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Kaixing Huang
School of Economics
University of Adelaide

Jinxia Wang
School of Advanced Agricultural Sciences, Peking University

Jikun Huang
Center for Chinese Agricultural Policy at Chinese Academy of Sciences, Institute of Geographical Sciences and Natural Resources Research

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The Potential Benefits of Agricultural Adaptation to Warming in China in the Long Run[1]

Kaixing Huang[a], Jinxia Wang[b,c] and Jikun Huang[b,c]*

[a] School of Economics, the University of Adelaide
[b] School of Advanced Agricultural Sciences, Peking University
[c] Center for Chinese Agricultural Policy at Chinese Academy of Sciences, Institute of Geographical Sciences and Natural Resources Research

Abstract: Understanding to what extent agriculture can adapt to climate change and the determinants of farmers' adaptation capability are of paramount importance from a policy perspective, especially for developing countries where agricultural production is potentially most vulnerable to climate change. Based on a panel of household survey data from a large sample in rural China, the present article adopts a panel approach to estimate the potential benefits of adaptation and to identify the determinants of farmers' adaptation capability. Empirical modeling results suggest that, under the most likely climate change scenario, the potential impacts of warming on agricultural profits will be rather mild (8.4 percent) by the end of this century if adaptations are taken into account. In addition, for all potential warming scenarios, adaptations are expected to consistently offset about 50 percent of the potential damages caused by global warming. Finally, households with higher labor and capital intensities are better placed to adapt to global warming. (JEL Q15, Q51, Q54)

Keywords: climate change impact, agriculture, adaptation capability

*Corresponding Author: E-mail address: jkhuang.ccap@igsnrr.ac.cn (Jikun Huang)

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I. Introduction

Estimating the potential impacts of climate change on agriculture is crucial for understanding food security issues and for assessing the potential costs associated with the effects of greenhouse gas emissions (Hansen 1991, Lobell and Asner 2003). However, any estimate of the impact of climate change is potentially biased if adaptation measures that are believed to determine the future severity of the impact of climate change on agriculture are not included(Lobell et al. 2008). Thus, investigating the extent to which effective adaptation measures are likely to be implemented is central to the study of the potential impact of climate change on agriculture (Burke and Lobell 2010, Di Falco, Veronesi, and Yesuf 2011, Di Falco 2014). An even more interesting issue from the policy perspective is to understand the determinants of adaptation capability, as identifying the determinants of farmers' adaptation capability can support the design of effective adaptation policies.

The adaptation of agriculture to climate change is usually defined in terms of production behavior adjustments by agricultural agents in order to moderate any negative effects or to exploit beneficial opportunities from the changed climate (Zilberman, Zhao, and Heiman 2012, Lobell 2014, Burke and Emerick 2015). Many previous studies have stressed the difference between long-term adaptations to climate change and short-term responses to weather fluctuations: in adapting to long-term climate change, farmers can adjust land use and other *ex ante* production behaviors, but in responding to random inter-annual weather variations, farmers can only make limited *ex post* adjustments due to the time constraints or because large fixed investments are required (Massetti and Mendelsohn 2011, Seo 2013).

However, climate change includes not only changes in the long-term (such as a period of 30 years or more) trend but also potential changes in the variation of the climate. Examining farmers' responses to inter-annual weather fluctuations or extreme weather events may shed important light on the possible adaptations to changes in climate variation. Previous studies that are interested in examining adaptations to changes in climate variation usually through examining farmers' responses to inter-annual weather fluctuations or extreme weather events (See, for example, Huang, Wang, and Wang 2015). However, in the present study, we focused only on adaptations to changes in the long-term climate trend; thus, for simplicity, the term "adaptation" in this paper refers only to the long-term adaptation to the climate trend and not to transient climatic variation.

Empirically, a major contribution to the field of adaptation study involved the hedonic approach proposed by Mendelsohn, Nordhaus, and Shaw (1994), which implicitly includes adaptations in its climate change impact estimation. The hedonic approach identifies climate change impacts through cross-sectional climatic differences. Since it is assumed that agricultural agents will have completely adapted to the climate of their particular regions, a full range of adaptations are included in this approach by examining how the local climate in different regions affects the value of farmland. Nevertheless, the benefits of adaptations cannot be explicitly evaluated by this approach (Hanemann 2000).

On the other hand, numerous farm-level studies have explicitly estimated the benefits of particular adaptation measures. For example, Kurukulasuriya and Mendelsohn (2008) examined the benefits of crop switching as a method of adaptation, while Seo and Mendelsohn (2008) provided evidence that farmers benefit from switching among different kinds of livestock when adapting to warming, and Falco and Veronesi (2013) identified the adaptation benefits from a portfolio of strategies, which included changing crop varieties and adopting water and soil conservation behaviors. Even though the existing farm-level adaptation studies in the literature have dramatically improved our understanding of adaptation, as argued by Mendelsohn, Nordhaus, and Shaw (1994), in reality, innumerable potential adaptation measures could be applied by farmers in response to climate change, and it is impossible to capture the benefits of the full range of adaptations by examining only individual adaptation measures. In addition, most of the farm-level studies explain the responses to weather fluctuations as adaptations, so interpretation of these studies might have precluded some of the potential benefits of long-term adaptation from adjusting *ex ante* production behaviors (Seo 2013).

Therefore, an approach to identifying the benefits of a full range of adaptations without examining individual adaptation measures would be valuable. The value of examining the full range of adaptations as a whole refers to the total benefits from all potential adaptation measures that could be taken by farmers given the current technological level and relative commodity prices.[2] However, this is not yet possible as an effective approach to evaluate the benefits of a full range of adaptations has not been developed. In the literature, the most validated method of identifying the benefits of a full range of adaptations is the panel approach, which infers adaptation benefits by comparing the damage estimated to be caused from inter-annual weather fluctuations and the damage identified to be caused from long-term climate trends (Burke and Emerick 2015). This long-term approach predicts that adaptations are likely to mitigate less than half, and more likely none, of the large negative potential impacts of climate change on productivity. However, there are some potential drawbacks to examining adaptation benefits through long-term climate trends; for instance, the historical climate trend is not large enough to accurately predict future impacts, farmers may have only partly recognized and adapted to the climate trend, and many other concurrent trends, such as technological improvements, might obscure the true effects of climate trend (Huang 2015).

The present study attempts to identify the value of a full range of adaptations by taking an alternative approach. In this approach, the value of adaptations was approximated by comparing the damages estimated from cross-sectional climate differences and the damages identified from inter-annual weather fluctuations. Specifically, based on the key fact that

[2] As in the hedonic approach and all other partial equilibrium studies, it is impossible to include the potential value of adaptations from future technological advancements and relative price changes.

inter-annual weather fluctuations are generally common across regions in the same year, 2 types of panel model were developed; one depended on cross-sectional climate differences, and the other on inter-annual weather fluctuations. Only the former model, i.e., that using cross-sectional climate differences, included the benefit of adaptations. Thus, we hypothesized that the differences between the predicted impacts from these 2 models should reflect the value of a full range of long-term adaptations. By combining this panel framework with a panel of large-scale household-level survey data from rural China, the present study not only predicts the potential damage of global warming on agricultural profits with farmers' adaptations applied, but also explicitly approximates the potential value of a full range of long-term adaptations.

Another at least equally important issue is identifying the determinants of farmers' adaptation capability. A great many studies within the adaptation literature are concerned with empirically assessing financial, informational, and institutional constraints on adaptation capacity (Kelly and Adger 2000, O'Brien, Sygna, and Haugen 2004, Parson et al. 2003). Some other studies take an experimental or empirical approach to infer the determinants of adaptation capability under climate change by examining farmers' responses to extreme weather conditions or natural disasters (See, for example, Golnaraghi and Kaul 1995, Podesta et al. 2002, Grothmann and Patt 2005, Huang, Wang, and Wang 2015). In these studies, the value of an adaptation is identified by comparing agricultural outputs from farms that take a certain adaptation measure with the outputs from those that do not take the adaptation measure. These studies shed important light on the determinants of adaptation capability and generally imply that farmers with better infrastructure, higher crop diversification, more financial and technical support, and better information are better at adaptation.

However, since they lack an explicit estimate of the value of a full range of adaptations, previous studies do not examine the determinants of the overall adaptation capability. Our study's panel approach allows us to explicitly identify the potential value of a full range of adaptations, so it is possible to examine the influencing factors of an overall adaptation capability. In our data set, complete farm and household characteristics are included, such as the capital and labor intensity of agricultural production and the farmers' ages and education levels. By combining these farm and household characteristics with the value of a full range of adaptations, we were able to examine the influence of these characteristics on adaptation value and were able to gain an additional understanding of the determinants of farmers' adaptation capability.

The following sections describe the data sources and summary statistics, the conceptual framework and econometric models, and the empirical results of the study.

II. Data sources and summary statistics

We utilized agricultural production and household characteristics data from a large-scale household survey conducted in rural China in late 2012 and early 2013. From this survey, 31 counties in eight sample provinces were selected to represent the various agricultural systems in China (see Figure 1). The number of sample provinces from each agricultural system was approximately proportional to the share of each agricultural system in the country's total agricultural output. Specifically, Jilin province in northeast China was selected to represent the monoculture agricultural system in cold areas, while Hebei, Henan, Anhui, Shandong, and Jiangsu were selected to represent the rotation agricultural system in the temperate climate zone, Jiangxi province was selected to represent rice production in southern China, and Yunnan province in southwest China was selected to represent agricultural production in the plateau climate zone.

[Figure 1]

We selected the townships and villages before interviewing the actual households. Within each of the 31 selected counties, we divided all the townships into 3 groups based on the condition of the agricultural production infrastructure and randomly selected 1 township from each group. We used the same approach to select 3 villages from each township. Finally, we randomly selected 10 households for face-to-face interviews in each sampled village. We identified a total of 2,790 households in the 8 provinces. After dropping the households with missing data for agricultural output, input, or household characteristics, the final sample used in the analysis comprised 2736 households.

To collect the detailed data for agricultural inputs and outputs, only data for 2 of the largest plots of each household were investigated if the household managed more than 2 plots. This sample section rule helped to reduce the measurement error. This was necessary, as, in rural China, each household generally manages many separate plots, and some plots can be quite small. For example, the smallest plot managed by each household is generally less than 0.03 hectare (or 0.5 Mu). Collecting data from such small plots might incur large measurement errors because, according to our experience, it is harder for farmers to precisely recall the unit land inputs and outputs for such a small plot.

According to the survey, farmers usually plant multiple crops in sequence within a year in a plot. The main growing season is usually used for staple food crops, such as rice, wheat, and maize, while other seasons are used for minor crops, such as oilseed rape, beans, and vegetables. It is worth pointing out that the production from orchards, forestry, and animal husbandry were excluded in this survey. Hence, the implications from this study apply only to the narrower definition of the agricultural sector and not to the broader agricultural definition that includes animal and forestry production.

Agricultural input and output data for each plot were collected for 2 years from 2010 to 2012.[3] Household-level agricultural profits per hectare were constructed as revenue minus cost. Since multiple crops are typically planted in a plot within a year, the revenues from a plot were taken as the market value of all the products harvested from this plot in a year, and the costs were the total production expenditure on this plot in a year. The costs included only expenses for seed, fertilizers, pesticides, labor, and machinery.[4] We first calculated profits per hectare for each plot and then derived the household-level profits per hectare as the area weighted average of the two sample plots. Finally, the profits were translated into US dollars (USD) using China's rural Consumer Price Indices (CPI) and the exchange rate between RMB and USD as of 2010. Agricultural profits were used as the dependent variable in the econometric regression.

[Table 1]

Detailed farm and household characteristics that have the potential to affect agricultural profits and adaptation capability were also collected in the survey. As defined in Table 1, the characteristics include the labor intensity and capital intensity of the household, education level and age of the household head, irrigation water used per hectare, and agricultural loss per hectare caused by natural disasters. The county-level agricultural land quality and road density were also included as control variables. The county-level land quality was measured by the percentage of loam in the soil, while the county-level road density was measured as the number of kilometers of paved road and railway within a county divided by the total area of the county. The summary statistics of the data are provided in Table 2.

[3] This survey was originally designed to investigate the effect of natural disasters (drought and flood) on agricultural production. For each county, a disaster year and a normal year are selected out of the three years from 2010 to 2012. Thus, the two sample years may differ among some counties, and consequently we can form only an unbalanced panel from this data set.

[4] Since the family members of each household provide most of the labor input, the labor costs are measured as the total labor inputs (in work days) on each hectare of farmland times the daily wage. The daily wage is the average daily wage for agricultural labor in their village.

[Table 2]

The county-level daily mean temperature and precipitation data were derived from the China Meteorological Data Sharing Service System (http://cdc.nmic.cn). This data set provides real data for each of the 677 meteorological stations throughout China and represents the most detailed and reliable climate data set in China. At least 1 meteorological station is sited in 22 of the 31 sample counties. For those counties with more than 1 meteorological station, the county-level climate was calculated as the sample average from all the meteorological stations within the county. For the other 9 sample counties in which meteorological stations were not available, we used the climate data from the nearest meteorological station instead. The daily mean temperature and precipitation were used to construct values for the county-level yearly degree-days (DD) and yearly total precipitation (TP).[5] DD measures the cumulative exposure to temperatures of between 8 ℃ and 32 ℃ during the year. For example, a day with a mean temperature below 8 ℃ contributes zero DDs, while between 8 ℃ and 32 ℃, it contributes the difference between the mean and 8 ℃, and above 32 ℃, it contributes 24 DDs. DD is the sum of daily measures across the calendar year. TP is the total precipitation in mm during the calendar year.

Finally, to predict climate change impacts, we collected the latest climate change projections that were developed for the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC). The climate projections from 21 modeling centers and 2 Representative Concentration Pathway (RCP) scenarios, namely RCP4.5 and RCP8.5, which

[5] Some previous studies focusing only on one or several crops used the growing season heat and precipitation measures. In the present study, since the agricultural profits relate to all the crops planted in the plots during the whole year and not for a specific crop, and since crops have quite different growing seasons, we preferred to use the yearly measures instead of the growing season measures. According to the survey, multiple planting in sequent seasons is a common practice in middle and low latitudes of China, and in some provinces there are almost always plants growing in the land in any season of the year. For example, farmers in Yunnan province usually plant potato in the same plots after the harvesting of rice in September each year, while farmers in Jiangxi province plant oilseed rape during January to April before the temperature is high enough for other crops. Hence, it is impossible to find a discrete “growing season” in the present study.

represent the medium and highest scenarios, respectively, were downloaded from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) data set (https://cds.nccs.nasa.gov/nex-gddp). Each model provides daily minimum temperature, maximum temperature, and precipitation under each scenario for the periods from 2006 to 2100, with a spatial resolution of 0.25 degrees $\times$ 0.25 degrees (about 25 km $\times$ 25 km). Each model also provides simulated historical daily data from 1950 to 2005 for the same spatial resolution. The climate change predictions were calculated as the difference between the 1976–2005 average and the 2071–2100 average. Specifically, we first mapped the gridded climate predictions into each sample province to formulate province-level climate predictions for each year, and then calculated the 30-year historical simulation average (1976–2005) and the 30-year prediction average (2071–2100) for each province.[6] Since point estimates depending on a single climate projection can be misleading (Burke et al. 2015),[7] we used the average prediction of the CMIP5 models in the following impact estimation.

III. Conceptual framework and econometric approach

Two sources of meteorological variation have usually been employed to identify the impact of climate change: cross-sectional climate differences used in the hedonic approach, such as in Mendelsohn, Nordhaus, and Shaw (1994), and inter-annual random weather fluctuations adopted by panel studies, such as in Deschênes and Greenstone (2007).[8] Econometric methods based on these 2 sources of meteorological variation differ in the ability to incorporate adaptations. Specifically, climate change impacts identified through cross-sectional climate variations should include the benefit of a full range of adaptations because,

[6] The spatial resolution of climate predictions does not allow us to calculate the county-level predictions.

[7] There are over twenty recognized climate change prediction models available, and large prediction discrepancies are observed across models. We do not have evidence that any particular model is more reliable than the others (Solomon 2007). See http://cmip-pcmdi.llnl.gov/cmip5/availability.html for details of the modeling centers.

[8] Climate describes the long-term average of weather outcomes for a given region, while weather refers to a particular year's realization of climate distribution (Dell, Jones, and Olken 2014).

as assumed in the hedonic approach, farmers should have adapted to the climate of their regions (Mendelsohn, Nordhaus, and Shaw 1994). On the other hand, impacts identified through inter-annual weather fluctuations do not include the benefits of long-term adaptations since farmers will have made only limited *ex post* adjustments in response to random weather outcomes (Massetti and Mendelsohn 2011, Seo 2013).

Thus, the hedonic approach provides a potentially ideal method for incorporating adaptations in climate change impact studies. Nonetheless, the hedonic approach cannot be used to explicitly estimate the value of adaptation (Hanemann 2000); indeed, adaptations are only implicitly included in this approach by examining how climate in different regions affects the value of farmland. Since explicitly estimating the value of a full range of adaptations is necessary for identifying the determinants of overall adaptation capability, an econometric approach that can be used to estimate the value of a full range of adaptations is valuable.

Based on the key fact that inter-annual weather fluctuations are generally common across regions in the same year, Huang (2015) combined the basic idea of the hedonic approach with panel data and developed a panel framework that could be used to explicitly estimate the value of adaptations. The basic idea of this panel framework is shown as equation (1):

$$w_{it} = T_i + d_t + \varepsilon_{it} \tag{1}$$

in which w_{it} is the weather outcome of county i in year t; T_i is the climate (i.e., long-term average weather outcome) of county i, which is assumed to be constant over time but to differ across counties; d_t measures the inter-annual weather fluctuations that are common across counties in the same year but vary over time; and ε_{it} represents county-specific weather shocks.[9] In a panel model with time-fixed effects, the inter-annual weather fluctuations that are common across observations (d_t) can be filtered out, and thus, the remaining meteorological variation pertains only to cross-sectional climate differences (T_i) and idiosyncratic local shocks (ε_{it}). Since the local shocks are quite small (as shown in Table 3), the impacts are mainly identified through cross-sectional climate differences, and therefore, the full range of adaptations is included. On the other hand, the county-fixed effect can be used to eliminate inter-county differences in climate T_i, which is constant over time, and then the remaining variation pertains only to common inter-annual weather fluctuations (d_t) and county-specific weather shocks (ε_{it}). Since the variation in county-specific weather shocks is very small, the impacts are mainly identified through the common inter-annual weather fluctuations and, thus, do not include adaptation benefits.

[Table 3]

Table 3 shows the actual size of the variation pertaining to ε_{it} and T_i . We found that 74.2 percent of the sample counties had deviations in the yearly mean temperature (T_i) from the sample mean that were larger than 0.4 ℃, while no counties had county-specific temperature shocks (ε_{it}) higher than 0.4 ℃ (see Panel A of Table 3). The same result applied to precipitation: 64.5 percent of the counties had more than 400 mm of deviation from the yearly total precipitation (T_i) from the sample mean, while only 2.1 percent of counties had local precipitation shocks (ε_{it}) of more than 400 mm (see Panel B of Table 3). These results support our argument that climate change impacts can be identified mainly through inter-county mean climate differences in a panel model with time-fixed effects and through common inter-annual weather fluctuations in a panel model with county-fixed effects.

[9] Here, we assume no time trend in T_i . In fact, the climate trend is captured in the second part d_t , because the trend is usually common across counties.

However, since these climatic variables were calculated only for a 3-year panel, it is likely that the small county-specific temperature and precipitation shocks, as shown in Table 3, are a result of too short a panel period. To test this possibility, we calculated the values for the same variables as shown in Table 3 using 30 years' weather data for the sample counties, and found quite similar results. Since the magnitudes of inter-annual weather fluctuations were quite similar across regions, it was a reasonable method to find small county-specific weather shocks after removing the inter-county climate differences and the common inter-annual weather fluctuations. Similar results have been found in previous studies using US data (Fisher et al. 2012).

The panel model used to identify climate change impact through cross-sectional climate differences is shown in equation (2), in which y_{ijt} denotes the agricultural profits per hectare of household i in county j and year t; C_{it} is a vector of county-level climate variables, including yearly DD, yearly total precipitation, and their quadratic terms; L_{ijt} is a vector of the farm and household characteristics as shown in Table 1; K_{jt} is a vector of the county-level soil quality and transportation controls as defined in the last 2 rows of Table 1; α, β, and γ are coefficients; and ρ_{pt} represents the province-by-year dummy. This was used to filter out the year-to-year weather and other fluctuations that were common across counties within each province.[10] Thus, the coefficients of the climate variables in this model were identified mainly through the inter-county mean climate differences and the benefits of adaptations could then be included. Lastly, we assumed that μ_{it} is a normally distributed independent error term.

$$y_{ijt} = C'_{jt}\alpha + L'_{ijt}\beta + K'_{jt}\gamma + \rho_{pt} + \mu_{ijt} \tag{2}$$

[10] The province-by-year fixed effect equates to imposing an individual year-fixed effect for each province. Since China covers a large geographic area, the province-by-year fixed effect is better than the year-fixed effect in accounting for inter-annual common fluctuations.

The model used to identify climate change impacts through inter-annual weather fluctuations is presented in equation (3). The settings for y_{ijt}, C_{jt}, L_{ijt}, and K_{jt} are the same as in equation (2). The only difference is in the use of fixed effects. Model (3) includes the county-fixed effects τ_j to eliminate inter-county climate differences and does not use any type of time-fixed effects, as these tend to eliminate most of the year-to-year weather fluctuations.[11] Thus, the climatic coefficients are mainly identified through the year-to-year weather fluctuations and do not include the benefits of adaptations. Finally, υ_{ijt} is a normally distributed independent error term.

$$y_{ijt} = C_{jt}^{'}\alpha + L_{ijt}^{'}\beta + K_{jt}^{'}\gamma + \tau_j + \upsilon_{ijt} \tag{3}$$

By combining the estimates of the climate variables from models (2) and (3) with the climate change predictions we were able to project the impacts with and without adaptations, respectively. The differences in the projected impacts between these 2 models can be interpreted as the benefits of long-term adaptation. It is worth pointing out that the adaptation benefit estimated by this approach reflects only the lower limit of the potential adaptation value, because this approach does not include the potential benefit of future innovations.

IV. Empirical results

The regression results are shown in Table 4. Column 1 presents the regression results from model (2), while column 2 represents the regression results from model (3).[12] For model (2), the estimated coefficients of the climate variables show the inverted U-shaped relationship that is usually found in climate change impact studies (Schlenker and Roberts 2009); i.e., that

[11] We are not seeking to control for the effect of price shocks induced by output fluctuations in model (3), because the price shock can be seen as a “natural insurance” of farmers to weather fluctuations. Eliminating price shocks will thus overestimate the impact of weather fluctuations (Fisher et al. 2012)

[12] The magnitudes of the estimated coefficients of model (2) and model (3) are not directly comparable because different fixed effects are used. However, as shown in the following, the impacts calculated from these coefficients are comparable. Here, we look only at the significance levels and the effect directions of the independent variables.

agricultural profits increase with climate variables (DD or precipitation) up to a turning point, after which they decline.

In addition, most of the farm and household characteristics have statistically significant effects on agricultural profits. First, labor intensity has a negative and statistically significant effect on agricultural profits. A potential explanation for this is that since labor is abundant in rural China, more labor input will drive down the marginal labor output. Second, the effect of capital intensity is positive and statistically significant, which implies that an increased capital input per hectare will enhance agricultural profits per hectare. This reflects the fact that production capital is scarce in rural China. Finally, agricultural profits significantly increase with the volume of irrigation water used and decrease with losses due to natural disasters.

[Table 4]

As shown in column 2 of Table 4, most of the estimated coefficients of model (3) have the same effect direction and significance level as that of model (2). However, the effect of precipitation is statistically insignificant in model (3), presumably due to county-fixed effects that eliminate all of the mean precipitation differences among the counties, while the remaining inter-annual precipitation for a given county is too small to identify a significant relationship. Thus, in the following calculation of the impacts of climate change and the benefits of adaptations, we focus only on the effect of warming.[13] In addition, the coefficients of *soil quality control* and *road density control* are not estimated in model (3) because these county-level variables are mainly time-invariant in the data and have already been accounted for by the county-fixed effect in the panel regression.

[13] The insignificance of the precipitation coefficient in the county-fixed effect model does not necessarily imply potential biases in the estimates of the coefficients of other variables.

[Table 5]

Table 5 reports the projected climate changes of scenarios RCP4.5 and RCP8.5 and their impact on agricultural profits, both with and without long-term adaptations. We combined the estimated coefficients of *DD* and *DD square* of models (2) and (3) with the climate change scenarios to predict the impacts of *warming* with and without adaptations, respectively. Columns (1) to (3) in Table 5 report the projected changes in climate for each scenario. The projected yearly mean temperature rise is 2.7℃ and 5.2℃ for RCP4.5 and RCP8.5, respectively. Despite dramatic differences in DD being predicted under these 2 scenarios (column 2), the predicted changes in precipitation are quite similar (column 3). Columns (4) and (5) report the predicted yearly impacts of warming on agricultural profits per hectare by the end of this century.[14] We found that the model that did not include adaptations (column 5) predicted twice as many damages than the model that included adaptations (column 4) for both scenarios. If we include adaptations, by the end of this century, the predicted changes in agricultural profits per hectare will be -196.9 and -996.3 USD per year for scenario RCP4.5 and RCP8.5, respectively, which corresponds to 8.4 percent and 42.5 percent of the current mean annual profits per hectare in China. In addition, relatively large standard deviations for the estimated damages are found, implying that there are significant regional differences in the impacts of warming.

[Figure 2]

To visually show the relationship between warming and the value of long-term adaptation, Figure 2 displays the estimated values of adaptation under a uniform warming (across regions)

[14] The estimated impacts reported in columns (4) and (5) do not take into account the effects of the predicted changes in precipitation. Including the effects of precipitation as shown in column (3) results in similar impact predictions: the predicted impacts are -226.2 and -438.8 under scenario RCP4.5 for the model with and without adaptation, respectively, and -947.2 and -2017.5 under RCP8.5 for the model with and without adaptation, respectively.

with mean temperature rises of 1 ℃ to 5 ℃. To obtain these values, we first calculated the corresponding changes in *DD* and *DD square* of the uniform temperature rises, and then combined these changes with the estimated temperature coefficients from models (2) and (3) to estimate the impacts with and without long-term adaptations, respectively. Finally, the benefits of adaptation under each warming scenario were approximated as the difference between the predicted impacts of models (2) and (3). As expected, the model without long-term adaptations consistently predicted much higher impacts than the model with adaptations, and furthermore, the value of adaptation almost linearly increased with warming. The values of adaptations ranged from 225.8 to 1512.8 USD per hectare per year (in 2010 constant dollars). Interestingly, we found that, for various degrees of warming, long-term adaptations will always help to offset about 50 percent of the damages predicted by the model that does not include long-term adaptations.

Finally, we investigated the effects of farm and household characteristics on the benefits of adaptation. We first calculated the impacts of warming predicted by RCP4.5 on agricultural profits for each household using the estimates from model (2) and model (3), respectively. Secondly, we calculated the household-level adaptation value as the difference in the estimated impacts from these 2 models. Finally, we performed a regression analysis of the household-level values of adaptation against the farm and household characteristics listed in Table 1 and controlled for the mean temperature differences (county-level mean DD over time and its square) among the counties. These regression results are shown in equation (4)[15]:

$$\begin{aligned}\text{Adaptation\_value} = 16.9^{***} \times \text{Labor\_intensity} + 2.1^{**} \times \text{Capital\_intensity} \\ -6.6^{***} \times \text{Education} - 5.7^{***} \times \text{Age} - 0.01^{***} \times \text{irrigation} \\ -5.3^{***} \times \text{Degree-day} + 0.001^{***} \times \text{Degree-day}^2\end{aligned} \quad . \tag{4}$$

[15] We also tried the regressions using adaptation values calculated from other warming scenarios and found almost no differences in the significance levels and effect directions of each variable.

We found that the cross-sectional adaptation value first decreased and then increased with the mean DD. In other words, very cold and very hot areas have higher adaptation values than temperate areas. This result is intuitive, because farmers in cold areas have more potential to take adaptation measures to exploit the beneficial opportunities of warming, while farmers in hot areas are more likely to take adaptation measures to moderate the negative effects. The implication here is not in conflict with the linear increasing benefits of adaptation as shown in Figure 2. Here, we examine the relationship between cross-sectional DD and adaptation values, while Figure 2 shows the effect of different warming scenarios on the average adaptation value of all the sample counties.

Further, the regression coefficients of farm and household characteristics implied that labor intensity and capital intensity have a statistically significant positive effect on the adaptation value. Farmers with higher labor and capital intensity will be good at adaptation, presumably because adaptation requires a large amount of labor and capital input. However, the farmers' education level had a negative effect on adaptation value. A possible explanation is that educated people have higher opportunity costs of adaptation; facing climate change, educated people may simply choose to shift to non-agricultural sectors instead of adapting to the new climate. In addition, the age of the household head also had a statistically significant negative effect on the adaptation value; this may reflect the fact that old farmers have less adaptation ability than young farmers. Finally, agricultural production that depends more heavily on irrigation had lower adaptation values; this can be explained by the fact that irrigation itself is an adaptation, so the currently irrigated farms might experience lower marginal benefits of further improvements in irrigation than the currently non-irrigated farms will.

V. Concludsions

Including adaptations in a climate change impact study helps avoid overestimation of the damage that results from omitting adaptations. In addition, explicitly estimating the potential value of adaptation and identifying the determinants of adaptation capability are crucial for designing adaptation policies. Using a large-scale household-level survey data from rural China, the present study employed a panel framework to estimate the potential effect of warming on agricultural profits in China and to calculate the potential value of adaptation as well as to identify the determinants of adaptation capability.

The empirical results show that, for the most likely climate change scenario RCP4.5, the potential impacts of climate change on agricultural profits in China are mild (8.4 percent or 196.9 USD per hectare per year) by the end of this century if adaptations are taken into account. However, the model that did not include adaptations predicted about twice the damages predicted by the model that included adaptations for all potential warming scenarios. Hence, adaptations are expected to consistently offset about 50 percent of the damages of warming, while omitting adaptations will dramatically overestimate the damage. This study also found that increasing farm-level labor and capital intensities will significantly enhance farmers' adaptation capabilities, presumably because adaptation requires a large amount of labor and capital input.

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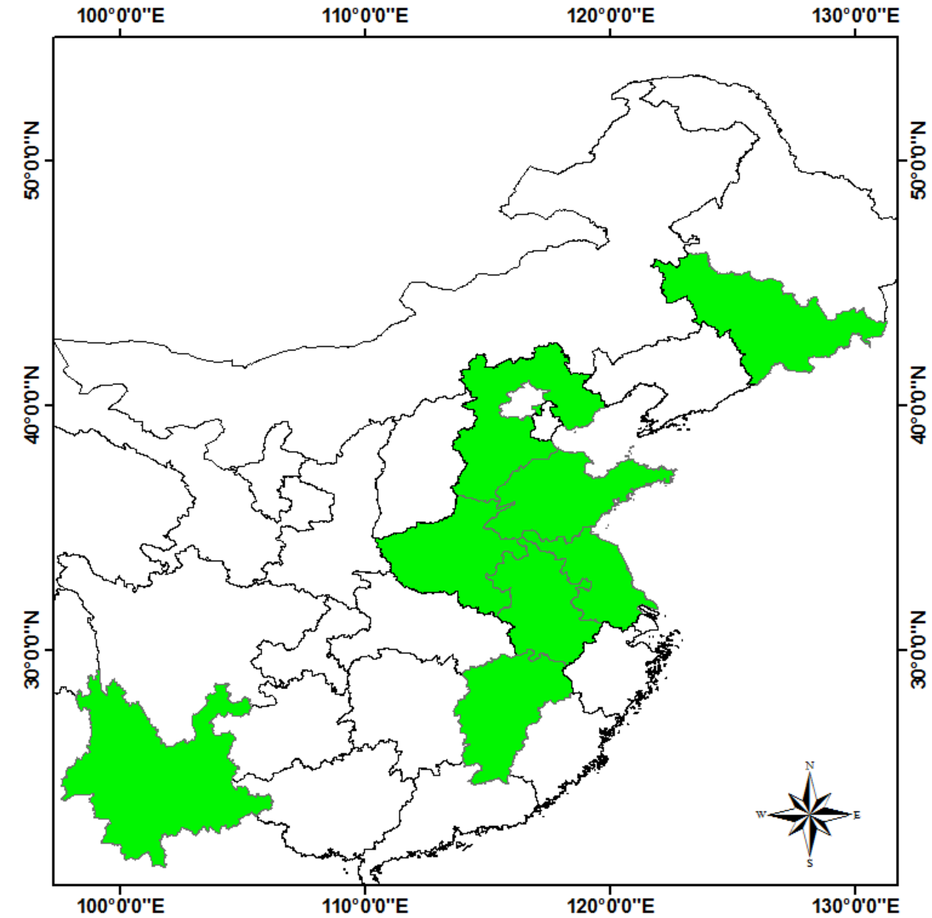

Figure 1 Sample provinces of the survey in China

Table 1. Definition of variables.

Variables	Definition
Dependent variable	
Agricultural profits	Revenue minus cost (2010 constant USD/ha)
Climate variables	
Degree-day	Yearly degree-day (degrees)
Degree-day^2	Square of yearly degree-day
Precipitation	Yearly total precipitation (mm)
Precipitation^2	Square of yearly total precipitation
Farm and household characteristics	
Labor intensity	Labor input per hectare (days/ha) [†]
Capital intensity	Production capital per hectare (1000 USD/ha)
Education	Education of household head (years)
Age	Age of household head (years)
Irrigation	Irrigation water used per year per hectare (m^3/ha)
Disaster loss	Loss per hectare caused by natural disasters (%)
Other control variables	
Loam	County-level land quality measured by loam in the soil (%)[#]
Road density	County-level density of paved road and railway (km/km^2) [§]

†: The labor intensity is measured by the total working days per hectare per year. Since there are usually multiple growing seasons within a year, the labor inputs are the sum across growing seasons within a year.

#: Loam is a standard indicator of soil quality. Loam is considered ideal for agricultural uses because it retains nutrients well and retains water, while still allowing excess water to drain away.

§: The road density is calculated from a shapefile of 1:100,000 scale road information map for the year 2008 in China. The road density is measured as kilometers of paved road and railway within a county divided by the total area of the county.

Table 2. Summary statistics of variables.

Variables	Mean	Standard deviation	Minimum value	Maximum value
Agricultural profits (USD/ha)	2343	1972	-2156	22156
Degree-day (degrees/year)	3472	999	1941	5688
Precipitation (mm/year)	1182	707	302	2866
Labor intensity (days/ha)	60.1	71.6	1.03	898
Capital intensity (1000 USD/ha)	2.16	5.56	0.00	4.45
Education (years)	5.6	2.7	0.0	15.0
Age (years)	51.6	9.9	21.5	87.0
Land scale (ha)	0.7	1.3	0.0	26.7
Irrigation (m^3 /ha)	3473	3872	0.0	14991
Disaster loss (%)	11.8	12.7	0.0	100.0
Loam (%)	31.0	4.5	21.8	40.0
Road density (km/km^2)	0.5	0.2	0.2	1.1

Note: the definitions of the variables are given in Table 1.

Table 3. The magnitudes of inter-county climate (T_i) variation and local weather shocks (ε_{it}).

Panel A. Percentage of counties with temperature variance below/above (℃):				
	±0.1	±0.2	±0.3	±0.4
Inter-county mean temperature variation	96.7	93.5	90.3	74.2
County-specific temperature shocks	22.5	4.3	2.1	0.0
Panel B. Percentage of counties with precipitation variance below/above (mm):				
	±100	±200	±300	±400
Inter-county total precipitation variation	96.7	93.5	83.9	64.5
County-specific precipitation shocks	18.3	5.4	4.3	2.1

Notes: Temperature is measured by the yearly mean temperature (℃), while the precipitation is measured by the yearly total precipitation (mm). The *inter-county mean temperature variation* and the *inter-county total precipitation variation* represent the climate (T_i) differences, which are calculated as the deviation of the county mean from the sample mean. The *county-specific temperature shocks* and the *county-specific precipitation shocks* measure the variation in local shocks (ε_{it}), which are calculated as the remaining variation after the county mean and the year mean are subtracted from each observation. All entries are calculated for the sample counties and sample years (2010-2012). See text for further details.

Table 4. Regression results of the effects of climatic variables and household characteristics on agricultural profits.

Independent variables	Model (2)	Model (3)
Climate variables		
Degree-day (100 degrees/year)	253.39***	1,260.34***
	(40.35)	(195.85)
Degree-day square	-3.56***	-17.15***
	(0.64)	(3.01)
Precipitation (100 mm/year)	91.89***	-55.90
	(21.79)	(41.24)
Precipitation square	-4.12***	2.88**
	(0.84)	(1.41)
Farm and household characteristics		
Labor intensity (days/ha)	-1.47***	-0.97***
	(0.29)	(0.34)
Capital intensity (1000 USD/ha)	6.91**	5.38**
	(3.47)	(3.33)
Irrigation (m^3/ha)	0.05***	0.02***
	(0.01)	(0.01)
Disaster loss (%)	-38.11***	-36.98***
	(1.70)	(1.72)
Education (year)	11.98	21.77***
	(7.53)	(7.50)
Age (year)	1.26	0.64
	(2.04)	(2.06)
Other controls		
Soil quality control	30.47***	-
	(7.30)	
Road density control	417.60***	-
	(80.25)	
Province-by-year fixed effects	Yes	No
County-fixed effects	No	Yes
Observations	5,472	5,472
R-squared	0.188	0.224

Note: Huber-White heteroscedastic consistent standard errors are reported in parentheses.

Table 5. Predicted climate changes and the impacts of warming on agricultural profits by the end of this century (2010 constant USD per hectare per year).

Scenario	Predicted climate change			Impacts of warming	
	(1) Mean temperature (℃)	(2) Degree-day	(3) Total precipitation (mm)	(4) With adaptation	(5) No adaptation
RCP4.5	2.7	684.0	98.2	-196.9	-479.1
	(0.3)	(127.2)	(76.2)	(113.5)	(394.5)
RCP8.5	5.2	1400.7	109.7	-996.3	-2017.5
	(0.5)	(211.4)	(66.5)	(326.6)	(1416.6)

Note: standard deviations are reported in parentheses.

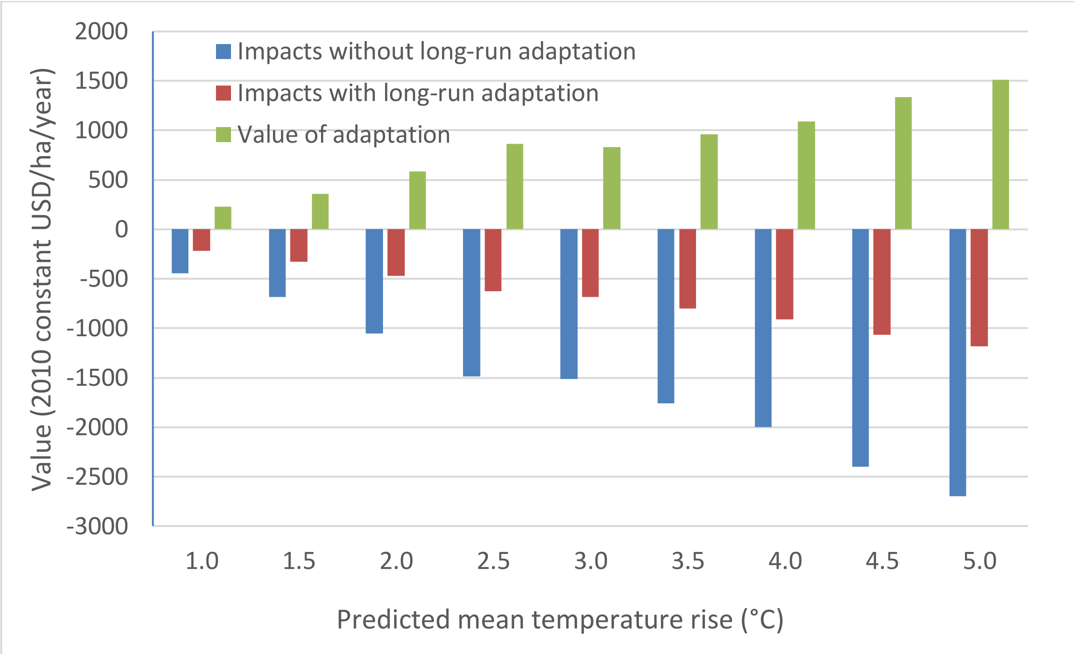

Figure 2 The impacts of warming on output per hectare of farmland with and without long-term adaptations and the value of adaptation