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Extreme Weather Impacts on Maize Yield: The Case of Shanxi Province in China †

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† This paper was presented at the Conference of Agriculture and Climate Change in Transition Economies IAMO Forum 2015, Halle (Saale), Germany, 17–19 June 2015 and at the Global Land Programme 3rd Open Science Meeting, Beijing, China, 24–27 October 2016.

Academic Editor: Adrian Muller
Received: 6 October 2016; Accepted: 19 December 2016; Published: 28 December 2016

Abstract: Extreme weather can have negative impacts on crop production. In this study, we statistically estimate the impacts of dry days, heat waves, and cold days on maize yield based on household survey data from 1993 to 2011 in ten villages of Shanxi province, China. Our results show that dry days, heat waves, and cold days have negative effects on maize yield, although these effects are marginal if these extreme events do not increase dramatically. Specifically, a one percent increase in extreme-heat-degree-days and consecutive-dry-days results in a maize yield declines of 0.2% and 0.07%, respectively. Maize yield also is reduced by 0.3% for cold days occurring during the growing season from May to September. However, these extreme events can increase dramatically in a warmer world and result in considerable reduction in maize yields. If all the historical temperatures in the villages are shifted up by 2 degrees Celsius, total impacts of these extreme events would lead to a reduction of maize yield by over 30 percent. The impacts may be underestimated since we did not exclude the offset effect of adaptation measures adopted by farmers to combat these extreme events.

Keywords: agriculture; climate change; consecutive dry days; heat waves; degree days; food security

1. Introduction

Extreme weather events are expected to be more frequent because of global warming [1] with negative impacts on crop yield and threats to food security [2]. Recent studies have focused on extreme heat effect on crop yield (e.g., [3–6]). In this study, we statistically estimate the impact of extreme weather, including dry days, heat, and cold days, on maize yield based on household survey data from 1993 to 2011 in ten villages evenly spread out in Shanxi province, China.

Previous statistical studies on climate change impact on crop yield in China have explored impact of air temperature and precipitation on crop yield based on provincial panel data (e.g., [7,8]). These studies did not estimate extreme weather impact on crop yield since the extreme weather events always took place in a smaller area within a province of China and have trivial impacts on provincial crop production. In a specific year, extreme weather events may damage crop production in one area of a province while good weather helps the crop production in another area of the same province. Hence, the impact of extreme weather events is unlikely to be observed at the provincial level. As such, it seems more suitable to analyze the impact of extreme weather based on several smaller scale data.

This study adopts household data from ten villages from the Shanxi province of China. The household-level data allow for marked improvement of the significance of our estimated parameters since each household is a yearly observation in a village where the weather condition is the same in a given year. The heterogeneity of household characteristics and operation patterns can provide additional information in order to identify the impact of climate variables, especially for extreme weather events. If instead we adopt mean yearly maize yield and land area at the village level, the statistical significance of estimated parameters is reduced due to the missing information associated with household observations.

In this study, we use degree days (or heat units), which are calculated from daily maximum and minimum temperatures, since degree days are considered a better indicator of temperature for crop production (e.g., [9]). The role of extreme-heat-degree-days for crop production has been recognized by some statistical studies on regions other than China (e.g., [5,6,10]). To our knowledge, no previous study has explored the issue for China. Hence, this study will provide evidence on the issue based on household level data in Shanxi. Moreover, we consider simultaneously the impacts of extreme cold days and consecutive dry days (Box 2.4, Chaper 2, [11]) on crop production. In China, among the three main cereal crops of wheat, rice, and maize, maize production is the most sensitive one to climate change, and Shanxi is one of the provinces where maize production is the most vulnerable to climate change among the three crops [12,13]. Hence, we explore the case of maize production in Shanxi province in this study.

We organize the remainder of the paper as follows. The next section describes the study regions, data, and methodology. Section 3 reports the results estimated from statistical regression models and offers a discussion on issues related to the main results. The last section concludes the paper.

2. Material and Methods

2.1. Study Regions

The study region is ten villages evenly located in Shanxi province of North China between latitude 34°34′–40°44′ north and longitude 110°15′–114°32′ east (Figure 1). In 2013, the rural population accounts for 47.4% of the total population of 36.3 million in Shanxi [14]. The provincial economy with coal extraction as a major industry has been growing at a lower rate than the national economy over the last three decades. However, in 2013, per capita income in Shanxi was still slightly above 80% of the average in China [14]. Maize is the major cereal crop in Shanxi province. In 2015, Shanxi produced 8.6 million tons of maize from 1.677 million ha land [15].

The climate in Shanxi is continental monsoon with most of the rainfall occurring in the summer. The province lies largely within the Loess Plateau. The Loess soils are still fertile and suitable for agricultural production [16] although the soils are vulnerable to wind and water erosion [17], leading to damages to agricultural production during at least 3000 years of history [18]. The main cereal crops are winter wheat and maize [19]. According to our data, maize is the major crop in the ten villages included in this study (Figure 1). On average, the households planted maize on 85% of their cropland during 2011. Heat waves and droughts are considered the main extreme weather events in the area.

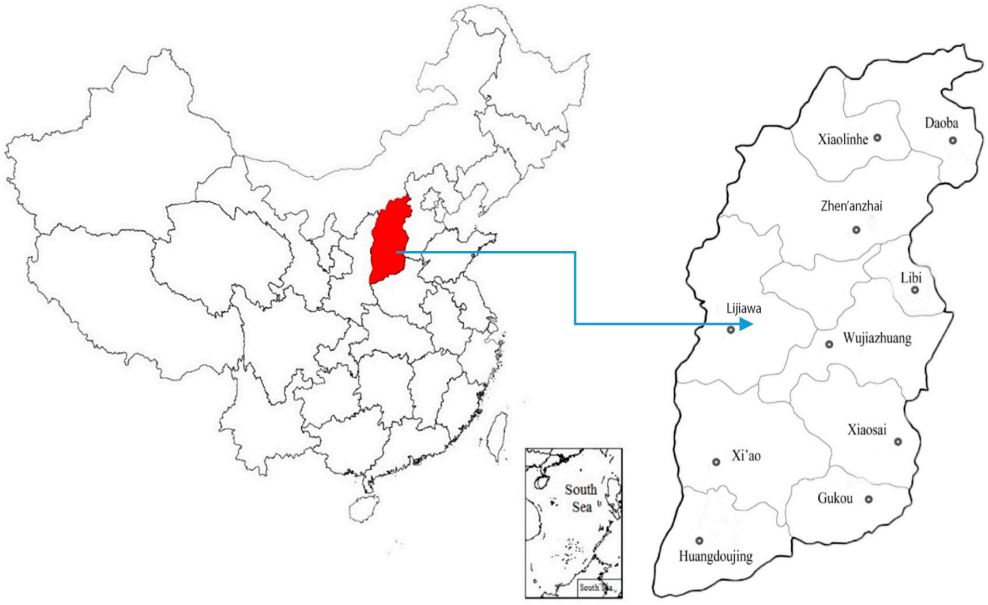

Figure 1. Distribution of the ten villages in Shanxi province of China.

2.2. Data

Data on maize production was collected annually through a household survey in the ten villages from 1993 to 2011, and was conducted by the Office of China Rural Fixed Observation Points (CRFOP), Ministry of Agriculture, China. Since 1984, CRFOP has operated a longitudinal survey system and recruited local villagers to survey rural households annually on their economic activities. The survey system covered about 350 villages in 30 provinces in 2012. In this study, we utilized the data for Shanxi province in the surveys from 1993 to 2011 since maize production data are not included in the surveys before 1993.

Climate data on temperature and precipitation are collected at 756 ground-based meteorological stations distributed throughout China (of which 19 are in Shanxi Province) by the China Meteorological Administration (http://data.cma.gov.cn). We estimated the daily village climate data using an algorithm presented by Thornton, Running, and White [20] that interpolated the climate data based on the observations from the closest meteorological station to each of the ten villages. The interpolated climate has been published in former studies (e.g., [21]). Based on the village climate data, we calculated degree days (DD) during the maize growing months from May to September. Following Matthews and Hunt [22], hourly temperature (T_h) is expressed by a cosinusoidal function assuming the maximum temperature occurs at 14:00,

$$T_h = \frac{T_{min} + T_{max}}{2} + \frac{T_{max} - T_{min}}{2} \cos\left(\frac{\pi}{12}(h - 14)\right) \quad (1)$$

where T_{min} and T_{max} are minimum and maximum daily temperatures, respectively; and h is time of day taking integers from 1 to 24.

Moderate degree days (MDD) are calculated as the sum of degree days above the lower threshold temperature of 8 °C [23] and below the upper threshold temperature of 29 °C [10,24]. In mathematical form, MDD can be expressed by

$$MDD = \sum_{d=1}^{153} \sum_{h=1}^{24} DD_h, \; where \; DD_h = \begin{cases} 0 & if \; T_h < T_{low} \; or \; T_h \geq T_{upp} \\ (T_h - T_{low})/24 & if \; T_{low} \leq T_h < T_{upp} \end{cases} \quad (2)$$

where DD_h is hourly degree days within a day; d is a day during maize growing months; and T_{low} and T_{upp} are the lower and upper threshold temperatures, respectively.

Temperatures above the upper threshold can lead to considerable damage to maize growth according to [3,5]. These extreme temperatures are represented by extreme heat degree days (EHDD),

$$EHDD = \sum_{d=1}^{153}\sum_{h=1}^{24} DD_h,\ where\ DD_h = \begin{cases} 0 & if\ T_h < T_{upp} \\ (T_h - T_{upp})/24 & if\ T_h \geq T_{upp} \end{cases} \quad (3)$$

Notice that hourly degree days (DD_h) are calculated differently from that for MDD.

To consider the role of temperatures below the lower threshold, we calculated extreme cold degree days (ECDD), which are always negative,

$$ECDD = \sum_{d=1}^{153}\sum_{h=1}^{24} DD_h,\ where\ DD_h = \begin{cases} 0 & if\ T_h \geq T_{low} \\ (T_h - T_{low})/24 & if\ T_h < T_{low} \end{cases} \quad (4)$$

Since our model specifications are double-log, we introduce a dummy variable to represent whether extreme cold days occurred during maize growing seasons,

$$COLD = \begin{cases} 0 & if\ ECDD = 0 \\ 1 & if\ ECDD < 0 \end{cases} \quad (5)$$

Besides temperature variables, we also considered the role of precipitation, with a particular focus on consecutive dry days (Box 2.4, Chaper 2, [11]), which is calculated as the maximum number of consecutive days with daily precipitation less than one millimeter (mm). All the variable definitions and descriptive statistics are summarized in Table 1. Figure 2 presents the variability of maize yield (a) and EHDDs (b) during the period from 1993 to 2011.

Table 1. Variable definitions and descriptive statistics.

Variable	Definition	Sample Size	Mean	Std. Dev.	Min	Max
Y	Maize yield of a household (kg/mu)	12,354	404.3	188.2	2.5	1176.5
LAND	Sown land for maize of a household (mu, i.e., 1/15 ha)	12,354	4.1	5.7	0.1	480.0
Degree days (DD) from May to September (°C-days)						
EHDD	Extreme heat degree days	12,354	14.8	14.7	0.1	141.1
MDD	Moderate degree days	12,354	1620.4	82.2	1326.2	1788.4
ECDD	Extreme cold degree days	12,354	−6.4	7.9	−49.1	0.0
COLD	Dummy of extreme cold days	12,354	0.9836	0.1271	0	1
GDD	Growing degree days	12,354	1789.7	158.6	1331.5	2406.4
Precipitation variables from May to September						
DRY	Consecutive dry days, i.e., the maximum number of consecutive days when daily precipitation is less than one millimeter (days)	12,354	17.0	5.2	8.0	45.0
PRCP	Total precipitation (mm)	12,354	383.8	90.4	175.7	626.3

Notes: In the data, we have 12,354 valid observations excluding 1994 when the household survey was not conducted. Over time, changes in households in a village lead to differences in yearly observations. Sources: Maize production data are obtained from household surveys 1993–2011 organized by the Office of China Rural Fixed Observation Points at the Ministry of Agriculture (see http://www.rcre.moa.gov.cn/jizn/jgsz/ncgdgcd/ for a Chinese introduction of the office: Nongcun Guding Guanchadian). Climate data are collected from China Meteorological Administration.

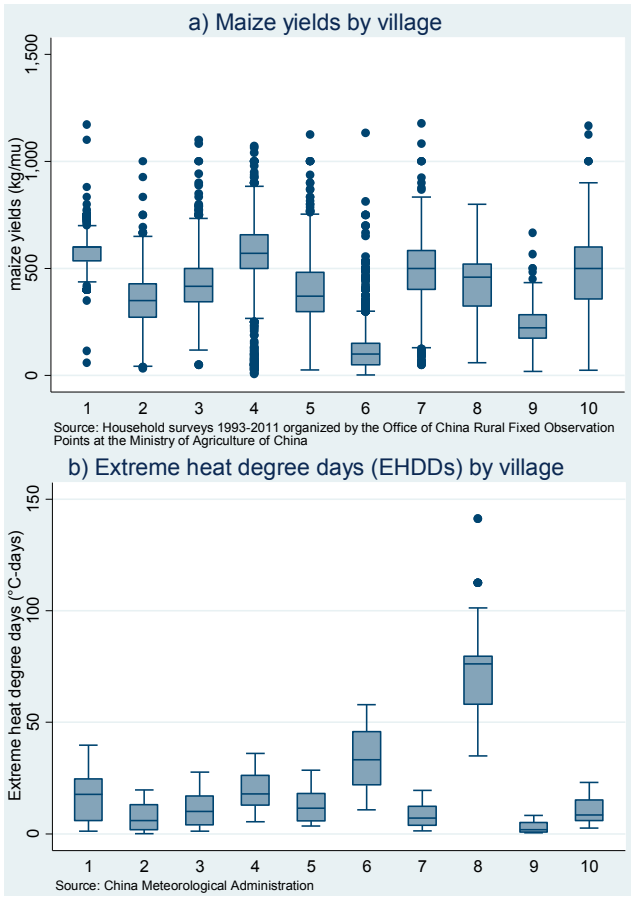

Figure 2. Variability of maize yield (**a**) and extreme heat degree days (EHDDs) (**b**) in Shanxi province of China during the period from 1993 to 2011.

2.3. Statistical Methods

In this study, we statistically estimated the following model of maize yield,

$$Y_{it} = \beta_1 EHDD_{vt} + \beta_2 COLD_{vt} + \beta_3 DRY_{vt} + \beta_4 MDD_{vt} + \beta_5 PRCP_{vt} + \beta_6 LAND_{it} + \omega_v + \emptyset_t + \varepsilon_{it}, \quad (6)$$

where Y_{it} is maize yield of household i in time t. Independent variables include three variables of degree days during maize growing season: extreme heat degree days (EHDD), a dummy of extreme cold degree days (COLD, 0 if no extreme cold days during maize growing seasons), and moderate degree days (MDD); two variables of precipitation during maize growing season: consecutive dry days (DRY) and total precipitation (PRCP); land sown for maize (LAND); village-specific dummies to capture unobservable time-invariant village characteristics (ω_v) such as soil type and other village-specific production conditions; time-specific dummies to capture non-linear time trends ($\emptyset_t$); and ε_{it} is the contemporaneous additive error term.

Following Wei et al. [8], we adopted a double-log specification in our regressions such that estimated coefficients can be interpreted as elasticities, measuring proportional responsiveness of maize yield to changes in corresponding independent variables. To capture potential non-linear effects of independent variables, we estimated other models by including squared terms for independent variables. With these specifications, elasticities are not constant and must be calculated for a specific value of an independent variable. Hausman [25] tests were utilized to determine whether the village- and time-specific effects should be considered fixed or random. For all our regressions, the tests fit the fixed effects model.

In the nonlinear case of Model 2 presented below, the elasticity is associated with a given value of a climate variable and only indicates the direction and possible impact on maize yield when the

variable changes marginally. To estimate impact on maize yield when a climate variable changes considerably, we adopted the estimated parameters of Model 2 to derive the average maize yield for all the ten villages from 1993–2011 in logarithm form

$$lnY = \alpha + \sum_C [\beta_{11} lnC + \beta_{12} (lnC)^2] + \beta_2 COLD \quad (7)$$

where C represents the climate variables including EHDD, MDD, DRY, and PRCP; and β_{11} and β_{12} are corresponding parameters estimated in Table 2.

Table 2. Estimates for Models of Maize Yields in Shanxi based on data 1993–2011.

	Model 1	**Model 2**	**Model 3**
EHDD	−0.0688 ***	−0.0271 *	−0.0266 *
	(0.00858)	(0.0128)	(0.0128)
EHDD squared		−0.0284 ***	−0.0286 ***
		(0.00337)	(0.00338)
MDD	1.841 ***	65.94 **	66.04 **
	(0.204)	(21.68)	(21.68)
MDD squared		−4.457 **	−4.466 **
		(1.472)	(1.472)
COLD	−0.320 ***	−0.299 ***	−0.297 ***
	(0.0711)	(0.0712)	(0.0712)
DRY	−0.103 ***	0.544 *	0.546 *
	(0.0206)	(0.222)	(0.222)
DRY squared		−0.108 **	−0.108 **
		(0.0388)	(0.0388)
PRCP	0.311 ***	3.724 ***	3.707 ***
	(0.0372)	(0.938)	(0.938)
PRCP squared		−0.299 ***	−0.297 ***
		(0.0791)	(0.0791)
LAND	−0.0498 ***	−0.0552 ***	−0.0666 ***
	(0.00612)	(0.00614)	(0.0107)
LAND squared			0.00555
			(0.00425)
Constant	−8.154 ***	−249.2 **	−249.4 **
	(1.563)	(80.41)	(80.41)
Fixed village effects	Yes	Yes	Yes
Fixed time effects	Yes	Yes	Yes
Observations	12354	12354	12354
R^2	0.597	0.602	0.602
Adjusted R^2	0.596	0.601	0.601
NRMSE	0.438	0.435	0.435

Notes: The dependent variable is maize yield (kg per mu, 1/15 ha). All parameters are estimated by ordinary least squares (OLS) regression where the dependent variable and independent variables excluding dummies are taken in their logarithm forms. *Standard deviations* are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. NRMSE refers to normalized root-mean-square error. Sources: Maize production data are obtained from household surveys from 1993–2011 organized by the Office of China Rural Fixed Observation Points at the Ministry of Agriculture (see http://www.rcre.moa.gov.cn/jizn/jgsz/ncgdgcd/ for a Chinese introduction of the office: Nongcun Guding Guanchadian). Climate data are collected from China Meteorological Administration.

In the results reported in Section 3.1, we did not consider labor inputs as one independent variable since our data did not separate labor input of a household into maize production for the whole period. In addition, previous studies have shown its insignificant effect on crop yield due to labor surplus in rural China (e.g., [7,8,26]). We introduced fixed capital as an independent variable in the regressions, but obtained insignificant estimates of the effect while trivial disturbance on estimates of other parameters appeared in the regressions. Hence, we did not report these results in this study.

The above model is based on a data-driven approach. Compared with other statistical models that include only mean growing season temperature or precipitation, our model includes many climate extreme variables such as EHDD, COLD, and DRY, which were used to capture the extreme climate signals. When compared with process-based crop models, our model needs much less exogenous parameters. A process-based model requires many parameters that we cannot provide at the regional level, for example, crop cultivars are unknown. This constrains the use of process-based model on the regional scale.

3. Results and Discussion

3.1. Estimated Parameters

The estimated main results are shown in Table 2. Model 1 is linear in independent variables and the other two models consider additional squared terms of independent variables. Model 3 differs from Model 2 by adding the squared term of land sown for maize. The fitness of these three models is almost similar as indicated by adjusted R^2 (~0.6) and normalized root-mean-square error (NRMSE ~0.436). Model 2 is the most suitable model since it captures the non-linear effects of independent variables and excludes the squared land term whose parameter is statistically insignificant, as shown by Model 3, although there is no statistical difference between Models 2 and 3. In all the three models in Table 2, the estimated parameters for climate variables are statistically significant at the 5% level at the very least. In the linear Model 1, they are all significant at the 0.1% level, indicating the strong effects of temperature and precipitation on maize yield.

We also calculated the elasticities of climate variables for Models 1 and 2 in Table 3. The elasticities for Model 2 are calculated at the means of the independent variables and may differ considerably if the independent variables deviate from their means. Hence, these elasticities are only valid in a small range around the means of the independent variables. The elasticities for the linear Model 1 are reported in Table 3 in order to highlight their differences from the elasticities of Model 2. In comparison with Model 2, the linear Model 1 tends to underestimate the negative effect of extreme-heat-degree-days, overestimate the negative effect of consecutive dry days, and overestimate the effects of moderate-degree-days and total precipitation.

Table 3. Estimates of elasticities for the means of climate variables.

	Model 1	**Model 2**
EHDD	−0.0688	−0.180
MDD	1.841	0.0617
DRY	−0.103	−0.068
PRCP	0.311	0.166

Our results confirm the negative effect of Extreme heat (EHDD) on maize yield. The marginal negative effect increases with additional EHDD according to non-linear specification of Model 2. The elasticities in Table 3 indicate that a one-percent change in EHDD leads to 0.18 percent decrease in maize yield according to Model 2, respectively. As the average EHDD is around 15 degree-days, these results imply that one additional EHDD can result in 1.2 percent decreases in maize yield. Figure 3 illustrates how maize yield is affected by changes in EHDD.

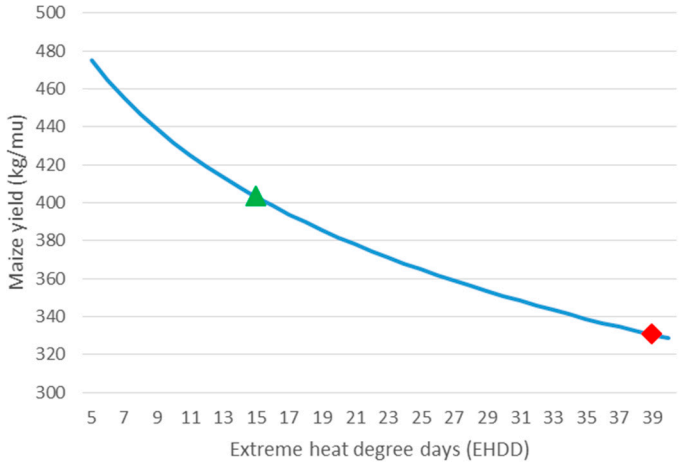

Figure 3. The effect on maize yield of extreme heat degree days (EHDD) based on Model 2. The triangle point corresponds roughly to the average case from 1993 to 2011 while the diamond point represents approximately the case where all temperatures from 1993 to 2011 were increased by 2 °C.

By contrast, the moderate degree days (MDD) have a positive effect on maize yield. At the mean of MDD, a one-percent change in MDD, or an additional 16 degree-days, can increase maize production by 0.06 percent according to Model 2. The positive effect diminishes with additional MDD. This is understandable, since the additional MDD can come only from higher temperatures in certain days of a limited number of days during the maize growing seasons. The negative effect of extreme hot days (EHDD) seems a natural continuation of the diminishing effect of growing degree days (GDD). The occurrence of extreme cold degree days (ECDD) can reduce maize yield. In all the three models, maize yield with occurrence of ECDD is around 0.3 percent lower than that without ECDD according to the estimated parameter for COLD in Table 2.

Dry days reduce maize yield in Shanxi and the negative effect enhances with more dry days. According to Model 2, a one percent change in dry days (DRY) can reduce maize yield by 0.062 percent on average. In other words, an additional dry-day from the mean can reduce maize yield by 0.36 percent. By contrast, more precipitation improves maize production although the positive effect is diminishing with additional precipitation (PRCP). A one-percent increase in precipitation, or around 4 mm additional rainfall, increases maize yield by 0.17 percent at the mean case according to Model 2.

We include only one non-climatic variable, namely land area sown for maize. Our results show that more land area is accompanied with less maize yield since marginal productivity of land is diminishing.

3.2. Impact When Temperature Increases

It seems that these extreme weather events have limited negative impacts on maize production, and, as such, that we do not need to worry about overall maize production. However, the impacts considered in Subsection 3.1 are marginal assuming small deviations of climate variables from the original ones. In a warming world, extreme weather events may increase dramatically even if the temperature increases slightly. For example, if all the temperatures in our dataset increase by 2 °C, extreme weather events may appear more frequently than expected.

3.2.1. Heat Waves and Extreme Cold Days

If all the temperatures are assumed to increase by 2 °C, then all the temperatures above 27 °C in the historical data would move from the calculation of MDDs to be an additional part of EHDDs. On average, a two-degree increase in temperature implies an additional 25 EHDDs, or nearly 170 percent of the historical mean EHDDs in our dataset from 1993 to 2011. This implies that the

increase in temperatures can lead to dramatic increases in heat waves (e.g., nearly triple of the frequency of historical high waves). Although the marginal impact of heat waves on maize yield is small, the dramatic increase in heat waves can considerably damage maize production. Based on Equation (7), a two-degree increase in temperature would lead to an 18.5 percent decrease in maize yield if we consider the change in EHDDs alone.

The increase in EHDDs also means a trivial decrease in MDD (e.g., about 1.5 percent decrease in MDD), which leads to a reduction of maize yield by only 0.2 percent. When temperature increases, the occurrence of extreme cold days decrease by 8.9 percent which increases maize production by 2.6 percent. The impacts of changes in both MDD and extreme cold days are positive, although small.

3.2.2. Consecutive Dry Days

It is hard to tell how the frequency of the consecutive-dry-days events might occur in the case of a 2 °C increase in temperatures. However, as shown by the RCP8.5 experiment in the Coupled Model Intercomparison Project phase 5 (CMIP5) model ensemble [27], the uncertainties concerning regional precipitation are much larger than the uncertainty concerning temperature, which may indicate higher frequency of droughts and floods at a regional level. Hence, we conservatively assume that the consecutive dry days happen to the same extent as the EHDDs (i.e., the dry days events are assumed to happen at nearly three times the historical occurrence 1993–2011). This assumption alone leads to a 15.7 percent decrease in maize yield by Equation (7).

3.2.3. Total Impact with a 2 °C Increase in Temperature

Total impact on maize yield of consecutive dry days, heat waves, and cold days would be considerable (i.e., a reduction in maize yield by 31.8 percent if all temperatures increase by 2 °C and total precipitation (PRCP) does not change). The maize yields would still experience about a 16 percent reduction even if the impact of the dry days was excluded.

Notice that our analysis does not explicitly include variables such as the maize variety, soil type, irrigation status, and overall management of the maize crop (agronomic issues), although effects of these variables are partially captured by village and time dummies. For example, different maize varieties may be used by households in a village in a given year and thus lead to various impacts of the same climate variables in the year. More importantly, farmers are rational and they adapt over time to the local environment. Therefore, they do not use the same maize variety if it is increasingly affected by the prevailing climatic conditions in their location. Farmers may also utilize certain irrigation systems to mitigate the negative effect of consecutive dry days. Hence, our analysis may underestimate the negative impacts of extreme weather events since these impacts can be reduced by adaptation measures practiced by farmers.

Notably, compared to crop growth models, our analysis does not distinguish the variable effect of extreme weather events depending on stages of maize growth and development. For example, the flowering stage can be very sensitive to extreme high and low temperatures as well as dry days.

3.3. Why Not GDD?

A traditional indicator of heat units is growing degree days (GDD), which is different from MDD by including hourly degree days of $DD_h = (T_{upp} - T_{low})/24$ in the extreme heat hours (i.e., when $T_h \geq T_{upp}$). We have tried to replace MDD with GDD, but obtained significant negative effects for its parameter in all the regressions. Meanwhile, we also noticed that the parameter of EHDD was not estimated to be significant. This indicates high collinearity between EHDD and GDD. If we run a regression with EHDD as the only independent variable, then the adjusted R-squared is 0.65 for GDD and only 0.029 for MDD. Hence, GDD capture too much of the effect of EHDD. In fact, nearly all the GDD can be explained by both MDD and EHDD (adj R^2 = 0.97) if we run a linear regression. To eliminate the collinearity problem, we dropped GDD as an independent variable in all our regressions.

3.4. Household-Specific Fixed Effect

In Table 2, a household in a year is treated as one observation independent on the household in another year. This may raise an issue of household-specific fixed effect, which might be captured by climate variables. To identify whether this is a serious problem for our estimates, we re-ran the models listed in Table 2 with village-level panel data where maize yield and land sown of households in a village were calculated as means of corresponding variables of all households in the village. We obtained the same signs of estimates for parameters of all independents but COLD and LAND as in Table 2, although the estimates of all parameters became statistically insignificant. The generation of insignificant estimates was likely due to limited observations at the village level. Hence, the results confirmed that the household-specific fixed effect should not be a serious issue for our estimates.

3.5. Sensitivity Analysis

We would obtain similar results to that in Section 3.1 if the upper threshold temperature was replaced by 27, 28, or 30 °C for the linear Model 1. However, we obtained insignificant estimates for MDD for nonlinear Model 2 in all the three alternatives and for EHDD in the cases of the upper thresholds of 27 and 28 °C. We would get a negative effect of MDD if the upper threshold became 31 °C even for the linear Model 1, thereby indicating too high of an upper threshold temperature.

On the other hand, if the lower threshold temperature was replaced by 6, 7, 9 or 10 °C, we would obtain similar results to that in Section 3 for all the alternatives. Maize yield seems insensitive to the choice of the lower threshold temperature.

4. Conclusions

In this study, we have statistically estimated the impacts of consecutive dry days, heat and cold days on maize yield based on household survey data from 1993 to 2011 in ten villages of Shanxi province, China. Our results show that dry days, heat and cold days have negative effects on maize yield and these effects are marginal if these extreme events do not increase dramatically. Specifically, a one percent increase in extreme-heat-degree-days and consecutive-dry-days results in a maize yield decline of 0.2% and 0.07%, respectively. Maize yield also is reduced by 0.3% for cold days occurring during the growing season.

However, these extreme events can increase dramatically in a warmer world and may result in considerable reductions in maize yields. If all the historical temperatures in the villages are shifted up by 2 degrees Celsius, then the heat waves indicated by EHDD would increase by 170 percent and the occurrence of extreme cold days would be reduced by nearly 10 percent. If we assume that consecutive dry days increase at the same extent as heat days, then the total impact of these extreme events would lead to a reduction of maize yield by over 30 percent. The impacts may be underestimated since we did not exclude the offset effect of adaptation measures by farmers to combat the impacts of these extreme events. Our simplified method ignores the potential changes in climate variability, and the combination of the changes in different climate variables. However, it would be possible to improve the estimates by adopting data of climate variables from downscaled climatic change scenarios.

Acknowledgments: We are grateful for constructive comments by two anonymous referees and participants at the IAMO Forum 2015 and the Global Land Programme 3rd Open Science Meeting in 2016. This study was supported by Research Council of Norway (grants No. 209671 and 260404), Chinese Academy of Sciences (grant No. GJHZ1204), and National Natural Science Foundation of China (grants No. 41661144006, 41301044, 71333010, 71473165, and 71673186).

Author Contributions: Solveig Glomsrød and Taoyuan Wei motivated the study, Tianyi Zhang and Qinghua Shi collected data and relevant explanation, Karianne de Bruin conducted a literature review on extreme weather events, Taoyuan Wei and Tianyi Zhang designed and carried out the model simulation. Taoyuan Wei coordinated and wrote the article and all other authors provided comments on the earlier versions of this manuscript.

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

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