprakaisang, S., Thiantanawat, A., Rangkadilok, N., Suriyo, T. and Satayavivad, J. 2013. Glyphosate induces human breast cancer cells growth via estrogen receptors. Food and Chemical Toxicology 59:129-136.

The United Nations Office for Disaster Risk Reduction (UNISDR). 2016. Report on Disaster Risk Reduction of the United Nations, Switzerland. http://www.unisdr.org/.

Tian, Y., Zhang, J., He, K., et al.. 2015. Analysis of farmers agricultural production of low-carbon behavior and its influencing factors—a case study of the use of chemical fertilizers and pesticides. *China Rural Survey*, 4:61-70.

Wang, Y., Huang, J., Wang, J. 2014. Household and community assets and farmers' adaptation to extreme weather event: the case of drought in China. Journal of Integrative Agriculture, 13(4), 687-697.

Whitehead, J. C. 2006. Improving willingness to pay estimates for quality improvements through joint estimation with quality perceptions. Southern Economic Journal, 100-111.

Xie, W., Ali, T., Cui, Q., Huang, J..2017. Economic Impacts of Commercializing Insect-resistant GM Maize in China. *China Agricultural Economic Review,* 9(3): 340-354.

Zhang, M., Zeiss, M.R. and Geng, S., 2015. Agricultural pesticide use and food safety: California's model. Journal of Integrative Agriculture 14 (11):2340-2357.

Zhao, X.. 2014. Review on farmer's climate change perception and adaptation, *Chinese Journal of Applied Ecology,* 8: 2440-2448.

Zhou, J., Liu, Q., Wang, Y. 2017. The impact of climate change on quality and safety of rice: based on the survey of 1063 farmers in main rice production region. Journal of Zhejiang University (Humanities and Social Sciences) 2: 1-10.

Zhou, J., Tang, L., Yu, X.. 2018. Estimating the average treatment effect of adopting stress tolerant variety on rice yield in China. *Journal of Integrative Agriculture*, Doi:10.1016/S2095-3119(17)61848-3.