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Abstract

Based on panel household data collected between 2004 and 2010, we assess the impact of weather shocks on maize yields in the two main producing regions in China, the Northern spring maize zone and the Yellow-Huai Valley summer maize zone. Temperature, drought, wet conditions, and precipitations have detrimental effects on maize yields in the two maize zones. Nonetheless, the magnitude of those effects appears to be low compared to other parts of the world. Adaptation seems to be key in the region where the largest impact is estimated. On the contrary, the lower impact found in the other region, the Yellow-Huai Valley summer maize zone, is low but likely to intensify.

Keywords: Weather shocks, Adaptation, Maize yield, China.

JEL Classification: I32; O18; Q54

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1 Introduction

The Intergovernmental Panel on Climate Change (IPCC, 2014) indicates with high confidence that climate variability together with extreme climatic events (heat waves, droughts, floods, and wildfires) threaten natural and human systems across the world. Distributional effects are expected but overall, climate changes are likely to reduce food production and potentially exacerbate food insecurity in many parts of the world (Burke et al., 2015).

In this paper, we assess the impact of weather shocks on maize yields in the two main producing regions in China. China is the second largest maize producer of the world. Variations in maize yields and production caused by weather events will strongly affect the world maize supply and demand. It has even been argued that shocks on Chinese maize supply could bear significant geopolitical consequences in other parts of world (Sternberg and Thomas, 2014). Moreover, with the dietary changes and higher meat consumption in China, the domestic demand for maize is strongly increasing. Maize is indeed widely used not only for human consumption but also for animal feeding and chemical industry in China. Therefore, understanding both the impacts of weather shocks on maize yields and the ability of Chinese farmers to adapt is key to unleashing the potential of Chinese maize production under limited land resources, improving food security in China, and foreseeing potential economic and geopolitical consequences for the rest of the world.

Our paper contributes to the literature seeking to identify the impact of climatic variations on agriculture (Dell et al., 2014). At the global level, extreme daytime temperatures have been documented to have a large negative effect on crop yields (IPCC, 2014). The relationship is unchanged since 1960 in both rich and poor countries (Burke et al., 2015). Global warming since 1981 has resulted in roughly 40 Mt or 5$ billion annual combined losses of three crops, wheat, maize and barley (Lobell and Field, 2007). In North America, although higher precipitation partly contributes to crop yield increases (Pearson et al., 2008; Nadler and Bullock, 2011), other climatic events, such as extreme heats and droughts have caused a marked increase in crop losses since 1999 (Hatfield et al., 2011). Temperature has also been found to be detrimental to agriculture in the United States (Schlenker et al., 2006; Fisher et al., 2012).[1] So far, little evidence has been provided for developing countries,

[1]Cross-sectional analysis has provided mixed evidence (Mendelsohn et al., 1994). However, such analysis is likely

especially for Asian countries (IPCC, 2014). Africa has received much of the academic interest, with an overall negative effect on yields of major cereal crops (Schlenker and Lobell, 2010; Lobell et al., 2011; Roudier et al., 2011; Blanc, 2012).

As reviewed by Dell et al. (2014), the detrimental impact of weather variations, in particular temperature shocks on rice yields, has also been documented for India (Guiteras, 2007), Indonesia, Thailand, as well as the Philippines (Welch et al., 2010). Maize has been found to be one of the most sensitive crops to weather shocks, in particular temperature variations (Schlenker and Lobell, 2010).[2] In China, weather variations also constitute a crucial determinant of maize yields and production, but there is little quantitative evidence on the impact of weather shocks on maize yields in the main maize producing regions (Tao and Zhang, 2010; Zhang and Huang, 2012; Yao et al., 2014; Zhang et al., 2015).

In this paper, we assess the impacts of weather shocks on maize yields from 2004 to 2010, using data from 4,861 households across seven Chinese provinces. These provinces are grouped into the two main producing regions in China, the Northern spring maize zone and the Yellow-Huai Valley summer maize zone. These provinces account for about two thirds of Chinese maize production. One of the strengths of our analysis is the use of a panel dataset of households. That allows us to track maize yields for the same households over time while controlling for unobserved determinants of crop yields at the farm level. We also use advanced weather indexes (such as the "standardized precipitation evaporation index", "moderate degree days" and "extreme heat days") to capture extreme weather shocks. Compared to previous studies on China (Tao et al., 2008; Tao and Zhang, 2010; Li et al., 2011; Zhang and Huang, 2012; Ming et al., 2015; Zhang et al., 2015), we provide a more credible identification by exploiting within-village variations in weather - and its related proxies for weather shocks together with observed and unobserved household characteristics to account for potential heterogeneity within villages. Our results indicate that in the Northern spring maize zone, an increase by one standard deviation in temperature translates into a fall of about 1.4% in maize

to suffer from omitted variables, since cross-sectional differences in climate may be correlated with many other characteristics (Deschenes and Greenstone, 2007; Dell et al., 2014).

[2]We use the term weather variations or shocks as we are looking at short-run temporal variation. The issue of adaptation we raise in Section 4 is at the core of the critical question to know how much the estimated impact of weather variations may be used to reflect on long-run effects of climates changes (Dell et al., 2014).

yields. The impact of a similar change in SPEI-based drought occurrence is almost twice as large, with a partial effect of -2.5%. Similar results are found for the Yellow-Huai Valley summer maize zone with much smaller partial effects of -1.09% and -0.8% for temperature and SPEI-based drought indexes, respectively.

The second contribution of the paper is to shed light on the issue of adaptation. The importance of adaptation, has been recently recognized as the missing link to bridge short-run impacts to long-run interpolation, while maintaining careful identification (Burke and Emerick, forthcoming; Dell et al. 2014). Adaptation has indeed been found to constitute a key strategy to cope with the negative effects of climate change (Costinot et al, forthcoming; Olmstead and Rhode, 2011). On average, adaptation seems to improve yields by the equivalent of 15-18% of current yields, but the effectiveness of adaptation has varied significantly across different regions of the world (IPCC, 2014). In our case study, we do find mixed evidence with respect to adaptation. In the Northern Spring maize zone, where the short-run impact of weather shocks has been the strongest, we do find some evidence for (limited) adaptation, in particular to temperature variations. About 14% of short-term yield losses from temperature have been alleviated in the long run. Adaptation strategies not only include moving out of agriculture, substituting the agricultural land allocated to other crops but also reducing the use of costly inputs (purchase of seeds, pesticide and payments of irrigation fees). On the contrary, intensification effects of temperature amounting to about 13% have been observed in the Yellow-Huai Valley summer maize zone. Farmers seem only to adopt adaptation strategies when a drought occurs. Rather than moving out of agriculture, farmers in this area reduce the share of land dedicated to maize as a response to drought. We should remain cautious about the prescriptive nature of such changes. However, it certainly calls for better understanding the regional differences in adaptation to weather shocks in developing countries. The analysis also warns against the limited ability of Chinese farmers to adapt to further climatic stresses on agriculture and the challenges that it could represent for food security in China and the rest of the world.

2 Study context

Although maize is cultivated in every Chinese province, maize cropping patterns and productions vary widely across the country. This study focuses on two maize zones of China, the Northern spring maize zone, and the Yellow-Huai River Valley maize zone.[3] These regions account for approximately 70% of Chinese maize area and close to 75% of total maize production (Meng et al., 2006). The principal grain planting area is also concentrated in North and Central China since 1996 (Zhou and Tian, 2006).

These regions differ substantially. The Yellow-Huai River Valley maize zone is characterized by warm temperate and semi-humid monsoon climate with hot, dry summers and cool, variably rainy winters. The annual precipitation ranges from 500 mm to 900 mm, and 60% precipitations fall in summer season. Part-time farming is common practice, and the trend has been increasing in recent years. Brown soil and cinnamon soil dominate in this region. There are three maize systems in the region: rainfed spring maize, rainfed summer maize, and irrigated summer maize. The predominant maize system in the Yellow-Huai River Valley zone is irrigated summer maize either rotated or relay-cropped with winter wheat in the plain areas. Irrigation practices are expected to better resist the detrimental impact of weather shocks. The summer maize growth cycle is on average 110-115 days in this region. The weather conditions in this region are moderate for maize on the whole, but the extreme heat, drought and the volatility of precipitations may be harmful to maize yields and production.

In the Northern spring maize zone, the climate is classified as frigid humid/semi-humid temperate with warm, wet summers and long, very cold winters. The annual precipitation ranges between 500 mm and 800 mm. Two thirds of precipitations fall between July and September. "Drought in summer and wet in autumn" is one distinct feature in this region. Agricultural profits represent the main income source for rural population. Maize is the most important crop in terms of area and production. Most of the crops are cultivated almost completely under rainfed conditions in spring.

[3]According to the official classification of the Chinese Ministry of Commerce, China is usually divided into six maize zones: Northern spring maize zone, Yellow-Huai River Valley summer maize zone, Southwest mountainy and hilly maize zone, South hilly maize zone, Northwest irrigated maize zone and Qinghai-Tibet Plateau maize zone (Figure A.1).

Black loamy and brown loamy soils predominate in this region. The average maize growth cycles are 130 days in Heilongjiang and 150 days in Liaoning, Jilin, and Inner Mongolia. In recent years, the maize cropping growth cycles have been decreasing. The shortening of growing periods and the occurrence of drought and excessive wet conditions are likely to hurt maize yields and production.

The growing periods, cropping systems and soil qualities are radically different between the two maize zones. In the Northern spring maize zone, most villages start sowing in April and harvest at the end of September. In the Yellow-Huai River Valley summer maize zone, the sowing time starts at the end of May and harvest at the end of September. The main type of maize in the Northern spring maize zone and the Yellow-Huai Valley summer maize zone are rainfed spring maize and irrigated summer maize, respectively. There is no multiple cropping in the Northern spring maize zone, while multiple cropping is prevalent in the other zone. Such apparent heterogeneity between the two maize zones calls for a region-specific analysis. The impacts of weather shocks in the two maize zones are expected to be different.

3 Empirical Analysis

3.1 Data

We use a unique household dataset named the National Fixed Point Survey (NFPS) dataset, implemented by the Research Center of Rural Economy (RCRE), a research unit of the Chinese Ministry of Agriculture. We combine such household information with weather station data from the Weather Channel Interactive Company and China Meteorological Bureau. The National Fixed Point Survey (NFPS) dataset comprises household panel data collected every year between 2004 and 2010 in seven provinces, Heilongjiang, Jilin, Liaoning, Neimenggu, Hebei, Shandong and Henan. These seven provinces represented in 2012 approximately 65% of the total maize planting area and nearly 70% of maize produced in China (Figure A.2). The average yield of 5776.34 kg per hectare in 2010 in these provinces is 5.8% higher than the national average yield. Given the wide heterogeneity in maize production described in Section 2, the seven provinces are classified into the abovementioned two maize zones: Heilongjiang, Jilin, Liaoning, Neimenggu and the north part of Hebei belongs to the

Northern summer maize zone and Shandong, Henan and the south part of Hebei are divided into Yellow-Huai Valley summer maize zone.[4]

We exploit a sample of 4,861 households, in which 2,039 and 2,822 households are located in the Yellow-Huai Valley summer maize zone and the Northern summer maize zone, respectively. As depicted in Figure 1, these households originate from 79 villages and have been surveyed every year between 2004 and 2010. The dataset provides household information about the maize planting area, maize production, specific materials, labor days as well as out-agricultural incomes. For the weather dataset, we use daily average temperature, daily maximum temperature, daily minimum temperature and daily precipitations, originating from 63 weather stations in both maize zones.[5]

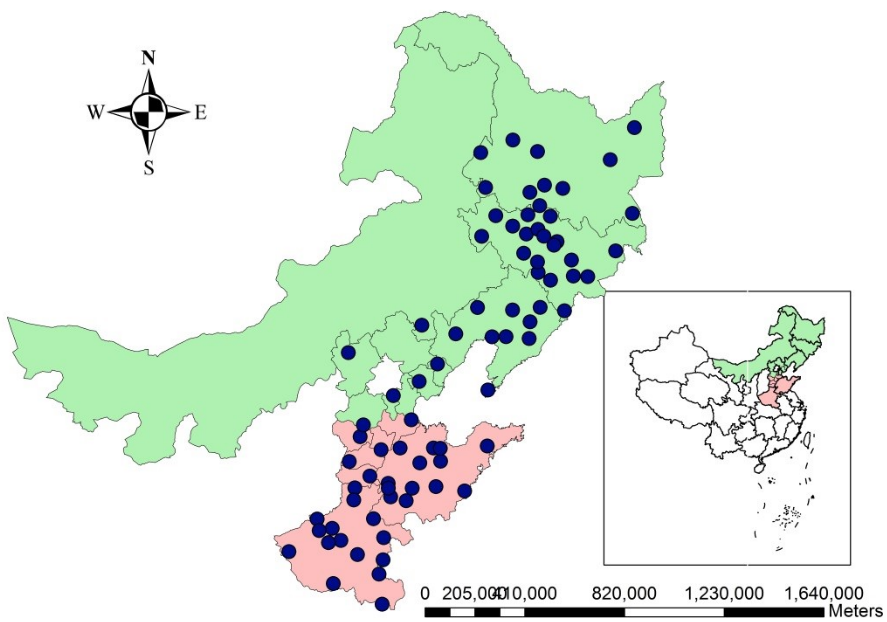

Figure 1: Distribution of sampled villages across seven provinces in the Northern spring maize zone and the Yellow-Huai Valley summer maize zone

Note: Points represent surveyed villages, whose households have been interviewed annually between 2004 and 2010 (balanced panel).

[4]Hebei province is divided into two parts, since the ecological conditions between these two parts are very different. However, our results do not depend on that geographical division since our results are robust to the exclusion of the Hebei province.

[5]The number of weather stations remains stable overtime and our analysis is not affected by non-random missing data generated by the entry and exit of weather stations overtime (Auffhammer et al., 2013).

3.2 Estimation framework

Given the large heterogeneity reported above, the analysis will be implemented on two distinct samples in order to pave the way for a comparative analysis between both regions. Our identification strategy will assess how within-household variations in maize yields are affected by within-location variations in weather conditions recorded between 2004 and 2010. More specifically, our estimating equation takes the following form:

$$Yield_{h(v)t} = \beta_0 + \beta_1 C_{vt} + \beta_2 X_{ht} + \delta_h + \delta_t + \epsilon_{hvt} \tag{1}$$

Where, $Yield_{h(v)t}$ represents maize yields in household h (living in village v) and year t; C_{vt} is a vector of climatic variables; X_{ht} is a vector of control variables; δ_h and δ_t stand for the inclusion of household and time fixed effects, respectively; h, v and t denote household, village and year, respectively. ϵ_{hvt} denote the error terms.

We exploit the panel nature of the dataset. The fixed effects, δ_h and δ_t, help to ensure that any perceived effects of weather variations is not due to differences between sites or years that may arise from omitted variables (Lobell et al., 2011; Dell et al., 2014). Within sites, omitted variables such as the use of fertilizers, herbicides or labor are more likely to be uniform, and any variation is assumed orthogonal to weather variations (Lobell et al., 2011; Blanc, 2012). Assume, for example, that on average less rain-fed areas are more likely to adapt more efficient irrigation systems, a simple OLS regression is likely to bias our estimates downward. Inversely, the panel data model can precisely control for unobserved heterogeneity among households. Time dummies would capture changes in maize yields that would be due to common time shocks or technical progress. For instance, time dummies would control for the common effects resulting from the total cancellation of agricultural taxes enforced in 2006 or the general fall in domestic demand experienced in 2009.

To deal with spatial and time dependency in the error terms usually encountered in climate studies (Auffhammer et al., 2013), we use the Driscoll and Kraay (1998) standard errors for coefficients estimated by fixed-effects (within) regression. Such a method has the advantage to deal with within- and between- correlations that are likely to constitute major concerns in our study. Driscoll and Kraay method can indeed adjust the bias caused by within- and between-groups correlation of residuals.

In addition, this method is also suitable for the large cross-sectional and small time dimensions, as featured in the dataset.

We now turn to the definition of the main variables. First, the dependent variable is defined as the amount of maize harvested per unit area for a given time, this is the standard measurement of yields. A logarithm transformation is applied. Second, the climatic variables, designated as C_{vt} in Equation (1), seek to capture the weather changes in annual growing conditions in a particular village, v, and the correspondent extreme weather shocks on agriculture. For the former, we use rainfall and temperature data from the Weather Channel Interactive Company and China Meteorological Bureau recorded across village-level weather stations during the growing periods between 2004 and 2010. Average temperature is defined as the mean daily average temperature over the whole growing period. The rainfall variable results from the aggregation of daily data, accumulated over the whole growing period.

Although widely used in the literature, temperature and rainfall are limited in capturing extreme events, potentially more detrimental to crop growth (Lobell et al., 2011, 2014). That is likely to be particularly the case in the Northern spring maize zone and the Yellow-Huai Valley summer maize zone where drought is a recurrent phenomenon. Drought is a complex phenomenon to capture with observational data. However, drought is usually characterized by a combination of abnormally high temperature (causing unusually high evaporation) combined with abnormally low or failing rainfall. In this paper, we use the Standardized Precipitation Evapotranspiration Index (SPEI) that has emerged as one of the most comprehensive index over the recent years (Begueria et al., 2010; Cook et al., 2014). Since the SPEI includes the effect of the evaporative demand on its calculation, it is more suited to explore the effects of warming temperatures on the occurrence of droughts (Begueria et al., 2010).[6] Our SPEI-based drought variable is generated by summing, over the growing period,

[6] The Standardized Precipitation Evapotranspiration Index (SPEI) is a multi-scalar drought indicator that includes both rainfall and temperature. The SPEI is based on a monthly climatic water balance (precipitation minus potential evapotranspiration, called PET) and is expressed as a standardized Gaussian variate with a mean of zero and a standard deviation of one. The SPEI uses the monthly difference between precipitation and PET. But unlike other water balance-based drought indices such as the Palmer Drought Severity Index, the SPEI does not rely on the water balance of a specific soil system (Begueria et al., 2010). It can be calculated for different time scales, and hence the SPEI has a much wider range of applications than the PDSI (Begueria et al., 2010).

indicator variables equal to one if the monthly SPEI value is below the 5th percentile of the monthly distribution. Such computation results in a continuous variable ranging from 0 ("no drought-month during the growing period") to 5 ("the maximum drought-months during the growing periods") in the Northern spring maize zone, while a continuous variable ranging from 0 to 6 in the Yellow-Huai Valley summer maize zone. We proceed to a similar construction for the abnormally wet climatic conditions by summing, over the growing period, indicator variables equal to one if the monthly SPEI value is above the 95th percentile of the monthly distribution.

Third, the National Fixed Point Survey (NFPS) dataset also provides information about the households and their farming activities, such as the non-agricultural income, total income, household size, education level of the household head, etc. We use that information to construct the following variables: the labor days inputs per Mu, and the total material inputs per Mu.[7] The advantage of exploiting that information is twofold. First, we use these household characteristics as control variables, in equation (1). While better controlling for changing characteristics, the inclusion of these variables are likely to be endogenous to changes in maize yields and to introduce potential multi-collinearity with our climatic variables. In other words, these variables can act as "bad controls" (Angrist and Pischke, 2013) or an "over-controlling problem" (Dell et al., 2014). We will therefore use these additional control variables as robustness checks, without over-emphasizing their interpretation. Second, we use non-agricultural income, the maize share in total agricultural land, the labour inputs, the seed inputs, the fertilizer inputs, the pesticide inputs and the irrigation inputs as alternative dependent variables to assess the adaptation strategies adopted by maize farmers or the risk of intensification in rural China (Section 4).

3.3 Descriptive Statistics

Descriptive statistics are provided in Table 1. The Northern spring maize zone, with an average yield of 499.64 kg/Mu, has a relatively higher yield level than the one prevailing in the Yellow-Huai Valley summer maize zone. These two regions have also experienced an increasing yield growth from 2004 to 2010 (Figure A.3). Maize planting area is on average larger in the Northern spring maize zone,

[7]Mu is a commonly used planting area statistic unit in China, 1 Mu= 0.067 hectares. Inputs per Mu are transformed into logarithm.

with an average planting area of 13.58 Mu, 4 times larger than the one in the Yellow-Huai River Valley summer maize zone. The increasing trend in maize yields has gone along with a similar rise in planting area.

The Northern spring maize zone also appears to be colder and receive less rainfall during the growing period. The average temperature in the Northern spring maize zone and the Yellow-Huai Valley summer maize zone stand at about 18°C and 25°C, respectively. Precipitations in the Northern spring maize zone amounts to about 332 millimeters, on average 16 millimeters less precipitations than in the Yellow-Huai River Valley zone. Cross-sectional differences in average temperature in our sample call for a fixed-effect framework, more likely to capture within-village variations in temperature shocks (Figures A.4 and A.5). Regarding the SPEI, the Northern spring maize zone appears to be dryer than the Yellow-Huai Valley summer maize zone. In both regions, high values are recorded in 2004 and 2010, while low values are found in 2006 and 2009 (Figure A.6). Wet-prone conditions have also been recorded in 2007 and 2008 in the Yellow-Huai summer maize zone (Figure A.7). High values translate into a high SPEI-based wet index, and the reverse for the SPEI-based drought index (Figure A.7). Such patterns correspond to major droughts and floods that occur in China. Major floods were recorded in 2004 and 2010 by EM-DAT in both zones.[8] A severe drought was also recorded in the Yellow-Huai summer maize zone (see Table A.1).

The total maize material inputs per Mu in the Northern spring maize zone and the Yellow-Huai Valley maize zone are 207.10 Yuan/Mu and 170.98 Yuan/Mu, respectively. As for the labor input, the average number of days per Mu amounts to about 10 days in the Northern spring maize zone, while producing maize requires approximately 6 additional days in the Yellow-Huai River Valley maize zone. Positive and negative trends are observed for the use of total material inputs per Mu and for the number of labor days per Mu, respectively. Controlling for farm characteristics is likely to be important given the apparent heterogeneity within each region.

[8]EM-DAT is an international disaster database (*www.emdat.be*). Table A.1 in Appendix summarizes some of the major events taking place in both regions between 2003 and 2010.

Table 1: Descriptive Statistics

Variables	Mean	Std. Dev.	Min.	Max.	N
Panel A. Northern spring maize zone					
Maize yield (kg/Mu)	499.642	163.58	50	1666.667	16296
Maize planting area (Mu)	13.581	12.879	0	149	11545
Average temperature in growing period (°C)	17.918	1.581	12.771	22.727	16296
Cumulative precipitation in growing period (mm)	332.389	160.841	0	789.700	16296
SPEI based drought	0.282	0.61	0	3	16296
SPEI based wet	0.267	0.618	0	3	16296
SPEI of one month	0.011	0.671	-1.122	1.349	16296
SPEI of three month	0.029	0.775	-1.451	1.437	16296
Maize material inputs (Yuan/Mu)	207.102	130.153	0	2976.389	11480
Maize labour inputs (day/Mu)	10.096	9.432	0	257.143	11460
Panel B. Yellow-Huai Valley summer maize zone					
Maize yield (kg/Mu)	416.804	119.855	50	1500	13992
Maize planting area (Mu)	3.394	2.328	0	20	11420
Average temperature in growing period (°C)	24.937	1.158	18.554	26.574	13992
Cumulative precipitation in growing period(mm)	348.925	120.228	129.1	926.4	13992
SPEI based drought	0.289	0.573	0	2	13992
SPEI based wet	0.253	0.556	0	3	13992
SPEI of one month	0.027	0.693	-1.329	1.467	13992
SPEI of three month	0.034	0.808	-1.76	1.408	13992
Maize material inputs (Yuan/Mu)	170.976	98.249	0	3335	11387
Maize labour inputs (day/Mu)	16.53	19.083	0.8	450	11303

Note: 1 Yuan= 0.1572 USD (Nov 09, 2015).

3.4 Main Results

Table 2 shows the main results of weather variations on maize yields in our two analytical samples. Column (1) of Panel A introduces the most straight-forward measurements of weather variations, total rainfall and average temperature over the growing periods in the fixed-effect framework for the Northern spring maize zone. Temperature seems to decrease maize yields, but the effect is different from zero at only 75 percent level of confidence. Rainfall is far from significant in this specification. Column (2) introduces the SPEI-based drought and wet indexes. As expected, drought has a negative and significant effect on maize yields. That result is confirmed when rainfall, temperature and the SPEI-based variables are introduced within the same specification (Column (3)). An increase by one standard deviation in temperature translates into a fall of about 1.4% in maize yields. The impact of a similar change in the SPEI-based number of drought months is almost twice bigger, with a partial effect of -2.5%. Similar results are found in Panel B for the Yellow-Huai Valley zone with much smaller partial effects of -1.09% and -0.8% for temperature and the SPEI-based drought, respectively (a impact of -0.5% on maize yield due to a change of one standard deviation is found for the SPEI-based wet indicator at 85 percent of level of confidence). For presentation purpose, Column (1) of Table 3 provides the partial effects on maize yields following a change by one standard deviation in the corresponding variables, based on the estimated coefficients of Column (3) of Table 2.

The detrimental impact of temperature and drought is largely in line with the existing literature on various countries and regions, such as the United States, Sub-Sahara Africa and Asia. Many papers on China also show the same sign of average temperature on maize yields (Liu et al., 2014; Zhang et al., 2015). We confirm such a detrimental effect using a fixed-effect framework, more likely to identify a causal relationship, and for a sample large enough to cover about 70 percent of the Chinese maize-producing areas, in contrast to a coverage of about 30% in Liu et al. (2014) or 38.83% in Li et al. (2011). Section 4 will discuss further the magnitude of the impact, which, at first sight, seems relatively low against international standards. For precipitation, our results give an unexpected negative sign. In the existing literature, the evidence is rather mixed. Positive effects on crop yields have been found in global studies on the US or Sub-Saharan Africa (Lobell and Field, 2007; Schlenker and Lobell, 2010; Blanc 2012; Burke and Emerick, forthcoming. Other papers conclude that precipitation has no effect or negative effect on crop yields (Li et al., 2011; Zhang and Huang, 2012; Massetti et al., 2014), especially in China. For example, Zhang and Huang (2012) found a negative correlation between precipitations and rice yields for 32% of the rice-producing areas in China, a negative impact for 18.5% of the cultivated areas, and no significant impact in over half of the maize-cultivated regions. Liu et al. (2014) also found a negative correlation between precipitations and maize yields in the northern plain of China, while an insignificant impact on wheat yields is reported by You et al. (2005).

When it comes to the SPEI-based drought and wet conditions, the signs of both indicators are negative as expected. Ming et al. (2015) also conclude that in most provinces of China, extreme droughts and wet conditions have detrimental effects on maize yields. Our paper confirms that threat with a wider coverage of maize producing regions and more precise measurements of extreme events (SPEI). The occurrence of drought has the largest impact in the Northern spring maize zone. The impact of about 2.5% following an increase by one standard deviation (about half a drought month) in the variable of interest is 3 times bigger than the effect in the Yellow-Huai Valley summer maize zone. The impact of average temperature in the Northern spring maize zone is also slightly bigger than the one in the Yellow-Huai Valley summer maize zone and more precisely estimated. A possible explanation is that the rain-fed type maize in the Northern spring maize zone makes yields more vulnerable to extreme drought and temperature. In the Yellow-Huai Valley summer maize zone, the relatively smaller maize farming size may also play a drought-mitigating role owing to larger margins of cost adjustments. Section 4 will further discuss how household strategies may help to cope with the harmful effects of weather shocks.

3.5 Robustness

Our main results may be sensitive to the adopted specifications. Therefore, we check the robustness of our results in Table 2 to (a) the choice of model specification, (b) the definition and the choice of functional forms of the weather-based variables, and (c) the definition of the analytical samples.

First, a legitimate concern may be that our results are capturing a spurious correlation. No

Table 2: Weather effects on maize yields

Dep. Var.	Maize yields (log)		
Panel A. North spring maize zone			
	(1)	(2)	(3)
Average temperature in growing period	-0.01251		-0.00888**
	(0.01204)		(0.00436)
Average precipitation in growing period	-0.00006		-0.00007***
	(0.00005)		(0.00002)
SPEI based drought		-0.04077*	-0.04424***
		(0.02465)	(0.00373)
SPEI based wet		-0.00467	-0.00503
		(0.00632)	(0.00342)
Observations	16,296	18,508	16,296
R-squared	0.041	0.041	0.041
Panel B. Yellow Huai Valley summer maize zone			
Average temperature in growing period	-0.01222*		-0.00949*
	(0.00502)		(0.00533)
Average precipitation in growing period	-0.00014**		-0.00014***
	(0.00004)		(0.00002)
SPEI based drought		-0.01142**	-0.01350***
		(0.00495)	(0.00500)
SPEI based wet		-0.01096**	-0.01244**
		(0.00550)	(0.00551)
N	13,992	13,992	13,992
R-squared	0.059	0.059	0.064

Note: Household and year fixed effects are included. Driscoll and Kraay (1998) standard errors in parentheses. * significant at 10%, ** at 5%, *** at 1%.

spurious trend is apparent in the geographical representations of our main variables, in particular between trends in weather and maize yields for the whole sample (Figures A.2-A.7). However, we cannot exclude that it may be the case at the village level. To deal with that concern, we augment our baseline model with village-specific time trends. The partial effects (following a change of one standard deviation) shown in column (2) of Table 3 suggest that it is a minor issue. The partial effects are pushed downward but the impact remains in a similar range with the introduction of village-specific time trends. We also face the risk of attributing to weather shocks changes in the composition of the village populations. To assess that risk, we also control for (potentially endogenous) household characteristics such as the total material inputs per Mu and the labour days per Mu of each household. The addition of control variables only slightly changes the coefficients of the weather variables in both maize zones. In contrast to this augmented model, the small impact of weather shocks on maize yields identified in a household-fixed-effect framework may be argued to be relying on too small margins. We cannot exclude that controlling for unobserved household heterogeneity may come at the cost of removing much variation. Nonetheless, our results appear to be unaltered when estimated with more aggregated village fixed effects, excepting for temperature in the Northern spring maize zone. The related partial effects are reported in column (3) of Table 3.[9]

Second, the weather-based variables are assumed to impact maize yields in a linear manner. The literature has pointed to the limited nature of such an assumption (Lobell et al., 2011; Schlenker and Lobell, 2010; Burke and Emerick, forthcoming; Massetti et al., 2014; Dell et al., 2014). We check the validity of that assumption by introducing quadratic terms of our main variables of interest. The linear form seems to be a good approximation of a potentially more complex response function. The coefficients of SPEI-based drought and wet conditions keep a similar negative sign in the two maize zones, when significant.[10] For temperature, we find an unexpected non-linear relationship between temperature and yields when adding the quadratic terms of temperature. In light of this mixed

[9] The detailed results corresponding to columns (2) and (3) of Table 3 are given in Table A.2 of the Appendix.

[10] Detailed results are provided in Table A.3. In columns (1) and (4) of Table A.3, we estimate the quadratic terms of average temperature and precipitation. We then augment the model with the SPEI-based indexes (columns 2 and 5). In columns (3) and (6), we introduce the linear and quadratic terms of the same SPEI-based indexes. It could be noted that precipitation shows an inverted U-shaped relationship in column (1) but such non-monotonicity disappears while estimated together with the SPEI-based indexes, assumed to constitute better proxies for extreme weather shocks.

Table 3: Partial effects of weather shocks

Dep. Var.	Maize yields (log)			
Panel A. Northern spring maize zone				
	(1)	(2)	(3)	(4)
Average Temperature	-0.01423	(-0.00728)	(-0.00953)	-0.02254
Average Precipitation	-0.01365	-0.02654	-0.04785	-0.01227
SPEI-drought	-0.02495	-0.01720	-0.02692	-0.02856
SPEI-wet	(-0.01049)	-0.01931	-0.02604	(0.00514)
Panel B. Yellow-Huai Valley summer maize zone				
Average Temperature	-0.01089	(-0.00872)	(-0.00785)	(-0.00550)
Average Precipitation	-0.01709	-0.01365	-0.01759	-0.02764
SPEI-drought	-0.00770	-0.00801	-0.00877	(-0.00519)
SPEI-wet	-0.00689	-0.00621	-0.00825	(0.00588)
In regressions used to compute partial effects in Panels A and B				
Time fixed effects	Yes	Yes	Yes	Yes
HH fixed effects	Yes	Yes	No	No
Village fixed effects	No	No	Yes	Yes
Village time trends	No	Yes	No	No
Drop Hebei Province	No	No	No	Yes

Note: 1."()" means that the estimated coefficient used to compute the partial effects is not significant at, at least, 90% level of confidence; 2. *Partial effect* $= \beta_i * \frac{SD_i}{Mean_{Yield}}$, in which i is the set of independent variables; 3. Village specific-time trends are generated by interacting the village fixed effects with time trends.

evidence for temperature, we further check the non-linearity of weather shock variables assuming more complex forms of non-linearity. The sum of degree days over the growing seasons is argued to better capture the effect of temperature on yields (Schlenker and Lobell, 2010; Lobell et al., 2011; Massetti et al., 2014). We follow Schlenker et al. (2006) and Schlenker and Lobell (2010) in introducing two related indexes, the Moderate Degree Days (MDD) and the Extreme Degree Days (EDD).[11] Adding MDD and EDD only causes a slight variation in magnitude of the SPEI-based drought and wet indexes (Table A.4). An increase by one standard deviation in the SPEI-based number of drought months and wet months decreases maize yields by 2.5% and 1.0%, respectively, in the Northern spring maize zone, and 0.8% and 0.7%, respectively, in the Yellow-River maize zone. We find an insignificant positive effect of a change in MDD on yields in both maize zones, meaning that an increase in temperature within the range of moderate degree days might benefit maize yields but is estimated with low confidence. By contrast, the increase of temperature within the range of extreme degree days has a significant and negative impact on maize yields in the Yellow-Huai summer maize zone and, to a lesser extent in the Northern spring maize zone. An increase by one standard deviation in EDD would translate into a decrease in maize yields by 1.3% in the Northern spring maize zone and 1.6% in the Yellow-River Valley summer maize zone, respectively, compared with the corresponding change of 2.5% and 0.9% for the SPEI-based drought index. The impacts of MDD and EDD on maize yields are consistent to most of the above-mentioned related literatures. Nonetheless, the magnitude of these impacts remains low, strengthening our confidence in the used combination of linear weather variations in "levels" and SPEI-based nonlinear extreme events.

A final point on the functional form of our weather-based variables relates to the threshold adopted

[11] Using daily temperature, Moderate Degree Days result from the sum of Celsius degrees falling in a range between a lower threshold and an upper threshold. Extreme Degree Days are computed based on the sum of Celsius degrees above an upper threshold. In the case of the Sub-Saharan Africa and based on agronomic literature, Schlenker and Lobell (2010) define the upper and lower thresholds at 10°C and 30°C . However, there is no consensus on the thresholds to be adopted, especially the upper one (Massetti, 2013). Similar to Burke and Emerick (2013), the choice of upper threshold is based on minimizing the Root Mean Square Error (RMSE). We found that the optimal upper thresholds in the Northern spring maize zone and the Yellow-Huai Valley summer maize zone are 20°C and 24°C , respectively. In terms of the lower threshold, we adopt a 8°C lower-bound similar to Schlenker et al. (2006), Lobell et al. (2011), and Massetti et al. (2014).

to define an extreme event. One could argue that the thresholds used (5th and 95th percentiles) are somehow arbitrary. We test the robustness of the drought and wet effects to the use of different thresholds. We assess the robustness of our main results to three alternative measurements of SPEI drought and wet based on the criteria of two-sided 10 percent percentile, one standard deviation, and two standard deviations.[12] The drought index which is measured by SPEI lower than the value of minus two standard deviations consistently has negative effects on maize yields in both regions (in the Yellow-Huai Valley summer maize zone only at 85% level of confidence). In the Northern spring maize zone, all the drought and wet indexes show negative relationships with maize yields. In the Yellow-Huai Valley maize zone, mild drought and wet indexes (based on one standard deviation and below 10% of the drought distribution) do not have significant effects on maize yields, which confirms the lower vulnerability of the Yellow-Huai Valley maize zone to droughts.

Third, our main analysis is based on the comparison of two analytical samples. As indicated in Section 3, the Hebei province is split into two, the North being part of the Northern summer maize zone and the South belonging to the Yellow-Huai Valley summer maize zone. That division may not be universally accepted since it is not based on an official administrative division. We test the robustness of our results to that sample choice. To that purpose, we alternatively drop the Heibei province from the analytical samples. When compared with the main results, we did not find large differences in the magnitude and signs of coefficients.[13]

4 Discussion

In this paper, we find average temperature, the SPEI-based drought and wet indexes, as well as precipitations have negative effects on maize yields in the two maize zones. In the Northern spring maize zone, an increase by one standard deviation in temperature translates into a minor fall of about 1.4% in maize yields. The impact of a similar change in SPEI-based drought occurrence is almost twice bigger, with a partial effect of -2.5%. Similar results are found for the Yellow-Huai Valley maize zone with much smaller partial effects of -1.09% and -0.8% for temperature and SPEI-based drought,

[12] Detailed results are provided in Table A.5 in Appendix.

[13] Table A.6 in Appendix presents the estimated results, excluding the Hebei province.

respectively. The SPEI-based wet variables have lower impacts on yields compared to the SPEI-based drought. One standard deviation change in SPEI-based wet indexes will decrease maize yields by about 1.05% and 0.69% in the Northern spring maize zone and the Yellow-Huai Valley summer maize zone, respectively. The weather shocks in the Northern spring maize zone have more impacts on maize yields than the shocks in the Yellow-Huai maize zone.

Table 4 lists the impact of weather variations on different crop yields found in the literature. Our estimated impact of weather variations on maize yields in China is relatively small. First, compared with other studies in China, we find a relatively small temperature impact on maize yields. Based on a first-difference model, Tao et al. (2008) find that a 1°C increase in temperature decreases average maize yields in six provinces by around 6% between 1951 and 2000. Zhang et al. (2015) also use the same statistical method to investigate the impact of weather shocks on maize yields. An increase by 1 °C deteriorates maize yields in Jilin and Anhui provinces by 12%. Second, compared with studies outside of China (Table 4), the estimated impacts appear to be relatively small compared to other countries or regions, such as the United States, Sub-Saharan Africa, India, or at the global level. The difference in the comparability of studies can obviously be called into question given the underlying differences in methods and sample designs. But the difference in magnitude is puzzling enough to motivate further investigation on possible explanations.[14]

The lower magnitude of the impact may be partly explained by the lower exposure of China to the occurrence of weather shocks, compared to other parts of the world. The SPEI in China is relatively mild compared to other parts of the world such as Sub-Saharan Africa and the Western part of the United States. However, the relatively low SPEI may not explain why the impact is much smaller

[14] One possible explanation for the low estimated effects of weather shocks on maize yields in rural China may be that the most affected farmers have no other choice than migrating. Weather shocks have indeed been found to significantly affect migration (Feng et al., 2010; Marchiori et al., 2012; Gray and Mueller, 2012). Although we will discuss possible adaptation outside of agriculture, the migration channel does not seem to be driving our results. Estimating the same models with unbalanced panel and village fixed effect, our results for temperature and drought are largely unaltered (see appendix Table A7). Coefficients for the average temperature seem to be slightly lower in magnitude in the unbalanced panel, suggesting a migration selection towards the most productive households. Although the effect seems to be marginal in affecting our results, such selection of the most productive households is in line with the emerging literature showing that those moving as a response to weather shocks are rather those able to overcome the migration costs under credit constraints (Dillion et al., 2011; Mueller et al., 2014; Maystadt et al., forthcoming) .

Table 4: The list of climate effects in other papers

Author	Changes of weather indexes	Crop	Location	Impact
This paper	1SD Δ Temperature	Maize	China(maize zone 1-2)[a]	-1.4%,-1.06%
This paper	1SD Δ Rainfall	Maize	China(maize zone 1-2)[a]	-1.3%,-1.7%
This paper	1SD Δ drought[b]	Maize	China(maize zone 1-2)[a]	-2.4%,-0.8%
This paper	1SD Δ wet[b]	Maize	China(maize zone 1-2)[a]	-1.0%,-0.5%
This paper	1SD Δ DDM	Maize	China(maize zone 1-2)[a]	1.2%,1.2%
This paper	1SD Δ EDD	Maize	China(maize zone 1-2)[a]	-1.3%,-1.6%
Lobell and Burke (2011)	1SD Δ rainfall[c]	Rice	China	0.30%[d]
Lobell and Burke (2011)	1SD Δ temperature	Rice	China	-0.20%[c]
Lobell and Burke (2011)	1SD Δ rainfall	Wheat	China	0.40%[c]
Lobell and Burke (2011)	1SD Δ temperature	Wheat	China	-1%[c]
Lobell and Burke (2011)	1SD Δ rainfall	Soybean	China	0.50%[c]
Lobell and Burke (2011)	1SD Δ temperature	Soybean	China	2.50%[c]
Ming et al. (2015)	SPEI $<$ -1	Maize	China(5 provinces)[d,i]	Yield$<$0
Ming et al. (2015)	SPEI $<$ -0.7	Maize	China(5 provinces)[d,ii]	Yield$<$0
Ming et al. (2015)	SPEI $>$ 0.9	Maize	China(5 provinces)[d,iii]	Yield$<$0
Tao and Zhang (2010)	1°C Δ temperature	Maize	China(5 provinces)[e]	-6%[f]
Tao and Zhang (2010)	10mm Δ precipitation	Maize	China(5 provinces)[5]	2.30%[f]
Tao et al. (2008)	1°C Δ temperature	Rice	China(6 provinces)[i]	6.1%-18.6%[j]
You et al. (2005)	1°C Δ temperature	Wheat	China	-0.30%
Zhang and Huang (2012)	1°C Δ temperature	Maize	China(two provinces)[*]	12%[f]
Li et al. (2011)	1°C Δ temperature	Maize	North-east of China	-10.18%
Li et al. (2011)	1°C Δ temperature	Maize	South-west of China	-10.98%
Li et al. (2011)	1mm Δ Precipitation	Maize	North-east of China	-0.02%
Li et al. (2011)	1mm Δ Precipitation	Maize	South-west of China	0.06%

The list of climate effects in other papers (Table 4 Continued)

Author	Changes of weather indexes	Crop	Location	Impact
Guiteras (2007)	+0.5°C , +4% rain	Crop	India	-0.13
Guiteras (2007)	1SD Δ temperature	crop	India	-4.30%
Guiteras (2007)	1SD Δ rainfall	crop	India	-1.10%
Lobell and Asner (2003)	1°C Δ temperature	Maize, Soybean	USA	-17%
Nicholls (1997)	1°C Δ temperature	Wheat	Australia	+30 +50%
Shaobing et al. (2004)	1°C Δ temperature	Rice	Philippines	-10%
Prajapati et al. (2010)	1°C Δ temperature	Maize yield	India	-3.20%
Barros et al. (2015)	1°C Δ temperature	maize	Argentina (Pampas)	-4.64%
Barros et al. (2015)	1°C Δ temperature	Wheat	Argentina (Pampas)	-3.14%
Blanc (2012))	1SD Δ rainfall	Maize	Sub-Saharan Africa (SSA)	9.16%
Schlenker and Lobell (2010)	1SD Δ Temperature	Maize	SSA	-24.6%
Schlenker and Lobell (2010)	1SD Δ Precipitation	Maize	SSA	-0.10%
Lobell and Field (2007)	1°C Δ in temperature	Maize	Average global	-8.30%
Lobell and Burke (2010)	+1°C temperature	Maize	198 sites in 16 countries	7.20%
Lobell and Burke (2010)	20% precipitation	Maize	198 sites in 16 countries	5.8%
Lobell et al. (2011)	1°C Δ in EDD above 30°	Maize	African	-0.027

Note: [a]: Maize zone 1 is Northern spring maize zone and maize zone 2 is the Yellow-Huai Valley summer maize zone. [b]: The value of 5% percentile monthly SPEI is -1.01 in our dataset and the value of 95% percentile monthly SPEI is 1.13. [c]: SD means standard deviation. [d]: Including Hebei, Henan, Shandong, Tianjin, Beijing. [i] covers 1962-1991, [i]i 1992-2011, and [i]ii 1962-1991. [e]: Including Shandong, Heilongjiang, Jilin, Liaoning. [f] Results are calculated or deductive by authors based on the estimations and graphs.[g]:Including Harbin, Hefei, Chengdu, Nanchang, Changsha, Guangzhou.[h]:According to the median values of the projected changes. [*]: Including Jilin and Anhui.

compared to other maize zones such as the East of United States, the Southern part of India or Argentina with similar levels of SPEI or drought occurrence. In these parts of the world, the SPEI is in a range of -0.84 to 1.28 similar to our sample, but as reported in Table 4, the impact is 3 to 4 times larger in magnitude.[15]

The lower magnitude of the impact may also be due to a high degree of adaptation from Chinese farmers to weather shocks. As recently reviewed by Dell et al. (2014), adaptation and intensification constitute limits of panel data analyses in assessing the impact of climate change (as opposed to weather shocks) on agricultural outcomes. Although our SPEI index partly takes into account the cumulative nature of water deficiencies as a result of higher temperature, the low magnitude of the impact may be due to the inability of the data to capture intensification effects. To assess the importance of adaptation and intensification, we proceed in two ways, by exploring: i) the use of long differences; ii) the changes in input uses at the farm level.

First, we follow Burke and Emerick (2015) in contrasting our panel results with a long-difference model. To do so, we average the main variables for 2004-2006 and 2008-2010, respectively. Aggregation aims at lessening random shocks that might appear in one single year. We then first-difference the averages. In Columns (1) and (4) of Table 5, we estimate the long difference models in the two maize zones. Columns (2) and (5) further control for provincial fixed effects. By controlling for provincial fixed effects, our estimation better controls for possible policy changes. For comparability reasons, we include the panel results with household fixed effects in columns (3) and (6) of Table 5. We then compare the long difference models with the panel data models. As discussed in Dell et al. (2014) paper, intensification effects denote that longer-run weather effects are larger than short-run weather effects, and adaptation, the reverse. In the Yellow-Huai Valley summer zone, the effects of temperature, precipitation, drought and wet conditions are larger in magnitude compared to those obtained with the long-difference estimations (with or without province fixed effects). Such differences provide evidence of intensification, pointing to a possible downward bias of our fixed-effects estimates. Such observation echoes Zhang et al. (2015) studies, according to which short term climate effects on yields are much smaller than long term effects in China. In the Northern spring maize zone, where larger

[15] The value is acquired based on the maps in the website *http://sac.csic.es/spei/map/maps.html*.

impacts had been estimated, we find supportive evidence for adaptation, rather than intensification. Effects only seem to intensify under wet conditions. We also quantify the extent of adaptation or intensification, using the formula $1 - \frac{\beta_{LD}}{\beta_{FE}}$. Table 6 illustrates further the evidence that there is more intensification in the Yellow-Huai Valley summer maize zone, while adaptation is more prevalent in the Northern spring maize zone.

Table 5: Comparison of long-difference estimations with fixed-effects estimations

Dep. Var.	Maize yields (log)					
	Northern spring maize zone			**Yellow-Huai Valley summer maize zone**		
	LD	LD	FE	LD	LD	FE
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	0.10554***	0.06851	-0.00888**	-0.11766***	-0.18793***	-0.00949*
	(0.02468)	(0.04247)	(0.00436)	(0.03328)	(0.04442)	(0.00533)
Precipitation	0.00034***	0.00019*	-0.00007***	-0.00041***	-0.00037***	-0.00014***
	(0.00011)	(0.00011)	(0.00002)	(0.00010)	(0.00010)	(0.00002)
SPEI Drought	-0.02098*	-0.00123	-0.04424***	-0.01226	0.01894	-0.01350***
	(0.01130)	(0.01208)	(0.00373)	(0.03287)	(0.03418)	(0.00500)
SPEI wet	-0.02627*	-0.02099	-0.00503	-0.05506**	-0.04496**	-0.01244**
	(0.01426)	(0.01850)	(0.00342)	(0.02163)	(0.02152)	(0.00551)
Fixed effects	No	Province FE	HH FE	No	Province FE	HH FE
N	17,713	17,713	16,296	12,907	12,907	13,992
R-squared	0.05517	0.13330	0.04081	0.04463	0.05695	0.06418

Note: Driscoll and Kraay (1998) standard errors in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6: Difference between the first-difference and the fixed effect models

	Northern spring maize zone		Yellow-Huai maize zone	
Temperature	14.074%	8.625%	-13.065%	-21.929%
Precipitation	5.214%	1.88%	-1.739%	-1.521%
SPEI-Drought	0.827%	1.574%	0.121%	2.322%
SPEI-Wet	-3.603%	-0.735%	-4.351%	-3.588%
Fixed effect	No FE	Provincial FE	No FE	Provincial FE

Note:The difference is calculated by the formula $1 - \frac{\beta_{LD}}{\beta_{FE}}$

Second, we investigate what are the possible sources of adaptation available to farmers in rural China. There are basically three channels to cope with the negative effects of weather variations on

Table 7: Weather effects on non-agricultural income

	(1)	(2)	(3)	(4)
Dep. Var.	**Non-agricultural income (log)**		**Maize share in total agricultural land**	
	Northern spring	Yellow-Huai	Northern spring	Yellow-Huai
	LD	LD	LD	LD
Temperature	0.11692*	0.00289	-0.03893	-0.05595***
	(0.07267)	(0.07800)	(0.02805)	(0.01907)
Precipitation	0.00091**	-0.00066***	0.00009	0.00005
	(0.00037)	(0.00023)	(0.00010)	(0.00004)
SPEI-based drought	0.09617***	0.10312	-0.01963**	-0.01852
	(0.03385)	(0.10427)	(0.00828)	(0.02756)
SPEI-based wet	-0.04917	0.02481	-0.00018	0.00268
	(0.04002)	(0.04981)	(0.01671)	(0.01258)
N	17,480	12,788	17,591	12,843
R-squared	0.02089	0.01614	0.12933	0.11191

Note: Driscoll and Kraay (1998) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

maize: i) going out of the agricultural sector; ii) reallocating part of the planting area of maize in favor of other crops, iii) changing the intermediate inputs of maize planting if farmers keep planting maize. Based on these channels, we estimate the effects of weather variations on non-agricultural income, maize share of cropped land, and the use of intermediate inputs.

In columns (1) and (2) of Table 7, we estimate the effects of weather variations on non-agricultural income. In the Northern spring maize zone, where the first-difference model gives us some evidence of adaptation, we observe farmers relying less on agriculture as a response to weather variations. The increase of temperature, precipitation and drought significantly raises the share of non-agricultural income. Farmers choose to move out of agriculture to cope with the detrimental effects of weather variations. In the Yellow-Huai valley summer maize zone, weather variations do not affect non-agricultural income. Farmers do not leave agriculture to cope with weather variations. That could be due to the lower magnitude of the estimated impact of weather shocks in that particular region or the existence of other margins of adjustment.

Farmers can also adapt to weather variations by changing the planting area or their use of inputs. Adaptation within agriculture may call for adopting other farming practices and techniques (e.g.

irrigation, multiple cropping, adjusting planting dates, etc). Farmers in the Northern Spring maize zone reduce the share of maize production planted on their land (column (3) of Table 7) as a response to more frequent droughts. The maize type in this zone is rainfed, which makes farmers more sensitive to droughts than in the other zone. In the Yellow-Huai Valley summer maize zone, a reduction in the share of maize is limited to the rise of temperature (column 4 of Table 7). In the Northern spring maize zone, Table 8 indicates that farmers also increase the use of fertilizers with the increase of temperature, precipitation, drought, but decrease the use of pesticide, seeds, irrigation and labor inputs as a response to temperature or drought. Such results are consistent with Smit and Skinner (2002) who find that in Ontario (Canada), farmers did nothing or reduced inputs or crop types in response to dry years. In that case, the main objective is to lower the costs or balance the profits, by reducing the most costly inputs. Coupled with the move out of agriculture, farmers seem to adapt to weather shocks in this maize zone by decreasing the inputs costs.

In the Yellow-Huai Valley summer maize zone, evidence for intensification and the lower impact of weather shocks is coupled with farmers increasing their seed inputs, increasing pesticide fees, and decreasing labor allocated to maize production to cope with the increase in temperature. That type of adjustment within agriculture may well result in long-run intensification of the impact of weather chocks on maize yields. Owing to the irrigated maize type in this maize zone, precipitations have a negative effect on the inputs of irrigation fees, indicating that farmers would decrease the irrigation inputs with abundant rainfall. We found a somewhat unexpected negative impact of drought on irrigation fees. Similar to Smit and Skinner (2002), that could potentially be explained by the increase of irrigation costs due to water scarcity under aridity conditions. Farmers would rather minimize the input costs by reducing the irrigation inputs.

Table 8: Input adjustments as a response to weather variations

	(1)	(2)	(3)	(4)	(5)
Dep. Var.	Labour	Seed	Fertiliser	Pesticides	Irrigation
	Day/Mu	Yuan/Mu	Yuan/Mu	Yuan/Mu	Yuan/Mu
Panel A. Northern spring maize zone					
Temperature	0.023587	-0.118659**	0.095785*	-0.252883***	-0.354636*
	(0.049989)	(0.056965)	(0.050299)	(0.070769)	(0.187420)
Precipitation	-0.000703***	-0.000125	0.000415*	-0.000373	-0.000965
	(0.000172)	(0.000212)	(0.000225)	(0.000274)	(0.000903)
SPEI Drought	-0.048342***	-0.042552*	0.027305	-0.204016***	-0.104528***
	(0.018264)	(0.024153)	(0.018189)	(0.027866)	(0.038836)
SPEI Wet	-0.005785	0.022066	-0.077493***	0.022645	0.060109
	(0.024639)	(0.026835)	(0.025167)	(0.032035)	(0.045973)
N	17,588	17,491	17,589	17,528	17,100
R-squared	0.034357	0.011995	0.016014	0.112437	0.060329
Panel B. Yellow-Huai Valley summer maize zone					
Temperature	-0.048826	0.159015***	0.176924***	0.291797***	0.237188***
	(0.045063)	(0.047501)	(0.045965)	(0.065460)	(0.083394)
Precipitation	0.000388**	0.000106	0.000119	0.000191	-0.000808***
	(0.000176)	(0.000170)	(0.000201)	(0.000194)	(0.000260)
SPEI Drought	-0.163353**	-0.099029	-0.189213**	-0.059587	-0.684949***
	(0.070820)	(0.066730)	(0.073529)	(0.089237)	(0.126903)
SPEI Wet	-0.057036*	0.017542	-0.123912***	-0.021986	-0.203081***
	(0.029895)	(0.036446)	(0.039424)	(0.040820)	(0.062493)
N	12,835	12,792	12,841	12,796	12,599
R-squared	0.031199	0.021231	0.036477	0.036700	0.100955

Note: Driscoll and Kraay (1998) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5 Conclusions

In this paper, we assess the impact of weather shocks on maize yields in the two main producing regions in China. One of the strengths of our analysis is the use of a panel dataset of households. That allows us to track maize yields for the same households over time while controlling for observed and unobserved determinants of crop yields at the farm level. We also use advanced weather indexes (such as the standardized precipitation evaporation indexes, moderate degree days and extreme heat days) to capture extreme weather shocks. Compared to previous studies on China, we provide a more credible identification by exploiting within-village variation in weather conditions - and its related proxies for weather shocks together with observed and unobserved household characteristics to account for potential heterogeneity within villages.

We find average temperature, the SPEI-based drought and wet indexes, as well as precipitations have negative effects on maize yields in the two maize zones. In the Northern spring maize zone, an increase by one standard deviation in temperature translates into a minor fall of about 1.4% in maize yield. The impact of a similar change in SPEI-based drought occurrence is almost twice bigger, with a partial effect of -2.5%. Similar results are found for the Yellow-Huai Valley maize zone with much smaller partial effects of -1.06% and -0.9% for temperature and SPEI-based drought, respectively. The SPEI-based wet conditions have lower impacts on yields compared to the SPEI-based drought index. One standard deviation change of SPEI-based wet index will decrease maize yields by about 1.09% and 0.86% in the Northern spring maize zone and the Yellow-Huai Valley summer maize zone, respectively. The weather shocks in the Northern spring maize zone have larger impacts on maize yields than the shocks occurring in the Yellow-Huai maize zone.

The impact of weather variations on maize yields is low when compared to other countries and regions, such as the United States, Africa, Argentina, or India. Adaptation, in particular outside of agriculture and maize production, seems to be key in the region where the largest impact is estimated but remains limited to at best 14% of the short-run impact. The lower impact found in the Yellow-Huai Valley summer maize zone is a good news in the short run but evidence of intensification suggests that the impact may exacerbate in the future. Further research should focus on better understanding the market and non-market conditions that facilitate the adoption of coping strategies. The implications for food security are likely to be of major importance.

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Appendix

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A Supplementary Figures

Figure A1: Six maize zones in China

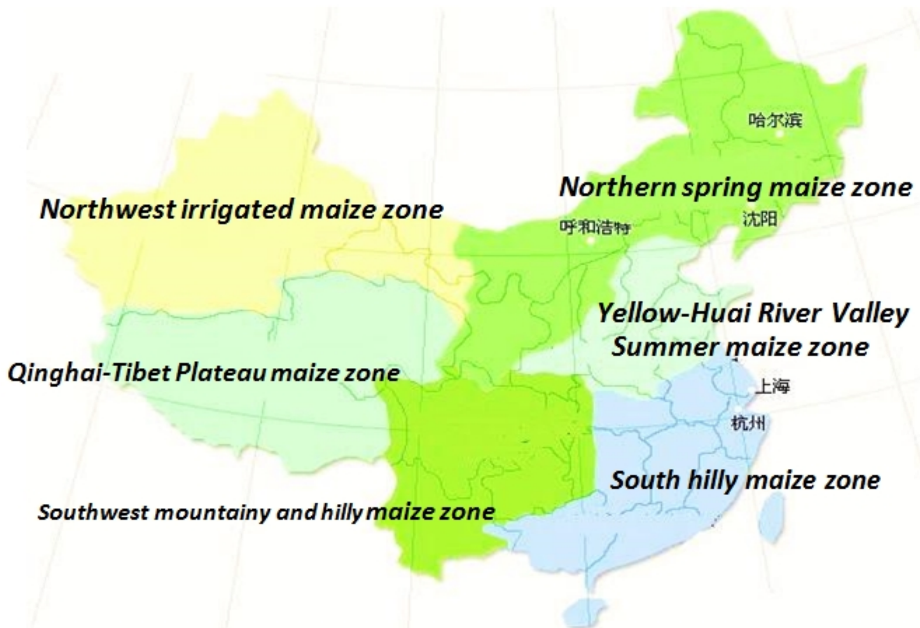
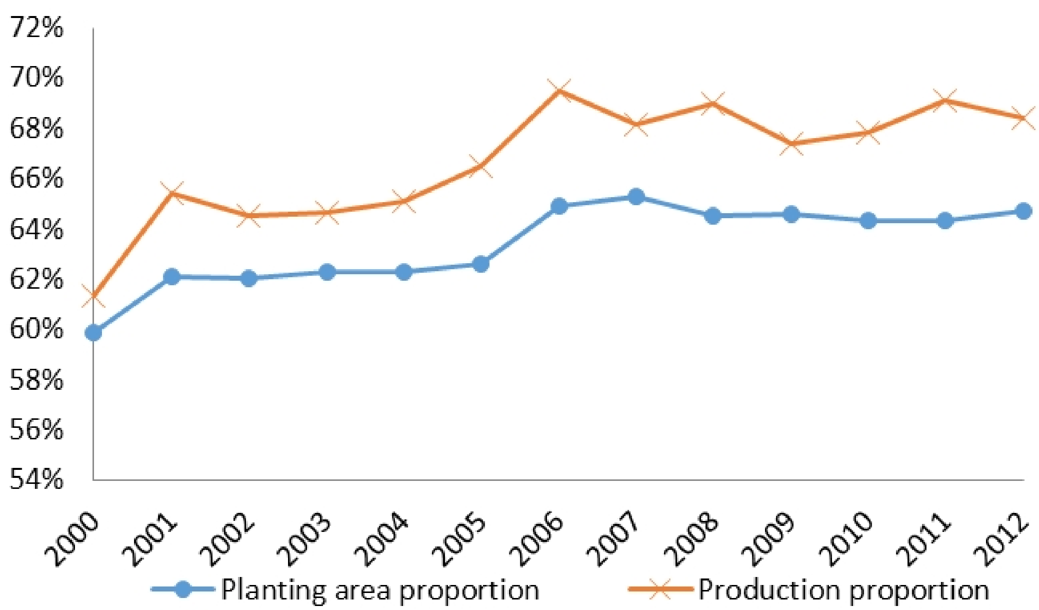


Figure A2: The planting area and production in two maize zones as a share of the total in China



Data Resource: China Ministry of Agriculture dataset (2014)

Figure A3:Maize yields and maize planting areas in two maize zones

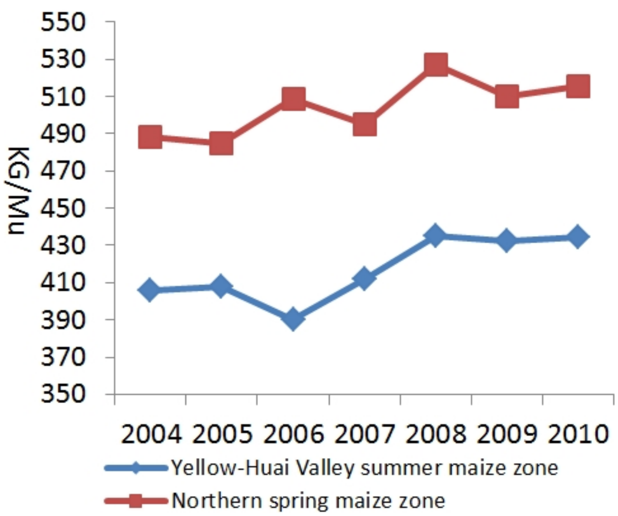


Figure A3a: Maize yield

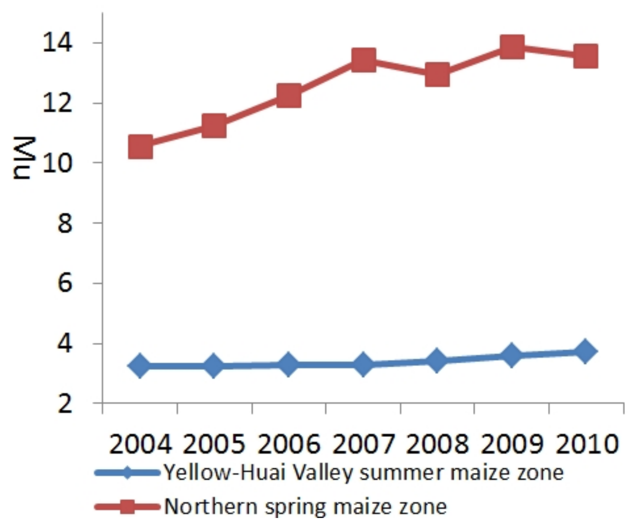


Figure A3b: Planting area

Figure A4:Average temperature and precipitation in the growing period

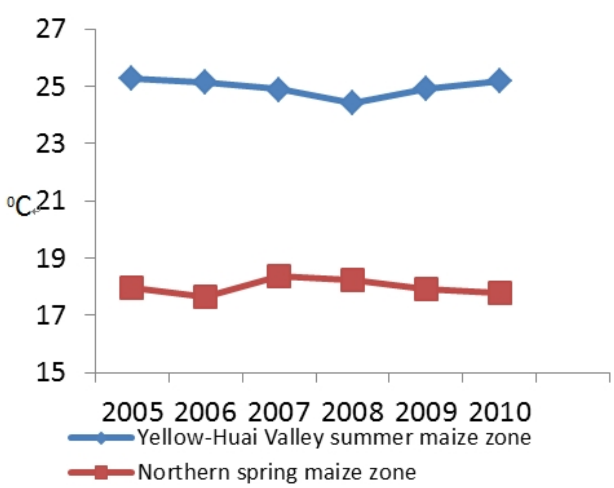


Figure A4a: Average temperature

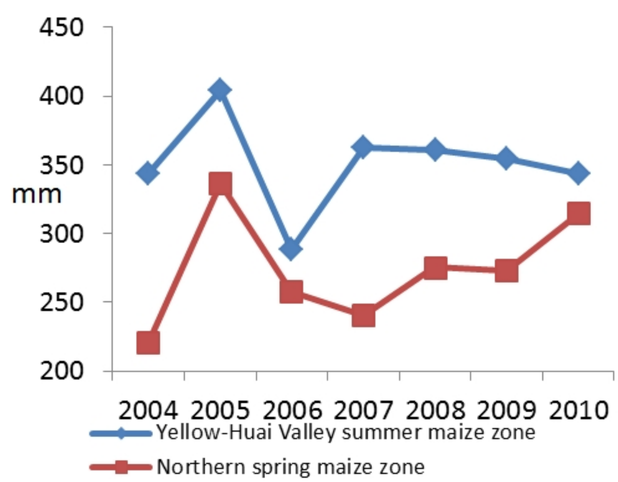


Figure A4b: Precipitation

Figure A6:Annual SPEI in growing period

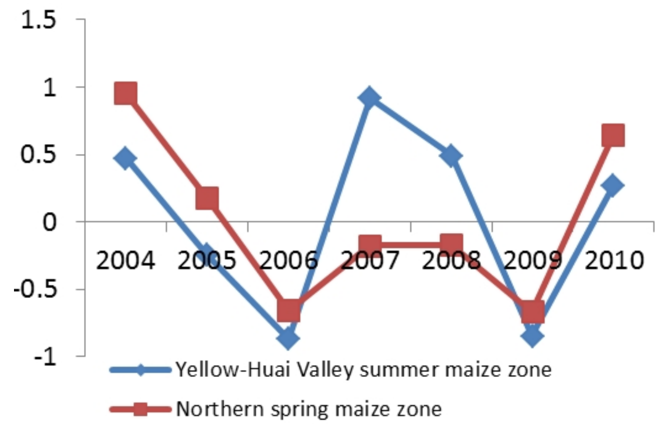


Figure A6a: SPEI (1 month)

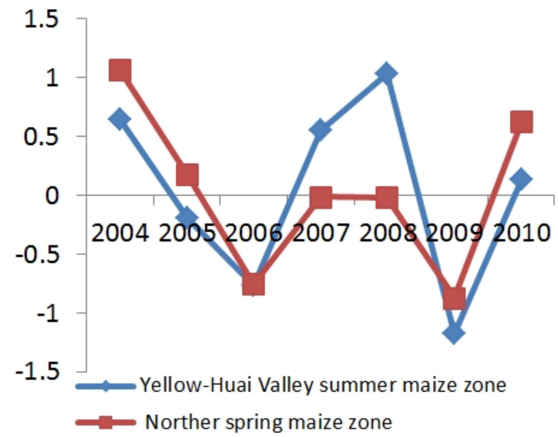


Figure A6b: SPEI (3 month)

Figure A5:Average temperature and mean total precipitation

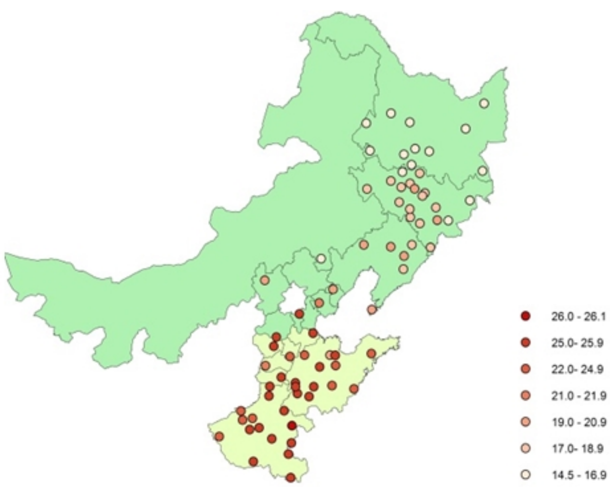


Figure A5a: Average temperature

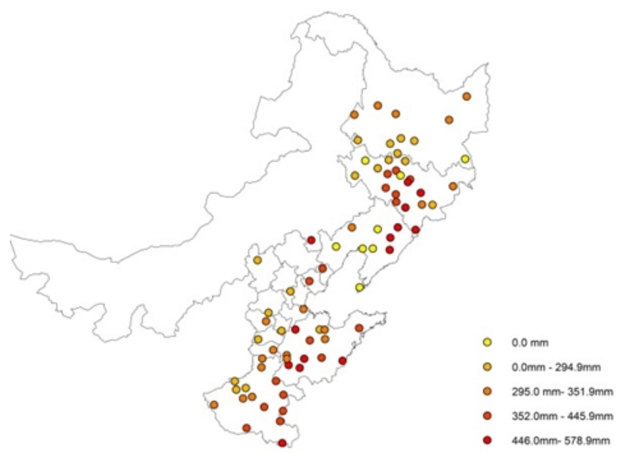


Figure A5b: Precipitation

Figure A7:SPEI-based indexes in growing periods

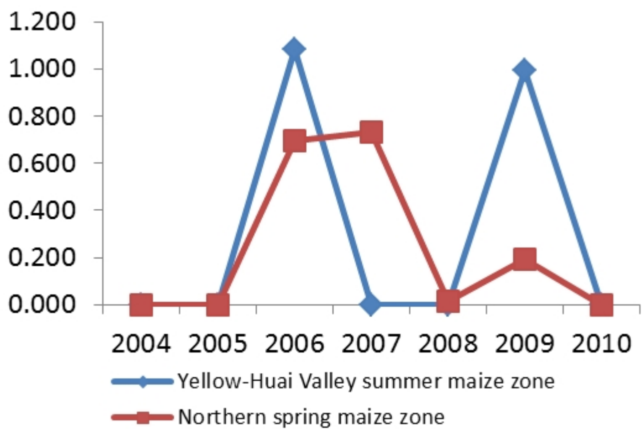


Figure A7a: SPEI-based drought index

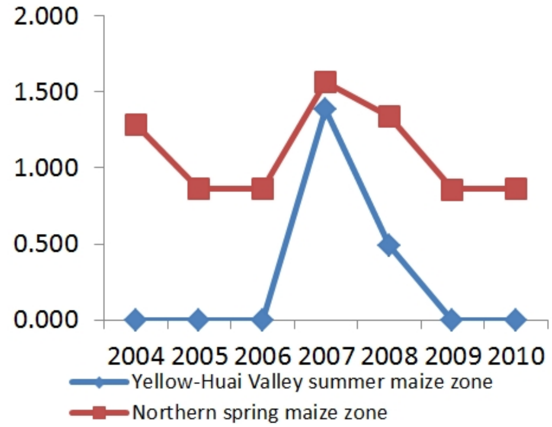


Figure A7b: SPEI-based wet index

B Supplementary Tables

Table A1.Weather-related disasters in Yellow-Huai Valley summer maize zone and in the Northern spring maize zone between 2003 and 2010

Start	End	Geo info.	Location	Disaster	Total affected (Persons)
00/1/2003	00/1/2003	China P Rep	Inner Mongolia Autonomous region, Henan, Anhui, Shanxi, Shaanxi,	Drought	48000000
00/11/2008	00/2/2009	China P Rep	Shandong, Hubei, Gansu, Hebei, Hebei Anhui, Gansu, Henan, Jiangsu provinces	Drought	3700000
00/12/2010	00/5/2011	China P Rep	Jiangsu, Shaanxi, Shandong, Shaanxi Chaiyang, Fuxin, Jinzhou	Drought	35000000
00/6/2009	00/7/2009	China P Rep	Huludao districts (Liaoning province)	Drought	160000
00/6/2010	00/8/2010	China P Rep	Jilin province,Shandong, Henan Hunan, Hubei	Flood	6000000
15/7/2004	20/7/2004	China P Rep	Guangxi, Chongqing, Yunnan provinces	Flood	33652026
24/8/2003	12/11/2003	China P Rep	Shaanxi, Gansu, Henan, Hubei Shandong provinces	Flood	200000

Sources: EM-DAT: The OFDA/CRED International Disaster Database *www.emdat.be*, Universite catholique de Louvain, Brussels (Belgium)

Table A2.Robustness to alternative specification

Dep.Variable	Maize yield(log)			Maize yield(log)		
Variables	**North spring maize zone**			**Yellow-Huai Valley summer maize zone**		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. With time trends						
Average Temperature	-0.00874		-0.00454	-0.00987		-0.00760
	(0.01785)		(0.00534)	(0.00791)		(0.00591)
Precipitation	-0.00013*		-0.00014***	-0.00011*		-0.00011***
	(0.00008)		(0.00002)	(0.00006)		(0.00002)
SPEI based drought		-0.02715**	-0.03050***		-0.01174**	-0.01404***
		(0.01155)	(0.00357)		(0.00512)	(0.00518)
SPEI based wet		-0.00836*	-0.00927***		-0.00883	-0.01122**
		(0.00434)	(0.00336)		(0.00545)	(0.00548)
HH fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Panel B. With time trends and control variables						
Average Temperature	-0.01533		-0.00594	-0.00886		-0.00684
	(0.03455)		(0.00873)	(0.00947)		(0.00735)
Precipitation	-0.00023*		-0.00025***	-0.00014**		-0.00015***
	(0.00013)		(0.00003)	(0.00007)		(0.00003)
SPEI based drought		-0.04230***	-0.04773***		-0.01042	-0.01538**
		(0.01639)	(0.00565)		(0.00683)	(0.00690)
SPEI based wet		-0.01022*	-0.01250***		-0.01090	-0.01489**
		(0.00607)	(0.00448)		(0.00677)	(0.00682)
HH fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Panel C. Using village fixed effect						
Average Temperature	-0.01251		-0.00888**	0.09005**		0.03492***
	(0.01115)		(0.00436)	(0.03710)		(0.00544)
Precipitation	-0.00006		-0.00007***	-0.00005		-0.00011***
	(0.00005)		(0.00002)	(0.00008)		(0.00002)
SPEI based drought		-0.04077*	-0.04424***		-0.02160***	-0.02936***
		(0.02282)	(0.00373)		(0.00526)	(0.00532)
SPEI based wet		-0.00467	-0.00503		0.00005	-0.00537
		(0.00585)	(0.00342)		(0.00587)	(0.00589)
HH fixed effects	No	No	No	No	No	No

Note: Household and year fixed effects are included. Driscoll and Kraay (1998) standard errors in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Table A3. Non-linearity of weather shocks effects

Dep.Variable	Maize yield(log)			Maize yield(log)		
Variables	**North spring maize zone**			**Yellow-Huai Valley summer maize zone**		
	(1)	(2)	(3)	(4)	(5)	(6)
Average Temperature	-0.11106	0.189137**		0.174892*	0.189137**	
	(0.075160)	(0.091519)		(0.096457)	(0.091519)	
Square of Temperature	0.002821	-0.004073**		-0.003839**	-0.004073**	
	(0.002042)	(0.001846)		(0.001951)	(0.001846)	
Precipitation	0.000640***	-0.000011		0.000009	-0.000011	
	(0.000230)	(0.000196)		(0.000199)	(0.000196)	
Square of precipitation	-0.000001***	-0.000000		-0.000000	-0.000000	
	(0.000000)	(0.000000)		(0.000000)	(0.000000)	
SPEI based Drought(<5%)		-0.000484**	-0.003852*		-0.000484**	-0.00083
		(0.000199)	(0.002105)		(0.000199)	(0.000000)
Square of Drought (<5%)			0.000038			0.000006
			(0.000024)			(0.000000)
SPEI based Wet(>95%)		-0.000297*	0.000627		-0.000297*	-0.00027
		(0.000154)	(0.000512)		(0.000154)	(0.000000)
Square of Wet(>95%)			-0.000012**			0
			(0.000005)			(0.000000)
Observations	16,296	13,992	18,508	13,992	13,992	13,992
Number of groups	2,328	1,999	2,644	1,999	1,999	1,999

Note: Household and year fixed effects are included. Driscoll and Kraay (1998) standard errors in parentheses. * significant at 10%, ** at 5%, *** at 1%.

Table A4. Effects of Moderate Degree days and Extreme Heat days

Dep.Variable	Maize yield(log)			Maize yield(log)		
Variables	**North spring maize zone**			**Yellow-Huai Valley summer maize zone**		
	(1)	(2)	(3)	(4)	(5)	(6)
Average Temperature			0.026154***			0.012646
			(0.008630)			(0.010012)
Precipitation	-0.000056		-0.000106***	-0.000133***	-0.000139***	-0.000132***
	(0.000050)		(0.000023)	(0.000040)	(0.000017)	(0.000018)
SPEI based Drought (<5%)		-0.001338*	-0.001518***		-0.000497***	-0.000515***
		(0.000731)	(0.000124)		(0.000157)	(0.000159)
SPEI based Wet (>95%)		-0.000154	-0.000105		-0.000337**	-0.000276*
		(0.000183)	(0.000113)		(0.000150)	(0.000143)
DDM between 8&24				0.000028	0.00005	
				(0.000033)	(0.000033)	
Extreme Heat days above 24				-0.000204***	-0.000199***	-0.000273***
				(0.000066)	(0.000062)	(0.000105)
DDM between 8&20	0.000009	0.000046				
	(0.000210)	(0.000189)				
Extreme Heat days above 20	-0.000108	-0.000095	-0.000476***			
	(0.000268)	(0.000236)	(0.000101)			
Observations	18,508	18,508	16,296	13,992	13,992	13,992
R-squared	0.042	0.042	0.042	0.065	0.065	0.065

Note: Household and year fixed effects are included. Driscoll and Kraay (1998) standard errors in parentheses.* significant at 10%, ** at 5%, *** at 1%.

Table A5. Different measurements of Drought and Wet

Dep.Variable	Maize yield(log)			Maize yield(log)		
Variables	**North spring maize zone**			**Yellow-Huai Valley summer maize zone**		
	(1)	(2)	(3)	(4)	(5)	(6)
SPEI based Drought (<10%)	-0.000031			0.000057		
	(0.000191)			(0.000412)		
SPEI based Wet (>90%)	-0.000204*			-0.000382*		
	(0.000114)			(0.000199)		
Drought (SPEI<-1∗SD)		-0.000480*			0.00021	
		(0.000247)			(0.000282)	
Wet (SPEI>1∗SD)		-0.000215*			0.000292***	
		(0.000125)			(0.000103)	
Drought (SPEI<-2∗SD)			-0.001768***			-0.002206
			(0.000641)			(0.000000)
Wet (SPEI>2∗SD)			-0.000318			0.000643
			(0.001346)			(0.000000)
Observations	18,508	18,508	18,508	13,992	13,992	13,992

Note: Household and year fixed effects are included. Driscoll and Kraay (1998) standard errors are in parentheses.
* significant at 10%, ** at 5%,*** at 1%.

Table A6. Estimations excluding Hebei Province

Dep.Variable	Maize yield(log)			Maize yield(log)		
Variables	**North spring maize zone**			**Yellow-Huai Valley summer maize zone**		
	(1)	(2)	(3)	(4)	(5)	(6)
Average Temperature	-0.01658		-0.01406***	-0.00722		-0.00480***
	(0.01460)		(0.00543)	(0.01155)		(0.00860)
Precipitation	-0.00005		-0.00006***	-0.00023***		-0.00023***
	(0.00005)		(0.00002)	(0.00002)		(0.00002)
SPEI based Drought		-0.04763*	-0.05064***		-0.00363	-0.00909***
		(0.02854)	(0.00456)		(0.00569)	(0.00595)
SPEI based Wet		0.00191	0.00247		0.01102*	0.01061
		(0.00936)	(0.00449)		(0.00645)	(0.00646)
Observations	16,296	18,508	16,296	13,992	13,992	13,992
R-squared	0.041	0.041	0.041	0.064	0.059	0.064

Note: Household and year fixed effects are included. Driscoll and Kraay (1998) standard errors are in parentheses.
* significant at 10%, ** at 5%,*** at 1%.

Table A7. The main results of unbalanced panel

Dep.Variable	Maize yield(log)			Maize yield(log)		
Variables	**North spring maize zone**			**Yellow-Huai Valley summer maize zone**		
	(1)	(2)	(3)	(4)	(5)	(6)
Average Temperature	-0.012045		-0.008708**	-0.013142***		-0.009965*
	(0.010937)		(0.004157)	(0.004787)		(0.005214)
Precipitation	-0.000062		-0.000078***	-0.000134***		-0.000138***
	(0.000044)		(0.000021)	(0.000043)		(0.000017)
SPEI based Drought		-0.001341*	-0.001493***		-0.000454***	-0.000509***
		(0.000732)	(0.000115)		(0.000155)	(0.000156)
SPEI based Wet		-0.000094	-0.000091		-0.000317**	-0.000368***
		(0.000203)	(0.000105)		(0.000141)	(0.000141)
Observations	18,570	21,421	18,570	15,016	15,016	15,016
R-squared	0.038	0.038	0.038	0.059	0.059	0.064

Note: Household and year fixed effects are included. Driscoll and Kraay (1998) standard errors are in parentheses.
* significant at 10%, ** at 5%,*** at 1%.

Table A8. Direct and indirect effects of weather variables in dynamic models

	Labor	Seed	Fertilizer fee	Pesticide fee	Irrigation fee
Northern spring maize zone					
Diff(Temperature)	-0.035832	-0.083248	-0.078689	-0.365948***	-0.138923
	(0.069888)	(0.071882)	(0.068080)	(0.082476)	(0.218502)
Diff (Precipitation)	-0.000340*	0.000168	0.000246	-0.000199	0.000028
	(0.000206)	(0.000242)	(0.000213)	(0.000313)	(0.001307)
Diff(Drought)	-0.002181***	-0.001128	0.001186*	-0.005286***	-0.004052***
	(0.000665)	(0.000879)	(0.000660)	(0.001067)	(0.001473)
Diff(Wet)	0.00019	0.00078	-0.000954	0.000979	0.005683***
	(0.000854)	(0.001010)	(0.000902)	(0.001175)	(0.001499)
Constant	-0.214273***	-0.091074	-0.050812	-0.659241***	-0.290153
	(0.072296)	(0.062316)	(0.071423)	(0.192310)	(0.232120)
Observations	17622	17524	17621	17560	17108
R-squared	0.0485	0.0231	0.045	0.154	0.143
FE	Province FE	Province FE	Province FE	Province FE	Province FE
Yellow-Huai Valley summer maize zone					
Diff(Temperature)	-0.122948	0.000843	0.154491*	0.335533***	0.024101
	(0.077089)	(0.081165)	(0.080412)	(0.108224)	(0.145098)
Diff (Precipitation)	0.000169	0.000091	-0.000281	0.000146	-0.000811***
	(0.000189)	(0.000166)	(0.000190)	(0.000217)	(0.000237)
Diff(Drought)	-0.003790*	-0.002439	-0.003199	-0.00437	-0.017603***
	(0.002163)	(0.002132)	(0.002286)	(0.003006)	(0.004712)
Diff(Wet)	-0.001487*	-0.000257	-0.002556***	-0.001192	-0.002489
	(0.000804)	(0.000789)	(0.000812)	(0.001151)	(0.001603)
Constant	-0.097587**	-0.163287***	0.151445***	0.121351*	0.164127**
	(0.040431)	(0.052025)	(0.052544)	(0.063370)	(0.073164)
Observations	12809	12763	12811	12767	12581
R-squared	0.043	0.023	0.018	0.052	0.085
FE	Province FE	Province FE	Province FE	Province FE	Province FE