Received: 13 December 2022 | Accepted: 12 November 2023

DOI: 10.1111/1467-8489.12545

The Australian Journal of Agricultural and Resource Economics AARES

ORIGINAL ARTICLE

Calamitous weather, yield risk and mitigation effect of harvest mechanisation: Evidence from China's winter wheat

Teng Wang[1] | **Fujin Yi**[2] | **Ximing Wu**[3] | **Huilin Liu**[1] | **Yu Yvette Zhang**[3]

[1]College of Economics and Management, Nanjing Agricultural University, Nanjing, Jiangsu, China

[2]China Academy for Rural Development, School of Public Affairs, Zhejiang University, Hangzhou, Zhejiang, China

[3]Department of Agricultural Economics, Texas A&M University, College Station, Texas, USA

Correspondence
Fujin Yi, China Academy for Rural Development and School of Public Affairs, Zhejiang University, 866 Yuhangtang Road, Hangzhou, Zhejiang 310058, China.
Email: yifujin@zju.edu.cn

Funding information
The Joint Agricultural Research Project between National Natural Science Foundation of China (NSFC) and the Bill & Melinda Gates Foundation (BMGF), Grant/Award Number: 72261147758; National Social Science Foundation of China, Grant/Award Number: 22VRC178; Leading Talents Project of Philosophy and Social Science Foundation in Zhejiang Province, Grant/Award Number: 24YJRC01ZD

Abstract
Stable agricultural production has been substantially challenged by increasingly frequent calamitous weather conditions. For winter wheat, continuous precipitation during the harvest season is particularly detrimental. This study utilises a county-level panel dataset of agricultural production in China for the period of 1998–2016 to evaluate the impact of continuous precipitation on the downside risk of winter wheat yield. Results show that the continuous precipitation during the harvest season remarkably increases the downside risk of winter wheat yield. At the same time, the progressive adoption of harvest machinery in recent decades has effectively mitigated the downside risk of winter wheat yield driven by continuous precipitation. The mitigation effects of harvest mechanisation are more pronounced for plain areas with better-developed transportation infrastructure.

KEYWORDS
calamitous weather, crop yield, downside risk, harvest mechanisation, mitigation effect

JEL CLASSIFICATION
O13, Q16, Q54, Q18

1 | INTRODUCTION

Calamitous weather, such as excessive precipitation during the crop-growing and harvest seasons, has drawn considerable interest in the literature under the backdrop of climate change. An increasing amount of evidence has shown that the increased frequency of calamitous weather

Fujin Yi and Teng Wang share the senior authorship.

exposes crop production to more severe risks than changes in mean climate, negatively affecting crop yields and food security (McCarl et al., 2008; Taraz, 2023; Urban et al., 2015). Not only can calamitous weather during the growing season affect crop yields, but those during the harvest season can also adversely affect crop yields, especially when calamitous weather prevents timely harvest (Amonoo, 2013; Gobin, 2018). A common cause of delayed crop harvest is excessive precipitation, which may impede field accessibility and cause grains to rot in the field, resulting in unsalvageable yield losses (Eck et al., 2020; Pelka et al., 2015; Van der Velde et al., 2011).

Risk management has become one of the highest priorities in the agricultural sector. The key objectives of the current agricultural policies include reducing the risk of agricultural production. Given that calamitous weather is likely to become more frequent (IPCC, 2019), researchers must explore strategies to mitigate the risks to grain production caused by calamitous weather and thus ensure global food security. Lobell and Field (2007) revealed that some impacts of calamitous weather may be offset by technological advancement. In terms of the effectiveness of adaptive strategies, some studies have examined the impact of these strategies on land values or average crop yields (Di Falco et al., 2011; Kien et al., 2023; Mendelsohn et al., 1994). Their effectiveness in risk management has also been explored (Huang et al., 2015; Issahaku & Abdulai, 2020; Wang et al., 2021). However, these studies primarily focussed on the mitigating effects of farm-level adaptive strategies in the preplanting and crop-growing seasons, and scant attention has been paid to the crop harvest stage.

Existing studies have shown that agricultural mechanisation can reduce weather-related risks during the harvest season because the timeliness of mechanical operations can facilitate quicker harvest and reduce weather-related yield losses (Belton et al., 2021; Hignight & Watkins, 2007; Just & Pope, 1978). For example, Moussa (2008) showed that combined harvesters could save 94 h per hectare compared with manual harvesting, shortening the harvest season by 4 days or more (Cao & Zhang, 2019; Gao & Song, 2014). Therefore, mechanised harvesting could reduce the risk of exposure to calamitous weather, especially continuous precipitation during the harvest season (Hignight & Watkins, 2007). However, to what degree harvest mechanisation mitigates the risk exposure of crop yield caused by calamitous weather is unknown. Answers to this question can provide valuable insights for designing effective adaptation policies.

This study investigates whether agricultural mechanisation helps mitigate weather-related risks during the harvest season. Specifically, we are interested in the mitigation effect of agricultural machinery on the downside risk caused by the continuous precipitation during the harvest season of winter wheat in China.[1] In particular, we focus on the skewness of crop yield distribution, commonly used to capture downside risk exposure (Di Falco & Chavas, 2009; Huang et al., 2015; Issahaku & Abdulai, 2020). Downside risk refers to the yield located at the low tail of the crop yield distribution (Kim et al., 2014). Based on a county-level panel dataset of agricultural production in combination with daily weather observations during the period of 1998–2016, our investigation shows that continuous precipitation during the harvest season of winter wheat remarkably increases the downside risk of winter wheat yield.

We examine the potential mitigation effect of harvest mechanisation on the downside risk of winter wheat yield. Our results suggest that mechanised harvesting considerably mitigated the downside risk of winter wheat yield caused by continuous precipitation. On average, machinery usage during harvest at 2.4 kW/ha (1 HP = 0.75 kW; HP refers to mechanical horsepower) could fully offset the adverse impacts of continuous precipitation. We further show that the

[1]The Expert Team on Climate Change Detection and Indices recommends consecutive wet days (CWD) as an indicator for extreme precipitation. It is the maximum number of consecutive days when precipitation is ≥1 mm (http://etccdi.pacificclimate.org). This indicator is usually called 'continuous precipitation' in China (Li et al., 2018).

mitigation effect is spatially heterogeneous and more pronounced for plain areas with better-developed transportation infrastructure.

This study makes three major contributions to the existing literature. First, to our knowledge, this is the first empirical analysis to estimate how continuous precipitation during the harvest season affects the downside risk of winter wheat yield. This work differs from previous studies that explored the adverse impacts of changes in growing season precipitation on average winter wheat yield (Chen et al., 2019; Gammans et al., 2017; McCarl et al., 2008). Substantial granular county-level data in the analysis provide further insights into the relationship between calamitous weather and winter wheat yield risk. Second, our findings contribute to the literature on the impacts of agricultural mechanisation on agricultural production by providing evidence of the efficacy of harvest mechanisation as an adaptation to calamitous weather. It raises awareness of the potential benefits of agricultural mechanisation in terms of risk management and assists them in making informed decisions on the use of machinery. Third, our findings on the different mitigation effects of harvest mechanisation provide valuable insights for policymakers. These insights underscore the imperative of prioritising public support for agricultural mechanisation in regions that lack developed transportation infrastructure to cope with the negative impacts of calamitous weather.

This study is organised as follows: Section 2 reviews the existing literature. Section 3 provides some background information about China's wheat production and agricultural mechanisation. Section 4 introduces the conceptual framework and empirical strategy. Section 5 describes the data, and Section 6 discusses the empirical estimates, followed by heterogeneity analysis. Section 7 presents the conclusions and policy implications of the study.

2 | LITERATURE REVIEW

The adverse impacts of climate change on crop yield have been extensively investigated in the existing literature (Gammans et al., 2017; Lobell & Field, 2007; Schlenker & Roberts, 2009; Wing et al., 2021). These studies have primarily concentrated on the impacts of predicted changes in the average level of climatic variables, such as temperature and precipitation, on average crop yields (Antón et al., 2012). A major challenge faced by agricultural production is the increased frequency and intensity of calamitous weather resulting from climate change. For example, Lesk et al. (2016) estimated that global cereal production was reduced by 9%–10% on average from the year 1964 to 2007 due to extreme heat and drought.

The increasing challenge of climate change to agricultural production has stimulated research on the relationship between calamitous weather and yield risk. Earlier studies (e.g. McCarl et al., 2008; Poudel & Kotani, 2013) used the mean–variance analysis developed by Just and Pope (1978) to examine the impacts of weather variables on yield variability. A key finding is that about one-third of yield variability can be attributed to global climate variability (Ray et al., 2015). Given that yield variance cannot distinguish between unanticipated favourable and unfavourable events, recent studies (e.g. Di Falco & Chavas, 2009; Issahaku & Abdulai, 2020; Wang et al., 2021) have used the moment-based approach proposed by Antle (1983) and used yield distribution skewness as a proxy for downside risk. Huang et al. (2015) used the third central moment of rice yield distribution to capture downside risk and demonstrated that drought and flood increased the downside risk of rice yield.

One major weather-related crop yield risk is excessive precipitation during the growing season. For example, Zampieri et al. (2017) argued that excess moisture contributes to wheat yield anomalies in major wheat-producing countries, such as China and India.

The sensitivity of crop yield to extreme humidity varies across growth stages (Urban et al., 2015), with the impact of precipitation during the harvest season being a particular concern (Amonoo, 2013). Excessive precipitation during the harvest season affects crop yield through three main channels. First, the wet conditions caused by excessive precipitation increase the incidence of pests and diseases (Hatfield et al., 2011). Second, a wet environment results in an early break of crop seed dormancy and induces preharvest sprouting (Kulwal et al., 2012). Third, excessive and continuous precipitation hinders field accessibility and timely harvesting (Eck et al., 2020). Moreover, the increased excessive precipitation under climate change is projected to increase crop yield risk during harvest season (Van der Velde et al., 2011).

Adaptation plays a vital role in reducing crop yield losses caused by calamitous weather (Ortiz-Bobea, 2021). Without accounting for the influence of adaptation, one may overestimate the damage from global warming (Mendelsohn & Massetti, 2017). Across the world, the agricultural sector has been able to adapt to climate change with region-specific adaptation systems in various ways, such as shifting the spatial distribution of crops (Cho & McCarl, 2017), changing crop planting dates (Cui & Xie, 2021), adjusting agricultural input usage (Chen & Gong, 2020) and planting cover crops (Won et al., 2023).

Some studies have used economic modelling approaches, such as computable general equilibrium (CGE) and integrated assessment models (IAMs), to capture the intricate socio-economic feedback from the impacts of weather changes on crop yield (Calvin & Fisher-Vanden, 2017; Ciscar et al., 2018). On the basis of the integrated models of economy, climate and crop yield, Nelson et al. (2014) found that economic responses to price increases that are caused by climate shocks, such as adjustments in management practices, planting area, consumption and international trade, were effective in mitigating the negative impacts on crop yields. Specifically, economic responses reduced global crop yield losses due to climate change from 17% to 11% while expanding major crop areas by 11%. Both effects, when combined, resulted in a 2% decline in overall production. However, the unavailability of required data often impedes the application of these models in practice (Salvo, 2013).

Another strand of literature relies on statistical methods to assess the impacts of specific adaptation measures on weather-related production risk, boasting the advantages of uncertainty quantification and robustness checks, which are crucial for risk analysis (Huang et al., 2015; Issahaku & Abdulai, 2020). For example, Wang et al. (2021) used the moment-based approach to explore the magnifying effect of insurance participation on crop yield risk associated with extreme heat. However, the adaptation capacity of farmers to cope with calamitous weather remains limited, underscoring the importance of public interventions for adaptation, including weather forecasts, public infrastructure and effective technologies (Hallegatte et al., 2011).

Agricultural machinery has been widely used in China's agricultural production over the past decades due to increasing agricultural labour scarcity (Shi et al., 2021; Yang et al., 2013). Several researchers investigated the positive impacts of machinery on production scale (Qian et al., 2022) and agricultural productivity (Benin, 2015; Paudel et al., 2019). Increased machinery usage has been suggested to be an adaptive strategy to mitigate the potentially disruptive effects of calamitous weather because it can improve the timeliness of operations and shorten the crop harvest period (Belton et al., 2021; Just & Pope, 1978). Machinery can guarantee a prompt harvest of the first crop and prepare the land for the subsequent crop ploughing and sowing. These operations must be completed in a short period for multicultivation areas, especially when precipitation events occur (Pingali, 2007; Verma, 2006). In addition, harvest machinery can mitigate the risk caused by unfavourable weather conditions due to timely operations (Belton et al., 2021; Hignight & Watkins, 2007).

3 | WHEAT PRODUCTION AND AGRICULTURAL MECHANISATION IN CHINA

3.1 | Wheat production

China is one of the world's major wheat producers, contributing approximately 18% of the world's total wheat production in 2021.[2] Maintaining stable wheat productivity in China is crucial to ensuring global food security. However, the net profit of wheat production dropped from 780 CNY (1 CNY = 0.21 AUD = 0.14 USD) per hectare in 1990 to −75 CNY per hectare without subsidy in 2020, resulting in a decline in the wheat-planting area from 31 million ha in 1990 to 23 million ha in 2020 (see Figure 1). This decline was accompanied by a rapid increase in corn planting acreage driven by domestic demand for food, feed and fuel (You et al., 2011). Fortunately, technological advancements in production have contributed to recent increases in China's wheat production (Fan et al., 2012). According to China's National Bureau of Statistics, wheat output has increased from 98 million tonnes in 1990 to 134 million tonnes in 2020, with an average annual growth rate of 1%.

Winter wheat accounts for the majority of wheat production in China. As shown in Figure 1, the total planting area of winter wheat in 2020 was 22 million ha, 95% of China's wheat-planting area. Moreover, winter wheat output reached 129 million tonnes, 96% of the total domestic wheat supply. The average yield of winter wheat has increased from 3.3 tonnes per hectare in 1990 to 5.8 tonnes per hectare in 2020, which is 30% higher than that of spring wheat.

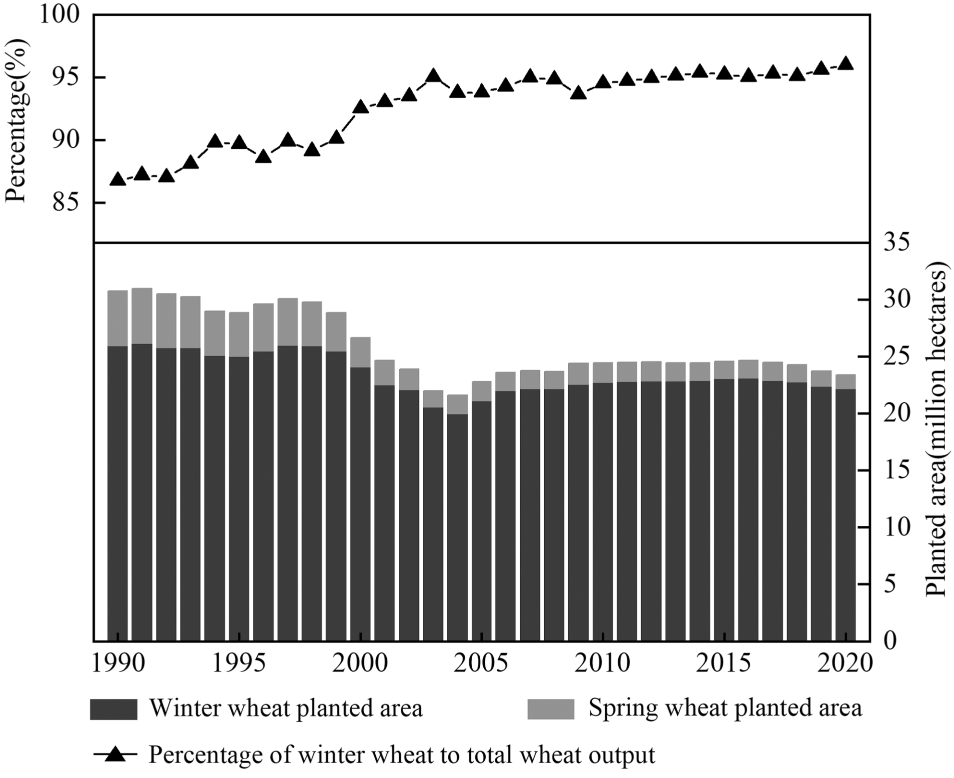


FIGURE 1 Wheat production in China. Data are available from China's National Bureau of Statistics.

[2]Source: http://www.fao.org/faostat/en/#data.

3.2 | Impact of continuous precipitation on winter wheat production

Winter wheat yield is highly vulnerable to continuous precipitation because the harvest season (May–June) coincides with the rainy season (April–September) in China. Continuous precipitation during the harvest season is typically characterised by low temperature, reduced daylight and waterlogging, which can cause winter wheat ears to germinate, grains to fall off and crops to become mouldy and rotten (Kulwal et al., 2012; Li et al., 2018). Furthermore, the wet conditions caused by excessive precipitation increase the chance of disease infestation in winter wheat (Hatfield et al., 2011). Hence, continuous precipitation has been recognised as a critical factor causing considerable risk to winter wheat yield. Given the importance of winter wheat in China's wheat output, identifying the impact of continuous precipitation on winter wheat yield losses can inform decisions about investment to mitigate weather-related risk and ensure a stable domestic food supply.

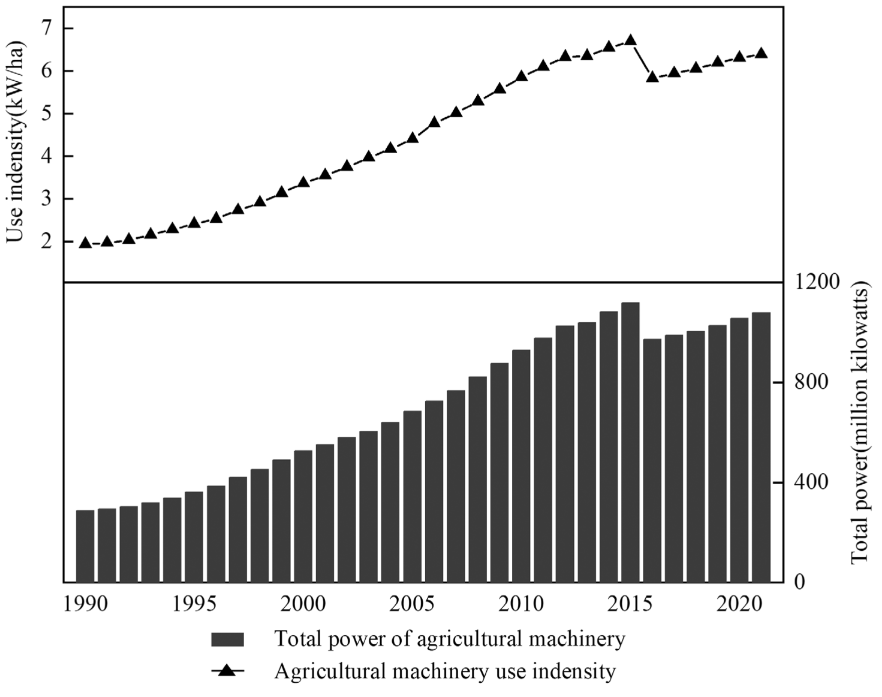
Recent studies have documented that the time intervals between winter wheat and succeeding crops have been remarkably shortened over the past few decades (Chen et al., 2009; Gao & Song, 2014). The trends observed in our study using site-level cropping data from the National Meteorological Information Center of China are consistent with these findings. In Figure S1, we plot the changes in time intervals between winter wheat maturity dates and succeeding summer corn planting dates (Panel A) or succeeding rice transplanting dates (Panel B). Both plots show that the time intervals were shortened for 1992–2013. Such changes might be driven by the efficiency improvement of harvest mechanisation or adaptations to avoid adverse weather.

3.3 | Agricultural machinery use in China

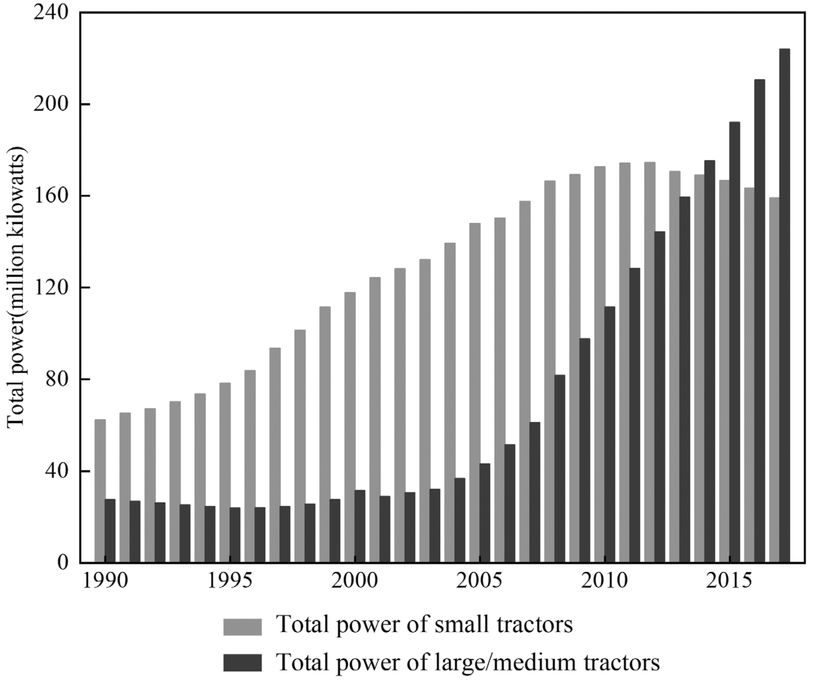
China has experienced rapid growth in agricultural mechanisation over the past decades. Panel a of Figure 2 shows that the total power of agricultural machinery, a proxy for the level of agricultural mechanisation, grew from 287 million kW in 1990 to 604 million kW in 2003. Since the launch of China's Promotion of Agricultural Mechanisation in 2004, government subsidies for purchasing agricultural machinery increased from 70 million CNY in 2004 to 27.7 billion CNY in 2020, stimulating the rapid growth of agricultural machinery. The total power of China's agricultural machinery grew from 640 million kW in 2004 to a peak of 1.1 billion kW in 2015 and subsequently levelled off at around 1 billion kW.

The rapid growth of agricultural machinery was accompanied by a considerable structural evolution. Panel b of Figure 2 shows that large- and medium-sized agricultural machinery experienced faster growth, overtaking small tractors in a short period. Specifically, the most recent data from the China Agriculture Statistical Report show that large- and medium-sized machinery increased from 28 million kW in 1990 to 224 million kW in 2017, an eightfold increase. Meanwhile, the growth of small farm machinery has largely plateaued in recent decades.

Given the increased adoption of agricultural machinery, China's overall mechanisation rate for ploughing, sowing and harvesting, an essential indicator of the level of mechanisation, has increased remarkably in recent years. According to the Ministry of Agriculture and Rural Affairs of China, the overall mechanisation rate of crops has increased from 22% in 1990 to 71% in 2020. Wheat has the highest overall mechanisation rate, reaching about 97% in 2020, considerably higher than rice (84%) and corn (90%). In particular, the rate of tractor ploughing, machine sowing and machine harvesting in wheat production in 2020 reached 99.9%, 93.2% and 97.5%, respectively, almost achieving the complete mechanisation of wheat production.



(a) Agricultural machinery



(b) Large/medium and small tractors

FIGURE 2 Agricultural mechanisation in China. Data for Panel a are from the China Statistical Yearbook 1990–2022 and data for Panel b are from the China Agriculture Statistical Report 1990–2018.

4 | CONCEPTUAL FRAMEWORK AND EMPIRICAL STRATEGY

4.1 | Conceptual framework

In this study, we use the moment-based model proposed by Antle (1983) to capture downside risk and investigate the risk mitigation effects of harvest mechanisation. This model provides a flexible representation of the relationship between input factors and crop yield under production uncertainty (Di Falco & Chavas, 2009). We assume that the crop production function can be written as follows:

$$y = f_1(\boldsymbol{x}, \boldsymbol{\beta}) + u, \tag{1}$$

where y represents crop yield, and $f_1(\boldsymbol{x}, \boldsymbol{\beta}) = E(y|\,\boldsymbol{x})$ is the corresponding first central moment (i.e. mean). $\boldsymbol{x}$ denotes the exogenous weather variables, and u is an error term that reflects the yield distribution (net of mean yield). The inclusion of economic input variables into $\boldsymbol{x}$ is discussed in the following section. To capture the risk component of crop yield, the higher order moments of y are specified as

$$u^2 = f_2(\boldsymbol{x}, \boldsymbol{\alpha}) + \varepsilon, \tag{2}$$

$$u^3 = f_3(\boldsymbol{x}, \boldsymbol{\gamma}) + \omega, \tag{3}$$

where $f_2(\boldsymbol{x}, \boldsymbol{\alpha})$ is the second central moment (i.e. the variance), characterising the dispersion of crop yield relative to its mean; $f_3(\boldsymbol{x}, \boldsymbol{\gamma})$ is the third central moment (i.e. the skewness), measuring the degree of asymmetry of the crop yield distribution around its mean. Given that variance assigns equal weight to observations on both sides of the mean and may bias the measure of risk (Roseta-Palma & Sağlam, 2019), we use the skewness of the crop yield to measure downside risk in this study. A negative skewness implies that the crop yield is more likely to be below the expected crop yield. A decrease in crop yield skewness, or more precisely, an increase in negative skewness, implies an increase in downside risk.

The impact of calamitous weather, as represented by continuous precipitation during the harvest season, is of particular concern on the skewness of crop yield. The adverse impact may prompt farmers to adopt technologies that can reduce the probability of crop failure. As discussed above, mechanised harvesting can reduce the risk of exposure to winter wheat yield due to continuous precipitation. Accordingly, we assume in Equation (3) that the error term u is a function of mechanised harvesting M and use it to model the relationship between harvest machinery use and weather-related crop yield skewness.

4.2 | Empirical strategy

This section presents the econometric specifications for identifying the impact of calamitous weather on the downside risk of winter wheat yield. On the basis of our conceptual framework, we first construct the mean yield function as follows:

$$Y_{gt} = \beta_0 + \beta_1 CP_{gt} + \beta_2 W_{gt} + \beta_3 T_t + c_g + u_{gt}, \tag{4}$$

where Y_{gt} denotes the average winter wheat yield (per hectare) in county g and year t; βs are the parameters to be estimated; CP_{gt} represents the amount of continuous precipitation during the winter wheat harvest season. W_{gt} represents a vector of weather variables, including the average daily maximum temperature (T_{max}), minimum temperature (T_{min}), solar radiation and the sum of daily precipitation for fall, winter and spring. In Equation (4), only weather variables are incorporated because weather changes may affect crop yield through their impacts on various input uses. In particular, including input factors may partially absorb the overall impact of weather variables on crop yield (Chen & Chen, 2018). Following Chen et al. (2016) and Miller et al. (2021), we use a linear time trend T_t to capture exogenous technological advancement driven by research and development (R&D). c_g is the county fixed effect. u_{gt} is a mean zero, potentially heteroskedastic error term.

We use the Jarque–Bera test to test the normality of winter wheat yield distribution (Jarque & Bera, 1980, 1987) and the D'Agostino test to test whether the winter wheat yield exhibits skewness (D'Agostino et al., 1990). All test results are reported in the 'Results and Discussions' section.

We then estimate the variance and skewness functions using the same set of regressors as in Equation (4). The models are specified as follows:

$$\left(\hat{u}_{gt}\right)^2 = \alpha_0 + \alpha_1 CP_{gt} + \alpha_2 W_{gt} + \theta_t + c_g + \varepsilon_{gt}, \tag{5}$$

$$\left(\hat{u}_{gt}\right)^3 = \gamma_0 + \gamma_1 CP_{gt} + \gamma_2 W_{gt} + \theta_t + c_g + \omega_{gt}, \tag{6}$$

where $\hat{u}_{gt}$ is the estimated error term from Equation (4), and $\left(\hat{u}_{gt}\right)^2$ in Equation (5) represents the yield variance, and $\left(\hat{u}_{gt}\right)^3$ in Equation (6) represents the yield skewness. θ_t denotes the year fixed effects, which helps account for unobserved factors that are common across counties in a given year (e.g. drought-tolerant seed application and policy shocks). αs and γs are the parameters to be estimated, and ε_{gt} and ω_{gt} are error terms. This study focusses on the impact of continuous precipitation on the skewness of winter wheat yield.

We further explore the mitigation effect of mechanised harvest on continuous precipitation by including the interaction between these two variables as follows:

$$\left(\hat{u}_{gt}\right)^3 = \delta_0 + \delta_1 CP_{gt} + \delta_2 CP_{gt} \times M_{gt} + \delta_3 W_{gt} + \theta_t + c_g + \vartheta_{gt}. \tag{7}$$

Augmenting Equation (6), we use M_{gt}, the machinery usage per hectare during the winter wheat harvest season, to capture the impacts of harvest mechanisation. Here, δ_2 is the key coefficient of interest, which is expected to be positive under the conjecture that harvest mechanisation mitigates the downside risk of winter wheat yield caused by continuous precipitation.

Given that the error terms u_{gt}, ε_{gt}, ω_{gt} and ϑ_{gt} may be heteroscedastic, we use the approach of weighted least squares to estimate the mean function with weights given by the inverse of the predicted variance of the error terms. We then estimate variance and skewness functions with robust standard errors to correct for heteroscedasticity. See Di Falco and Chavas (2006) for details on this estimation procedure.

In addition, Auffhammer et al. (2013) and Cui (2020) argued that error terms, such as ε_{gt}, ω_{gt} and ϑ_{gt}, might correlate within counties and across years; therefore, we cluster all regression standard errors at the county and province-by-year levels to capture potential serial and spatial correlations in the error structure. This two-way clustering strategy allows serial correlation over the years within a county and spatial correlation across counties within a province–year combination (Cameron et al., 2011). We also conduct the Hausman test to choose between the fixed and random effects model.

5 | DATA

5.1 | Agricultural data

We assemble an unbalanced panel dataset of county-level agricultural production and fine-scale weather in China from the year 1998 to 2016. The county-specific winter wheat yield for the period of 1998–2016 was obtained from the Institute of Agricultural Information at the Chinese Academy of Agricultural Science (CAAS). We focus on eight major winter wheat-planting provinces, that is Hebei, Shanxi, Shandong, Shaanxi, Jiangsu, Anhui, Henan and Hubei. These provinces accounted for 83% of China's winter wheat-planting areas during the sample period.

To our knowledge, data on county-level machinery use for various crops are not available. However, data on aggregated machinery usage in each county can be obtained from CAAS, and that of provincial crop-specific machinery inputs per hectare (in the period of 1998–2016) is available from the China Agricultural Product Cost and Revenue Compilation. This study tackles the above challenge (i.e. missing data on county-level crop-specific machinery use) by designing a maximum entropy procedure provided in Appendix S1, using the above-mentioned machinery data.

Our results show that the differences between yearly observed aggregate machinery usage and those recovered by the maximum entropy procedure across counties are less than 1%. [3] On the basis of the obtained data on total machinery use in the winter wheat growing season, we calculate the machinery use in the winter wheat harvest season. According to Xue et al. (2020), agricultural mechanisation can be categorised into ploughing, sowing, harvesting, crop protection and irrigation with weights of 0.22, 0.20, 0.22, 0.18 and 0.18, respectively. Accordingly, machinery usage during the winter wheat harvest season is 22% of the total agricultural machinery usage during the winter wheat growing season. The summary statistics for these quantities are shown in Table 1.

TABLE 1 Summary statistics.

Variables	N	Mean	SD	Min	Max
Winter wheat yield (tonne/ha)	15,416	4.537	1.827	0.006	12.031
T_{min}: fall (°C)	15,416	7.174	2.741	-6.179	14.821
T_{min}: winter (°C)	15,416	−2.931	3.776	−20.623	5.037
T_{min}: spring (°C)	15,416	9.366	2.012	−1.173	13.831
T_{max}: fall (°C)	15,416	17.054	2.164	0.764	23.338
T_{max}: winter (°C)	15,416	6.284	2.931	−7.378	13.841
T_{max}: spring (°C)	15,416	20.473	2.019	2.720	25.592
Precipitation: fall (cm)	15,416	7.123	4.850	0	34.630
Precipitation: winter (cm)	15,416	4.759	6.017	0	45.550
Precipitation: spring (cm)	15,416	14.218	9.502	0.170	95.730
Solar radiation: fall (h)	15,416	5.180	1.124	1.268	8.285
Solar radiation: winter (h)	15,416	4.671	1.047	0.687	7.680
Solar radiation: spring (h)	15,416	6.595	1.314	2.203	9.605
Continuous precipitation (cm)	15,416	0.815	2.499	0	45.270
Harvest machinery (kW/ha)	15,416	1.936	0.870	0.277	5.492
Fertilizer (tonne/ha)	15,416	0.360	0.098	0.118	0.660
Labour (day/ha)	15,416	99.269	35.051	42.750	214.050
Ratio of irrigated area (%)	15,360	41.115	18.686	3.705	98.927

Note: The number of observations for the ratio of irrigated area is reduced due to missing values.

[3]Detailed comparison is available upon request.

5.2 | Weather data

Weather data are collected from the China Meteorological Data Sharing Service System, which records the daily maximum, minimum and average temperatures, precipitation and solar radiation data from 820 weather stations for the period of 1998–2016. Following the common practice in the literature (Chen & Gong, 2020; Deschenes & Greenstone, 2007; Yi et al., 2016), we spatially interpolate the climate data from the weather stations to individual counties using inverse-distance weighted method, with a grid spacing of 500 m. The average across all grids located in a county was assigned to that county.

To locate the harvest season for winter wheat in each region, we obtained the planting and harvest dates of winter wheat across regions from the Major World Crop Areas and Climate Profiles by the US Department of Agriculture. Overall, the growing season for winter wheat is between September and June of the following year, and the harvest season spans May and June.

Mao and Wei (2015) suggested that continuous precipitation occurs when precipitation lasts for 3 or more days (precipitation ≥ 0.1 mm in 24 h) with the accumulated precipitation exceeding 40 mm in North China or when precipitation lasts for 5 or more days (precipitation ≥ 0.1 mm in 24 h) with the accumulated precipitation exceeding 50 mm in South China (such as the Huanghuai, Jianghuai and Jianghan regions). Accordingly, our analysis uses the amount of continuous precipitation during the winter wheat harvest season in each county as the primary measurement of continuous precipitation in our analysis. As shown in Figure S2, the amount of continuous precipitation during the winter wheat harvest season has experienced a fluctuating upward trend from the year 1992 to 2016. The alternative indicator of the frequency of continuous precipitation during the winter wheat harvest season also exhibits a steadily increasing trend in the same period.

This study uses seasonal weather variables to capture the relationship between weather and winter wheat yield. While various types of climatic/weather variables have been used to examine the impacts of climate/weather on crop yields, including temperature bins (Gammans et al., 2017; Schlenker & Roberts, 2009) and degree–day variables (Chen et al., 2016; Miller et al., 2021), the rationale for utilising seasonal weather variables is grounded in the unique nature of the winter wheat growing season, which spans from September to June of the following year. In contrast to 'spring' crops, the dormancy period of winter wheat breaks up specific stages that are normally continuous in time, resulting in distinct within-season weather effects that must be carefully considered in model specifications. Furthermore, using whole-season precipitation to measure adequate water availability for crops has limitations (Ortiz-Bobea, 2021). For example, while two seasons might record identical total precipitation, one could be much drier due to different temperature conditions. This difference emphasises the importance of the amount of precipitation throughout the growing season and the timing of precipitation. The primary way to address this concern is to use the seasonal weather variables for the year (Ortiz-Bobea, 2021).

As suggested by Tack et al. (2015) and Chen et al. (2019), we divide the winter wheat growth cycle into three seasons: fall (from wheat planting to November), winter (from December to February of the following year) and spring (from March to wheat maturity). To assess the impact of temperature changes on winter wheat yield, we use the seasonal average of daily minimum temperature $\left(T_{min}\right)$ and maximum temperature $\left(T_{max}\right)$ because the response of crop yield to temperature changes is likely to be driven by the relative warming of minimum and maximum temperatures (Lobell & Ortiz-Monasterio, 2007; Peng et al., 2004). Given the high correlation between T_{min}, T_{max}, solar radiation and precipitation (Chen et al., 2019; Welch et al., 2010), we also include average daily solar radiation and accumulated precipitation for the three seasons in the baseline regression.

6 | RESULTS AND DISCUSSIONS

Before presenting our estimation results, we first report some specification testing results. To explore the distribution of the winter wheat yield, we use the Jarque–Bera test to examine the normality of winter wheat yield. The p-value is lower than 0.01, rejecting the null hypothesis that winter wheat yield is normally distributed. This result is confirmed by the D'Agostino test, which rejects the null hypothesis of normality at the 1% level of significance because of the presence of skewness. Figure S3 in the Appendix reports the distribution of the winter wheat yield during the sample period, further demonstrating the left-skewed nature of the winter wheat yield. Given that the p-values for the Hausman test of fixed versus random effects models are all below 0.01 for the mean, variance and skewness functions, the subsequent estimations are based on the fixed-effect models.

6.1 | Impact of continuous precipitation on yield skewness

Column (1) of Table 2 reports the mean yield function estimation results based on Equation (4). The impacts of weather variables vary across the growing season. Precipitation for each of the three seasons and continuous precipitation during the harvest season have significantly negative impacts on winter wheat yield, consistent with the literature findings (Chen et al., 2019; McCarl et al., 2008). The weather variables in Column (1) are measured in different units, thus hindering the direct comparison regarding the impacts of weather variables on winter wheat yield; therefore, we use the per standard deviation (SD) of weather variables to express the marginal effects (Welch et al., 2010). Table S1 of the Appendix shows that the most crucial driver of winter wheat yield reduction is T_{max} in spring. In particular, one unit change in SD of continuous precipitation during the winter wheat harvest season reduces winter wheat yield by 13.2 kg/ha.

No significant impact of continuous precipitation on winter wheat yield variance is found in Column (2) of Table 2. On the surface, this result might suggest that continuous precipitation poses no threat to yield risk. However, we caution that this conclusion can be misleading, because variance is a generic indicator of production risk and does not distinguish upside and downside risks. Therefore, we further examine the impacts of continuous precipitation on winter wheat yield skewness.

Columns (3)–(5) in Table 2 report the baseline results regarding the impact of continuous precipitation on the winter wheat yield skewness. Column (3) only considers continuous precipitation during harvest as the sole covariate. The temperature, precipitation and solar radiation variables for each season are incrementally included in the regressions reported in Columns (4) and (5). All estimation results confirm that continuous precipitation has significantly negative impacts on the winter wheat yield skewness. The richer model reported in Column (5) suggests that a one-centimetre increase in continuous precipitation during the harvest season corresponds to a decrease in winter wheat yield skewness by 0.3 units. This finding indicates that continuous precipitation during the harvest season considerably increases the downside risk of winter wheat yield and the probability of failure in winter wheat yield. Our findings are consistent with previous studies that suggest excessive precipitation during the harvest season is a major threat to timely crop harvest, which can remarkably increase the risk of crop yield (Eck et al., 2020; Pelka et al., 2015).

We then explore the potential heterogeneous impacts of continuous precipitation on winter wheat yield skewness across regions based on the results provided in Column (5) of Table 2. We use the SD of continuous precipitation for each province to measure the extent to which the same variation in continuous precipitation affects yield skewness in different regions. The result shows that one SD change in continuous precipitation is associated with a 0.8-unit

TABLE 2 Regression results for mean, variance and skewness of yield.

	Mean yield	**Variance of yield**	**Skewness of yield**		
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Continuous precipitation	−0.0060***	−0.0305	−0.3274*	−0.2978*	−0.3014*
	(0.0014)	(0.0246)	(0.1659)	(0.1583)	(0.1620)
T_{min}: fall	0.0383***	−0.0026		−0.1828	−0.0869
	(0.0066)	(0.0716)		(0.4976)	(0.5124)
T_{min}: winter	−0.0097	0.2063*		1.6297*	1.4739*
	(0.0089)	(0.1068)		(0.8542)	(0.8048)
T_{min}: spring	0.0147	−0.2531**		−2.4607***	−2.4218***
	(0.0095)	(0.1145)		(0.8352)	(0.8098)
T_{max}: fall	−0.0073	0.0343		0.0703	−0.0191
	(0.0060)	(0.0522)		(0.3549)	(0.4342)
T_{max}: winter	0.0163**	−0.0635		−0.9971	−0.7598
	(0.0065)	(0.1297)		(0.8513)	(1.0522)
T_{max}: spring	−0.0353***	0.1326		1.0944	1.0202
	(0.0074)	(0.0830)		(0.6871)	(0.6221)
Precipitation: fall	−0.0033***	−0.0167		−0.1036	−0.1011
	(0.0008)	(0.0121)		(0.0883)	(0.0919)
Precipitation: winter	−0.0100***	0.0281*		0.1863	0.1843
	(0.0015)	(0.0163)		(0.1214)	(0.1177)
Precipitation: spring	−0.0021***	−0.0003		−0.0273	−0.0288
	(0.0007)	(0.0090)		(0.0491)	(0.0513)
Solar radiation: fall	0.0081	−0.0017			0.2056
	(0.0075)	(0.0689)			(0.6038)
Solar radiation: winter	−0.0093	−0.1108			−0.4870
	(0.0102)	(0.1700)			(1.2614)
Solar radiation: spring	0.0441***	0.0077			0.1539
	(0.0084)	(0.1096)			(0.7344)
Constant	4.3435***	1.3253	1.3080***	13.3182**	13.5718*
	(0.0858)	(1.0287)	(0.2028)	(5.8049)	(7.3117)
County fixed effect	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes
Number of observations	15,416	15,416	15,416	15,416	15,416

Note: The standard errors are in parentheses. Standard errors for columns (2)–(5) are clustered at the county and province-by-year levels.
***$p<0.01$; **$p<0.05$; *$p<0.1$.

reduction in winter wheat yield skewness during the sample period. Lest the aggregate data at the national level obscuring heterogeneous impacts of continuous precipitation across regions, we report the estimated changes in yield skewness at the provincial level in Figure 3. The results suggest that Shaanxi, Hubei, Hebei and Anhui are more vulnerable to continuous precipitation during the harvest season. In particular, one SD change in continuous precipitation in Shaanxi reduces the yield skewness by 1 unit during the sample period. We also notice a small

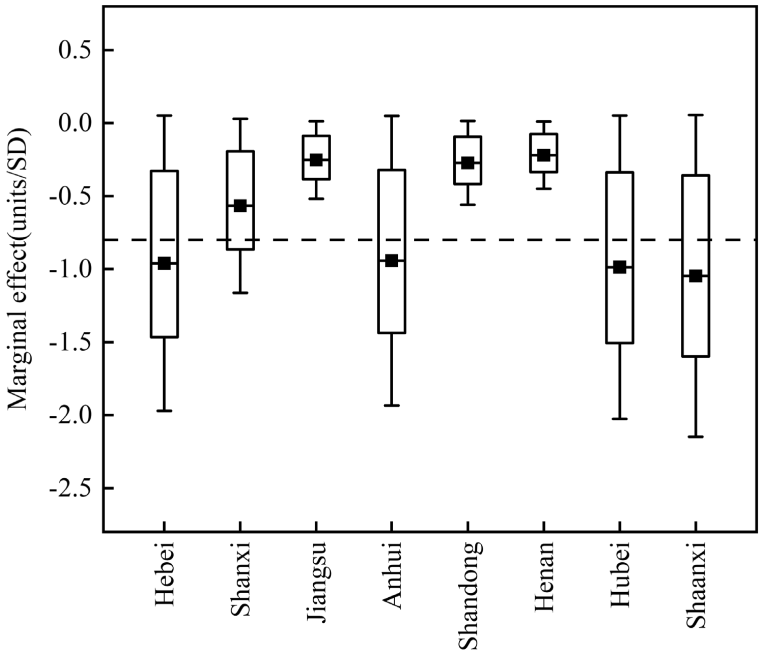


FIGURE 3 Winter wheat yield skewness across regions. We use the SD of continuous precipitation for each province to measure the extent to which the same change in continuous precipitation affects yield skewness in different regions. The dotted black line indicates the marginal effect per SD change of continuous precipitation on yield skewness during the 1998–2016 period. The boxes cover the interquartile range and contain black lines indicating the median and represent the point estimate. The whiskers, denoted by horizontal black lines, represent 95% confidence intervals constructed on the basis of the county and province-by-year clustered standard errors.

probability of winter wheat failure in Shandong, Jiangsu and Henan, with slight changes in continuous precipitation during the harvest season.

In addition, we examine the sensitivity of the baseline results by controlling agricultural inputs, including fertilizer, machinery and labour, throughout the winter wheat growth cycle to the yield moment function. Although excluding nonweather factors, such as socio-economic variables, helps estimate the total marginal effects of weather on winter wheat yield (Chen & Chen, 2018), omitting socio-economic variables may lead to bias if these variables are systematically associated with the local climate. Given that irrigation may mitigate the detrimental impact of weather variables on crop yields (Chen et al., 2016; Cui, 2020), the ratio of practical irrigated areas to total planted areas of all crops is used to proxy for farmers' adjustment behaviour to weather conditions. As shown in Column (1) of Table S2 in the Appendix, the yield mean function results are consistent with the baseline estimates, and the continuous precipitation remarkably increases the downside risk of winter wheat yield in Column (2), in line with our main findings.

One potential concern is that the model specification of the mean yield function might influence the identification of the relationship between the higher-order moments and continuous precipitation. As discussed in Antle (1983) and Antle et al. (2013), the specification errors in the mean yield function might be transmitted to the higher-order moments. Although the R^2 value for the mean yield function in Column (1) of Table 2 is 0.96, we also use the raw moments model suggested by Tack et al. (2012) to explore this concern. As shown in Columns (3)–(5) of Table S2, the continuous precipitation effects are statistically significant for all moment equations, indicating that our main findings are not sensitive to the model specification of the mean yield function.

6.2 | Mitigation effect of harvest mechanisation

Table 3 presents the estimation results regarding the mitigation effect of mechanised harvest on the winter wheat yield skewness, which is captured by the interaction between continuous precipitation and harvest mechanisation. The estimated coefficients, across all specifications,

TABLE 3 Mitigation effect of mechanised harvest.

	Skewness of yield		
Variables	**(1)**	**(2)**	**(3)**
Continuous precipitation	−0.9021***	−0.9106***	−0.9246***
	(0.3052)	(0.3126)	(0.3153)
Continuous precipitation × harvest machinery	0.2689**	0.2866**	0.2907**
	(0.1070)	(0.1131)	(0.1121)
T_{min}: fall		−0.1281	−0.0222
		(0.4917)	(0.5043)
T_{min}: winter		1.6288*	1.4148*
		(0.8538)	(0.7966)
T_{min}: spring		−2.5156***	−2.4322***
		(0.8399)	(0.8077)
T_{max}: fall		0.0250	−0.0688
		(0.3499)	(0.4265)
T_{max}: winter		−1.1101	−0.7958
		(0.8587)	(1.0514)
T_{max}: spring		1.2158*	1.0876*
		(0.7007)	(0.6276)
Precipitation: fall		−0.1120	−0.1101
		(0.0904)	(0.0941)
Precipitation: winter		0.1963	0.1923
		(0.1228)	(0.1187)
Precipitation: spring		−0.0229	−0.0244
		(0.0497)	(0.0519)
Solar radiation: fall			0.2058
			(0.6043)
Solar radiation: winter			−0.6528
			(1.2442)
Solar radiation: spring			0.2658
			(0.7284)
Constant	1.3067***	12.3854**	12.7264*
	(0.2030)	(5.7127)	(7.2344)
County fixed effect	Yes	Yes	Yes
Year effect	Yes	Yes	Yes
Number of observations	15,416	15,416	15,416

Note: Standard errors (in parentheses) are clustered at the county and province-by-year levels.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

are stable and statistically significant at the 5% level, validating the conjecture that harvest machinery reduces the downside risk of winter wheat yield caused by continuous precipitation. These results support the common notion that increasing the availability of harvest machinery is essential to reduce crop yield losses associated with adverse weather conditions (Belton et al., 2021; Hignight & Watkins, 2007; Just & Pope, 1978). We also control for harvest machinery use separately. The estimates reported in Table S3 of the Appendix confirm that harvest machinery does not affect yield skewness independently, implying that its main effect enters through the interaction with continuous precipitation.

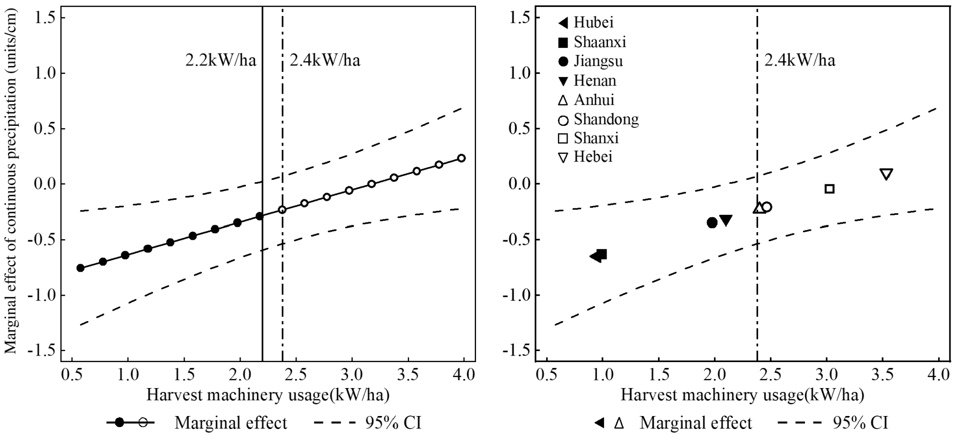
We use the estimated coefficients in Column (3) of Table 3, which includes the complete controls in the model specification, to conduct a ballpark calculation of the benefits of using harvest machinery. Our findings indicate that an additional use of 1 kW/ha of harvest machinery results in an approximate 0.3-unit increase in weather-related winter wheat yield skewness. Under the assumption of a constant conditional mean, E (y|x), this result implies that using an additional 1 kW/ha of harvest machinery would increase winter wheat yield by 669.4 kg/ha. Given that the wheat price in 2015 was about 1.7 CNY/kg, the benefit of reduced winter wheat yield losses from an additional 1 kW/ha of harvest machinery use would be about 1137.9 CNY/ha.[4] These benefits in terms of reduced winter wheat yield losses due to using harvest machinery are in addition to the primary benefit of using harvest machinery, which, as extensively discussed in the literature (e.g. Paudel et al., 2019; Wang et al., 2016), lies in the reduction of labour costs.[5]

In addition to estimating the mitigation effect at the mean level, we explore the variations of the mitigation effect across different levels of harvest machinery usage across regions. In particular, we are interested in identifying a critical level of machinery usage during harvest, other things being equal, that fully offsets the downside risk of winter wheat yield caused by continuous precipitation. For illustration, we plot the marginal effect of the continuous precipitation on the winter wheat yield skewness under different levels of harvest machinery usage in Panel a of Figure 4. The result suggests that the marginal effect of continuous precipitation on the yield skewness is gradually enhanced (i.e. the downside risk is reduced) with the level of harvest machinery. Specifically, our calculation indicates that at 2.4 kW/ha, the beneficial impact of using machinery in the harvest is expected to offset fully the downside risk of winter wheat yield caused by continuous precipitation.

Comparing the historical and present levels of harvest machinery with the critical value would inform us about the potential of harvest machinery expansion in stabilising winter wheat output. The average level of harvest machinery input reached 2.2 kW/ha in 2015, close to the critical value of 2.4 kW/ha. Our estimation suggests that on average, the downside risk caused by continuous precipitation can be mitigated by mechanised harvest. Nonetheless, exploring the mitigation effect at the regional level is worthwhile. We plot the estimated regional mitigation effects in Panel b of Figure 4. These effects vary across regions. The harvest machinery has effectively offset the downside risk caused by continuous precipitation in Hebei,

[4]As discussed in Section 3.3, agricultural machinery usage peaked in 2015. Therefore, we used wheat price in 2015 to calculate the benefits of using harvest machinery. The wheat price in 2015 was obtained from the China Agricultural Product Cost and Revenue Compilation and is reported at 1998 prices.

[5]We also compare the actual labour cost of increasing harvest machinery use with the counterfactual labour cost of using 'business-as-usual' technology (i.e. keeping the amount of labour and machinery use constant in 2015 compared to 1998). The difference between actual and counterfactual labour costs can be attributed to the benefits of increased use of harvest machinery. The results show that a 1 kW/ha increase in harvest machinery use from 1998 to 2015 could reduce labour costs by 1129.1 CNY/ha, whereas machinery costs would only increase by 221.9 CNY/ha. By contrast, a 1 kW/ha increase in harvest machinery use in 2015 would require an investment of about 61.6 CNY/ha. These figures strongly suggest that the benefits of labour savings more than offset the investment costs of harvest mechanisation. Data on machinery and labour costs are obtained from the China Agricultural Product Cost and Revenue Compilation, and data on the investment costs for harvest mechanisation are available from the China Agricultural Machinery Industry Yearbook. All costs are reported in 1998 prices.



(a) Mitigation effect of harvest machinery usage **(b)** Mitigation effect across regions

FIGURE 4 Mitigation effect of mechanised harvest. Solid symbols denote the statistically significant negative impact of continuous precipitation at the 10% level with a given level of harvest machinery usage, and hollow symbols represent quantities statistically insignificant at the 10% level. The black dashed line indicates a critical value of 2.4 kW/ha for harvest machinery usage that fully offsets the downside risk of winter wheat yield caused by continuous precipitation. The solid black line indicates that the average level, 2.2 kW/ha, of harvest machinery usage in China in 2015.

Shanxi, Shandong and Anhui. At the same time, the remaining four provinces have yet to reach the critical level. In particular, our results suggest that Hubei and Shaanxi will benefit from more harvest machinery to reduce the downside risk of winter wheat yield caused by continuous precipitation.

To address the limitation of the skewness function in capturing the asymmetric effects of harvest machinery on winter wheat yield distributions, we further use the partial moment model proposed by Antle (2010) to investigate the relationship between harvest machinery and the negative skewness of winter wheat yield. The estimation results in Table S4 of the Appendix reveal that the interaction term coefficient is significant only for the negative partial moments. This finding confirms our previous results, suggesting that mechanised wheat harvest reduces the downside risk of winter wheat yield caused by continuous precipitation during the harvest season. Moreover, the quantile moment approach developed by Kim et al. (2014) can capture the downside risk. This method, however, entails the potentially subjective specification of proper quantile levels (Kulkarni & Rossi, 2023).

6.2.1 | Endogeneity

Although we utilise the fixed-effect model to assess the mitigation effect of harvest machinery on the downside risk of winter wheat yield, we may still have biased coefficient estimates due to potential endogeneity. First, a reverse causal relationship may exist between the downside risk of winter wheat yield and the use of harvest machinery. The use of harvest machinery is likely to be more prevalent in regions where continuous precipitation is frequent during the winter wheat harvest season. Second, the use of harvest machinery may be subject to a self-selection, as the decision to use harvest machinery is not arbitrary. It may be influenced by various unobserved regional factors, such as land fragmentation and local labour markets, and the results may be biased without consideration of these factors. Third, omitted variables may render the estimated relationship between harvest machinery and winter wheat yield skewness unreliable. An example of omitted variables that are difficult to measure is changes in crop management practices resulting from agricultural mechanisation, such as adjustments in planting density.

The instrumental variable approach is utilised to address the potential endogeneity issue discussed above (Acemoglu et al., 2001; Maggio et al., 2021). Specifically, we instrument the harvest machinery usage for each county with the average lagged harvest machinery usage in its neighbouring counties. It constitutes a suitable instrument variable because the harvest machinery usage of neighbouring counties is correlated due to the prevalent cross-regional machinery services and adjacent counties sharing similar agricultural policies, such as agricultural machinery purchase subsidies, which are a major driver of harvest mechanisation. By contrast, the average lagged harvest machinery usage in neighbouring counties does not directly influence the county's current yield skewness. Column (1) in Table 4 reports the first

TABLE 4 Estimation results based on IV regression and additional climate experience controls.

	Instrumental variable regression		**Climate experience**			
	First stage	**Second stage**	**3 years**		**5 years**	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Continuous precipitation	0.1588**	−0.9957**	−0.9404***	−0.9395***	−0.9587***	−0.9825***
	(0.0731)	(0.3865)	(0.3199)	(0.3199)	(0.3214)	(0.3270)
Continuous precipitation× lagged average harvest machinery use in neighbouring counties	1.0174***					
	(0.0316)					
Continuous precipitation× harvest machinery		0.3010**	0.2948***	0.2948***	0.2984***	0.3065***
		(0.1403)	(0.1090)	(0.1106)	(0.1094)	(0.1115)
Moving average of continuous precipitation			−0.1487		−0.3968	
			(0.4315)		(0.5951)	
Moving standard deviation of continuous precipitation				−0.1597		−0.4928
				(0.2643)		(0.3209)
Constant			12.6000*	12.7172*	12.9959*	12.9352*
			(7.2092)	(7.1951)	(7.1955)	(7.1779)
Additional weather variables	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	14,500	14,500	15,416	15,416	15,416	15,416

Note: The *F*-statistic for the first stage is 1034. The empirical analyses conducted in this paper are based on unbalanced panel data from the year 1998 to 2016, containing a total of 15,416 observations. The number of observations in columns (1)–(2) is reduced to 14,500 because we instrument the harvest machinery usage for each county with the average of one-year lagged harvest machinery usage in its neighbouring counties. Additional weather variables include T_{min}, T_{max}, precipitation and solar radiation for fall, winter and spring. The standard errors (in parentheses) are clustered at the county and province-by-year levels.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

stage estimates: The F-statistic is 1034, much greater than the critical value of 10, indicating the strength of the instrumental variable. The coefficients for continuous precipitation and the interaction term in Column (2) in Table 4 remain statistically significant and quantitatively similar to their counterparts reported in Column (3) of Table 3, indicating that the findings reported in the previous section do not suffer from potential endogeneity.

6.2.2 | Past climate experience

Past climate experience of economic agents may alter their perspective about future climate and their likelihood to implement adaptation behaviour (Niles et al., 2015). Accordingly, an indicator of historical continuous precipitation during the winter wheat harvest season is incorporated into Equation (7) to test the sensitivity of mitigation effect to past climate experiences. Similar to Cui and Xie (2021), this study uses the moving average of continuous precipitation or moving standard deviation of continuous precipitation from the previous 3 or 5 years as proxy variables for past climate experience, respectively. We expect that farmers are more likely to undertake strategies to mitigate the downside risk of winter wheat yield if they have experienced more fluctuating weather. The estimation results of incorporating the past climate experience variables into Equation (7) are reported in Columns (3)–(6) of Table 4. All the moving average or moving standard deviation coefficients are not statistically significant, indicating that our results are insensitive to incorporating past climate experience.

6.2.3 | Alternative harvest season adjustments

Our sample period witnessed some changes in the conventional harvest schedule. To examine their potential influences, we perform a series of robustness tests on the adjustment of winter wheat harvest season, that is shortening the length of the harvest season while keeping the plant and harvest dates fixed. Given that the harvest season can be shortened by 4 days or more due to mechanised wheat harvest (Cao & Zhang, 2019; Gao & Song, 2014), we shorten the harvest season by 1–5 days in our examination. Table 5 reports the estimation results of these various experiments. It shows that the estimated mitigation effects of mechanised harvest on winter wheat yield skewness are not affected by these adjustments of the harvest season.

6.2.4 | Alternative continuous precipitation measurement

To explore the sensitivity of our results with respect to the measurement of continuous precipitation, we also experiment with two alternative indicators of continuous precipitation based on the adjustment of continuous precipitation duration during the harvest season. The first alternative indicator is precipitation that lasts for 2 or more days (precipitation ≥ 0.1 mm in 24 h) with accumulated precipitation exceeding 40 mm in North China; or precipitation that lasts for 4 or more days (precipitation ≥ 0.1 mm in 24 h) with accumulated precipitation exceeding 50 mm in South China. The second alternative indicator for continuous precipitation considers the precipitation duration lasting 4 or more days (precipitation ≥ 0.1 mm in 24 h) in North China, for 6 or more days (precipitation ≥ 0.1 mm in 24 h) in South China, whereas the accumulated precipitation during the precipitation process is consistent with that of the first indicator. Columns (1)–(2) of Table S5 in the Appendix report the estimation results. The coefficients for the continuous precipitation and the interaction terms are quantitatively similar to our previous results and remain statistically significant.

TABLE 5 Mitigation effect under alternative harvest seasons.

Variables	Shorten the length of harvest season by				
	1 day	2 days	3 days	4 days	5 days
	(1)	(2)	(3)	(4)	(5)
Continuous precipitation	−0.8896***	−0.8435***	−0.9003***	−0.8374**	−0.7709**
	(0.1160)	(0.2102)	(0.2094)	(0.2478)	(0.2602)
Continuous precipitation× harvest machinery	0.2625***	0.1784***	0.1917***	0.1705**	0.1593*
	(0.0249)	(0.0480)	(0.0503)	(0.0674)	(0.0706)
Constant	12.7791	12.7495	12.5055	12.3296	12.4173
	(7.3197)	(7.3841)	(7.3301)	(7.2009)	(7.1964)
Additional weather variables	Yes	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes
Number of observations	15,416	15,416	15,416	15,416	15,416

Note: Additional weather variables include T_{min}, T_{max}, precipitation and solar radiation for fall, winter and spring. Standard errors (in parentheses) are clustered at the province level.

***$p<0.01$; **$p<0.05$; *$p<0.1$.

6.2.5 | Placebo test

To confirm that our measurement of continuous precipitation during the harvest season is not some form of ad hoc indicator, we further use a placebo test to investigate the sensitivity of the results regarding the harvest season by considering alternative target periods. The placebo test determines whether the estimation results are driven by chance (Mohan, 2017). Specifically, it tests whether the impact of continuous precipitation on the winter wheat yield skewness remains significant when another measurement period of continuous precipitation is randomly substituted in place of the actual winter wheat harvest season. In practice, we select an alternative 20-day period 2 weeks later than the end of the winter wheat harvest season to avoid the overlap with the actual harvest and then calculate the amount of continuous precipitation in this period. We expect the coefficients associated with this 'irrelevant' continuous precipitation to be statistically insignificant, given that postharvest precipitation does not affect yield skewness. The results of the placebo test are shown in Column (1) of Table 6. As expected, the continuous precipitation after the harvest season and the interaction terms have no significant impact on winter wheat yield skewness.

6.2.6 | Spatial correlation

We further investigate the sensitivity of our results with respect to a more careful treatment of spatial dependence. The two-way clustering strategy in the baseline estimates allows spatial correlation across counties within a province–year combination. However, adjacent counties might have used similar production practices due to the large-scale cross-regional service of machinery. Accordingly, we used first- and second-order spatial weighting matrices to capture the spatial correlation. The estimation results reported in Columns (2)–(3) of Table 6 indicate that the spatial autoregressive coefficients of the error term (λ) in the spatial error model (SEM) and the dependent variable (ρ) in the spatial autoregression model (SAR) are statistically significant at 1% levels. These tests imply a significant spatial correlation among the samples

TABLE 6 Estimation results based on placebo test and alternative estimation strategies.

		Spatial correlation				
		First-order correlation[a]		Second-order correlation		
	Placebo test	SEM	SAR	SEM	SAR	Conley correction
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Continuous precipitation after harvest	−0.1273					
	(0.0939)					
Continuous precipitation after harvest × harvest machinery	0.0721					
	(0.0458)					
Continuous precipitation		−0.6135***	−0.6028***	−0.6048***	−0.6052***	−0.9246***
		(0.1674)	(0.1658)	(0.1656)	(0.1659)	(0.3451)
Continuous precipitation × harvest machinery		0.2064***	0.2047***	0.2071***	0.2070***	0.2907**
		(0.0708)	(0.0702)	(0.0701)	(0.0702)	(0.1355)
λ		0.0437***		−0.0187		
		(0.0129)		(0.0186)		
ρ			0.0436***		−0.0169	
			(0.0129)		(0.0185)	
Constant	14.6136**					−0.0000
	(7.3822)					(0.2402)
Additional weather variables	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	15,416	14,497	14,497	14,497	14,497	15,416

Note: Additional weather variables include T_{min}, T_{max}, precipitation and solar radiation for fall, winter and spring. Standard errors (in parentheses) for column (1) are clustered at the county and province-by-year levels.***$p<0.01$; **$p<0.05$; *$p<0.1$.

[a]The spatial weighting matrices are defined as follows: in the first-order matrix, if counties g_1 and g_2 share a common boundary, then $(g_1, g_2) = 1$, and 0 otherwise. In the second-order matrix, if county g_1 is adjacent to county g_2 and county g_3 is adjacent to county g_2, then $(g_1, g_2) = (g_1, g_3) = (g_2, g_3) = 1$ and the rest elements are 0. In columns (2)–(5), SEM refers to the spatial error model, SAR refers to spatial autoregression model. λ is the spatial autoregressive coefficient of the error term. ρ is the spatial autoregressive coefficient of the dependent variable. The number of observations in columns (2)–(5) is reduced to 14,497. This reduction results from the exclusion of counties with missing values in order to construct a balanced panel dataset and fulfil the prerequisites of the SEM and SAR model estimation. Standard errors for columns (2)–(5) are in parentheses. Conley spatial HAC standard errors in parentheses for column (6) using the 300 km cut-off point. Other cut-off choices, including 100, 200, 400 and 500 km, produce similar results, which are not reported here but are available upon request.

despite λ and ρ being insignificant in the specification of the second-order matrix in Columns (4)–(5) of Table 6. Across various specifications, the mitigation effect of harvest mechanisation on yield risk remains stable and statistically significant at the 1% level.

Nevertheless, excluding counties with missing values to construct a balanced panel dataset for the period of 1998–2016 and fulfil the prerequisites for the SEM and SAR model estimation may result in the omission of specific information from the sample data. To address this concern, we further use an alternative approach for calculating the standard errors. This method, which hinges on correcting for spatial autocorrelation without diminishing the sample size, was proposed by Conley (1999) and applied using the procedure developed by Colella et al. (2019). The results presented in Column (6) of Table 6 show that the significance of the estimated coefficients for continuous precipitation and the interaction terms is largely unaffected by the chosen method of spatial correlation correction.

6.2.7 | Heterogeneity of the mitigation effect

The robustness checks reported above support the conjecture that mechanisation can reduce the downside risk of winter wheat yield caused by continuous precipitation during the harvest season. Given the vast heterogeneity across regions in China, we conduct further granular analysis, considering various topographic or socio-economic factors.

We first explore whether the mitigation effect of mechanised harvest on yield skewness varies across the spectrum of transportation infrastructure. Given that agricultural mechanisation development in China depends on machinery service across regions due to small farming scale, transportation infrastructure is critical to guarantee a timely machinery service by transporting harvest machinery (Zhou et al., 2020). Hence, the mitigation effect of mechanised harvest in a region with improved transportation infrastructure would be higher than those with an underdeveloped transportation network. We divided the sample according to their highway density, which was calculated as the ratio of highway length to its land areas, a proxy for the transportation infrastructure. The subsample estimation results are reported in Columns (1) and (2) of Table 7. The coefficient of continuous precipitation and the corresponding interaction term exhibit the expected sign and are statistically significant for both groups. We further use Fisher's permutation test to infer the significance level of the difference between the two sets of estimated coefficients (Cleary, 1999; Lian et al., 2010). The *p*-value of 0.050 for Fisher's permutation test suggests that the mitigation effects of harvest mechanisation in regions with improved transportation conditions are considerably higher than those with poorer transportation conditions.

We also compare the mitigation effects of harvest mechanisation on yield skewness in different topographic conditions, as in Qian et al. (2022). The sample was divided into two groups, plain and hill/mountain areas, according to the township classification of the China Statistical Yearbook. The estimation results of these two groups are reported in Columns (3) and (4) of Table 7, suggesting that the harvest machinery in plain areas is more likely to reduce the downside risk of winter wheat yield caused by continuous precipitation. By contrast, the mitigation effect in hilly and mountainous areas is barely significant, probably because the rugged terrain hinders the wide adoption of mechanisation.

The mitigation effect of harvest mechanisation in northern and southern China may differ because of the varying degrees of exposure to continuous precipitation. For example, continuous precipitation stress considerably decreased from the south of the Qinling–Huaihe line to the north in a banded pattern (Li et al., 2018). Accordingly, we used the Qinling–Huaihe line, the geographical separator of northern and southern China, to divide our sample into two subsamples with different weather patterns. The results reported in Columns (5) and (6) of Table 7 indicate that the interaction terms remain positive and significant. The *p*-value of Fisher's permutation test of 0.492 suggests that the coefficients for the interaction term are not significantly different between the two areas.

7 | CONCLUSIONS AND POLICY IMPLICATIONS

Agricultural production risk caused by calamitous weather associated with climate change poses severe threats to global food supplies. Although recent studies have assessed the mitigation effects of microlevel farm management measures on agricultural production risk due to calamitous weather, the relationship between agricultural machinery and calamitous weather-induced

TABLE 7 Heterogeneous effects analysis.

	Highway density		Topographic conditions		Geographical location	
	High	Low	Plain	Hill and mountain	North	South
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Continuous precipitation	−1.1813***	−0.9462**	−1.0239***	−0.6255*	−0.6317**	−0.9591***
	(0.0952)	(0.2087)	(0.2655)	(0.2653)	(0.2330)	(0.0469)
Continuous precipitation × harvest machinery	0.5291***	0.2873***	0.4353***	0.2099	0.2419***	0.2349*
	(0.0632)	(0.0132)	(0.1012)	(0.1276)	(0.0537)	(0.0955)
Constant	9.1563	17.6929	−9.4427*	20.6466	7.6594	14.0462
	(7.8156)	(9.8800)	(4.7247)	(17.6765)	(8.3738)	(12.3793)
Additional weather variables	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	7922	7494	6806	5444	11,133	4283
Empirical p-values[a]	0.0500*		0.0900*		0.4920	

[a]Empirical p-values of the Fisher's permutation test are obtained by the bootstrap method with 1000 repetitions, which are estimated based on the null hypothesis that the coefficients of continuous precipitation × harvest machinery are equal for the two samples under consideration. The number of observations for the topographic conditions group is reduced to 12,250 because the classification in the China Statistical Yearbook (Township) does not include all counties in the sample. Additional weather variables include T_{min}, T_{max}, precipitation and solar radiation for fall, winter and spring. Standard errors (in parentheses) are clustered at the province level.

***$p<0.01$; **$p<0.05$; *$p<0.1$.

downside risk of yield has yet to be carefully studied. This study constructs a county-level panel dataset of winter wheat production in China and estimates how continuous precipitation during the harvest season has affected the yield risk of winter wheat. Continuous precipitation during the harvest season considerably increases the downside risk of winter wheat yield, threatening food security. Harvest mechanisation has mitigated the downside risk of winter wheat yield caused by continuous precipitation. The mitigation effect of harvest machinery is heterogeneous, depending on topographic conditions and the level of transportation infrastructure.

The benefits of harvest machinery in mitigating weather-related risk during the crop harvest season highlight the necessity of government policies to support the development of agricultural mechanisation in developing countries. Policies that promote R&D and innovation in agricultural machinery technology to improve its applicability in hilly and mountainous areas would be particularly beneficial. Furthermore, investment in transportation infrastructure, such as rural roads, may help enhance the mitigation effect of harvest machinery in response to calamitous weather in vulnerable areas. Overall, our findings suggest that adopting modern agricultural production technologies may not only promote productivity but also mitigate the adverse impacts of calamitous weather. Investment decision that considers only the productivity enhancement but not the risk reduction in agricultural technology may undervalue the contribution of modern agricultural technologies.

Our study focusses on exploring the effectiveness of harvest mechanisation in reducing crop yield losses, whereas discussion about the full benefits and costs of investing in harvest mechanisation is outside the analysis framework because the model used in this study cannot quantify the additional socio-economic impacts of using harvest machinery, such as labour-saving benefits and the associated infrastructure development. Future research is warranted to analyse the benefits and costs of harvest mechanisation more accurately by integrating the parameters we estimated with positive modelling approaches, such as CGE or IAMs, which can comprehensively capture the socio-economic feedback.

ACKNOWLEDGEMENTS

The authors would like to thank Dr. Funing Zhong at Nanjing Agricultural University, and Dr. Xiaoguang Chen at Southwestern University of Finance and Economics for their helpful comments. The authors would also like to thank the Editor-in-Chief, Dr. Tihomir Ancev, the Associate Editor and the four anonymous reviewers for their constructive and valuable suggestions. The authors are responsible for all errors.

FUNDING INFORMATION

Fujin Yi gratefully acknowledges the financial support by the Joint Agricultural Research Project between National Natural Science Foundation of China (NSFC) and the Bill & Melinda Gates Foundation (BMGF) (72261147758), the National Social Science Foundation of China (22VRC178), and the Leading Talents Project of Philosophy and Social Science Foundation of Zhejiang Province (24YJRC01ZD).

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

The weather data used in our manuscript are available upon request, while the agricultural production data are proprietary and available from the Institute of Agricultural Information at the Chinese Academy of Agricultural Science.

ORCID

Fujin Yi https://orcid.org/0000-0001-9513-4383

REFERENCES

Acemoglu, D., Johnson, S. & Robinson, J.A. (2001) The colonial origins of comparative development: An empirical investigation. *American Economic Review*, 91(5), 1369–1401.

Amonoo, S.E. (2013) *Effect of late season precipitation on cotton yield distributions*. Jackson, MS: Mississippi State University Press.

Antle, J.M. (2010) Asymmetry, partial moments, and production risk. *American Journal of Agricultural Economics*, 92(5), 1294–1309.

Antle, J.M., Mu, J.E. & Abatzoglou, J. (2013) *Climate and the spatial-temporal distribution of winter wheat yields: Evidence from the U.S. Pacific northwest, 2013 AAEA & CAES joint annual meeting, Washington, DC*. Milwaukee, WI: Agricultural and Applied Economics Association, p. 2617.

Antle, J.M. (1983) Testing the stochastic structure of production: a flexible moment-based approach. *Journal of Business & Economic Statistics*, 1(3), 192–201.

Antón, J., Kimura, S., Lankoski, J. & Cattaneo, A. (2012) *A comparative study of risk management in agriculture under climate change*. OECD Food, Agriculture and Fisheries Papers, No. 58. Paris: OECD Publishing.

Auffhammer, M., Hsiang, S.M., Schlenker, W. & Sobel, A. (2013) Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy*, 7(2), 181–198.

Belton, B., Win, M.T., Zhang, X. & Filipski, M. (2021) The rapid rise of agricultural mechanization in Myanmar. *Food Policy*, 101, 102095.

Benin, S. (2015) Impact of Ghana's agricultural mechanization services center program. *Agricultural Economics*, 46(S1), 103–117.

Calvin, K. & Fisher-Vanden, K. (2017) Quantifying the indirect impacts of climate on agriculture: An inter-method comparison. *Environmental Research Letters*, 12(11), 115004.

Cameron, A.C., Gelbach, B.J. & Miller, L.D. (2011) Robust inference with multiway clustering. *Journal of Business & Economic Statistics*, 29(2), 238–249.

Cao, G. & Zhang, J. (2019) The development and progress of agricultural mechanization in China. *China Agricultural Machinery Safety Supervision*, 11, 8–14.

Chen, C., Wang, E., Yu, Q. & Zhang, Y. (2009) Quantifying the effects of climate trends in the past 43 years (1961–2003) on crop growth and water demand in the North China plain. *Climatic Change*, 100(3–4), 559–578.

Chen, S., Chen, X. & Xu, J. (2016) Impacts of climate change on agriculture: evidence from China. *Journal of Environmental Economics and Management*, 76, 105–124.

Chen, S. & Gong, B. (2020) Response and adaptation of agriculture to climate change: evidence from China. *Journal of Development Economics*, 148, 102557.

Chen, X. & Chen, S. (2018) China feels the heat: negative impacts of high temperatures on China's rice sector. *Australian Journal of Agricultural and Resource Economics*, 62(4), 576–588.

Chen, X., Tian, G., Qin, Z. & Bi, X. (2019) High daytime and nighttime temperatures exert large and opposing impacts on winter wheat yield in China. *Weather, Climate, Society*, 11(4), 777–790.

Cho, S.J. & McCarl, B.A. (2017) Climate change influences on crop mix shifts in the United States. *Scientific Reports*, 7, 40845.

Ciscar, J.-C., Fisher-Vanden, K. & Lobell, D.B. (2018) Synthesis and review: An inter-method comparison of climate change impacts on agriculture. *Environmental Research Letters*, 13(7), 070401.

Cleary, S. (1999) The relationship between firm investment and financial status. *Journal of Finance*, 54(2), 673–692.

Colella, F., Lalive, R., Sakalli, S.O. & Thoenig, M. (2019) *Inference with arbitrary clustering*. IZA Discussion Paper No. 12584.

Conley, T.G. (1999) Gmm estimation with cross sectional dependence. *Journal of Econometrics*, 92(1), 1–45.

Cui, X. (2020) Beyond yield response: weather shocks and crop abandonment. *Journal of the Association of Environmental and Resource Economists*, 7(5), 901–932.

Cui, X. & Xie, W. (2021) Adapting agriculture to climate change through growing season adjustments: evidence from corn in China. *American Journal of Agricultural Economics*, 104(1), 249–272.

D'Agostino, R.B., Belanger, A. & D'Agostino, R.B., Jr. (1990) A suggestion for using powerful and informative tests of normality. *American Statistician*, 44(4), 316–321.

Deschenes, O. & Greenstone, M. (2007) The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American Economic Review*, 97(1), 354–385.

Di Falco, S. & Chavas, J.P. (2009) On crop biodiversity, risk exposure, and food security in the highlands of Ethiopia. *American Journal of Agricultural Economics*, 91(3), 599–611.

Di Falco, S. & Chavas, J.-P. (2006) Crop genetic diversity, farm productivity and the management of environmental risk in rainfed agriculture. *European Review of Agricultural Economics*, 33(3), 289–314.

Di Falco, S., Veronesi, M. & Yesuf, M. (2011) Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, 93(3), 829–846.

Eck, M.A., Murray, A.R., Ward, A.R. & Konrad, C.E. (2020) Influence of growing season temperature and precipitation anomalies on crop yield in the southeastern United States. *Agricultural and Forest Meteorology*, 291, 108053.

Fan, M., Shen, J., Yuan, L., Jiang, R., Chen, X., Davies, W.J. et al. (2012) Improving crop productivity and resource use efficiency to ensure food security and environmental quality in China. *Journal of Experimental Botany*, 63(1), 13–24.

Gammans, M., Mérel, P. & Ortizbobea, A. (2017) Negative impacts of climate change on cereal yields: statistical evidence from France. *Environmental Research Letters*, 5, 54007.

Gao, M. & Song, H. (2014) Spatial convergences and difference between functional areas of grain production technical efficiency: concurrently discuss ripple effect in technology diffusion. *Management World*, 07, 83–92.

Gobin, A. (2018) Weather related risks in Belgian arable agriculture. *Agricultural Systems*, 159, 225–236.

Hallegatte, S., Lecocq, F. & De Perthuis, C. (2011) *Designing climate change adaptation policies: an economic framework*. Policy research working paper 5568, the World Bank, Washington, DC.

Hatfield, J.L., Boote, K.J., Kimball, B.A., Ziska, L.H., Izaurralde, R.C., Ort, D. et al. (2011) Climate impacts on agriculture: implications for crop production. *Agronomy Journal*, 103(2), 351–370.

Hignight, J. & Watkins, K. (2007) The value of rice harvesting efficiency. *AAES Research Series*, 560, 283–287.

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

IPCC. (2019) *Climate change and land: An IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems*. Geneva, Switzerland: IPCC.

Issahaku, G. & Abdulai, A. (2020) Adoption of climate-smart practices and its impact on farm performance and risk exposure among smallholder farmers in Ghana. *Australian Journal of Agricultural and Resource Economics*, 64(2), 396–420.

Jarque, C.M. & Bera, A.K. (1980) Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters*, 6(3), 255–259.

Jarque, C.M. & Bera, A.K. (1987) A test for normality of observations and regression residuals. *International Statistical Review*, 55(2), 163–172.

Just, R.E. & Pope, R.D. (1978) Stochastic specification of production functions and economic implications. *Journal of Econometrics*, 7(1), 67–86.

Kien, N.D., Dung, T.Q., Oanh, D.T.K., An, L.T., Dinh, N.C., Phan, N.T. et al. (2023) Climate-resilient practices and welfare impacts on rice-cultivating households in Vietnam: does joint adoption of multiple practices matter? *Australian Journal of Agricultural and Resource Economics*, 67(2), 263–284.

Kim, K., Chavas, J.P., Barham, B. & Foltz, J. (2014) Rice, irrigation and downside risk: a quantile analysis of risk exposure and mitigation on Korean farms. *European Review of Agricultural Economics*, 41(5), 775–815.

Kulkarni, K. & Rossi, D. (2023) Determinants of downside risk exposure: An analysis of Korean rice farms using partial and quantile moments. *Applied Economic Perspectives and Policy*, 45(3), 1356–1373.

Kulwal, P., Ishikawa, G., Benscher, D., Feng, Z., Yu, L.-X., Jadhav, A. et al. (2012) Association mapping for pre-harvest sprouting resistance in white winter wheat. *Theoretical and Applied Genetics*, 125(4), 793–805.

Lesk, C., Rowhani, P. & Ramankutty, N. (2016) Influence of extreme weather disasters on global crop production. *Nature*, 529(7584), 84–87.

Li, Y., Qin, Y., Xie, Z., Ning, X. & Zhang, L. (2018) Disaster risk assessment of continuous rain during harvest period of winter wheat in China. *Journal of Natural Resources*, 33(11), 1926–1939.

Lian, Y., Peng, F. & Su, Z. (2010) Financing constraints and liquidity management. *Journal of Financial Research*, 10, 158–171.

Lobell, D.B. & Field, C. (2007) Global scale climate–crop yield relationships and the impacts of recent warming. *Environmental Research Letters*, 2(1), 14002.

Lobell, D.B. & Ortiz-Monasterio, J.I. (2007) Impacts of day versus night temperatures on spring wheat yields: a comparison of empirical and ceres model predictions in three locations. *Agronomy Journal*, 99(2), 469–477.

Maggio, G., Mastrorillo, M. & Sitko, N.J. (2021) Adapting to high temperatures: effect of farm practices and their adoption duration on total value of crop production in Uganda. *American Journal of Agricultural Economics*, 104(1), 385–403.

Mao, L. & Wei, L. (2015) *Journal of natural resources*. Beijing: China Meteorological Press.

McCarl, B.A., Villavicencio, X. & Wu, X. (2008) Climate change and future analysis: is stationarity dying? *American Journal of Agricultural Economics*, 90(5), 1241–1247.

Mendelsohn, R., Nordhaus, W.D. & Shaw, D. (1994) The impact of global warming on agriculture: a Ricardian analysis. *American Economic Review*, 84(4), 753–771.

Mendelsohn, R.O. & Massetti, E. (2017) The use of cross-sectional analysis to measure climate impacts on agriculture: theory and evidence. *Review of Environmental Economics and Policy*, 11(2), 280–298.

Miller, N., Tack, J. & Bergtold, J. (2021) The impacts of warming temperatures on US sorghum yields and the potential for adaptation. *American Journal of Agricultural Economics*, 103(5), 1742–1758.

Mohan, P. (2017) The economic impact of hurricanes on bananas: a case study of Dominica using synthetic control methods. *Food Policy*, 68, 21–30.

Moussa, A. (2008) Mechanical and traditional harvesting methods for wheat crop. *Misr Journal of Agricultural Engineering*, 25(4), 1094–1111.

Nelson, G.C., Valin, H., Sands, R.D., Havlik, P., Ahammad, H., Deryng, D. et al. (2014) Climate change effects on agriculture: economic responses to biophysical shocks. *Proceedings of the National Academy of Sciences*, 111(9), 3274–3279.

Niles, M.T., Lubell, M. & Brown, M. (2015) How limiting factors drive agricultural adaptation to climate change. *Agriculture Ecosystems & Environment*, 200, 178–185.

Ortiz-Bobea, A. (2021) Climate, agriculture and food, arXiv Preprint *arXiv*: 2105.12044.

Paudel, G.P., Dilli Bahadur, K.C., Rahut, D.B., Justice, S.E. & Mcdonald, A.J. (2019) Scale-appropriate mechanization impacts on productivity among smallholders: evidence from rice systems in the mid-hills of Nepal. *Land Use Policy*, 85, 104–113.

Pelka, N., Musshoff, O. & Weber, R. (2015) Does weather matter? How rainfall affects credit risk in agricultural microfinance. *Agricultural Finance Review*, 75(2), 194–212.

Peng, S., Huang, J., Sheehy, J.E., Laza, R.C., Visperas, R.M., Zhong, X. et al. (2004) Rice yields decline with higher night temperature from global warming. *PNAS*, 101(27), 9971–9975.

Pingali, P. (2007) Agricultural mechanization: adoption patterns and economic impact. *Handbook of Agricultural Economics*, 3, 2779–2805.

Poudel, S. & Kotani, K. (2013) Climatic impacts on crop yield and its variability in Nepal: do they vary across seasons and altitudes? *Climatic Change*, 116(2), 327–355.

Qian, L., Lu, H., Gao, Q. & Lu, H. (2022) Household-owned farm machinery vs. outsourced machinery services: the impact of agricultural mechanization on the land leasing behavior of relatively large-scale farmers in China. *Land Use Policy*, 115, 106008.

Ray, D.K., Gerber, J.S., Macdonald, G.K. & West, P.C. (2015) Climate variation explains a third of global crop yield variability. *Nature Communications*, 6, 5989.

Roseta-Palma, C. & Sağlam, Y. (2019) Downside risk in reservoir management. *Australian Journal of Agricultural and Resource Economics*, 63(2), 328–353.

Salvo, D. (2013) Measuring the effect of climate change on agriculture: a literature review of analytical models. *Journal of Development and Agricultural Economics*, 5(12), 499–509.

Schlenker, W. & Roberts, M.J. (2009) Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences*, 106(37), 15594–15598.

Shi, M., Paudel, K.P. & Chen, F.-B. (2021) Mechanization and efficiency in rice production in China. *Journal of Integrative Agriculture*, 20(7), 1996–2008.

Tack, J., Barkley, A. & Nalley, L.L. (2015) Effect of warming temperatures on US wheat yields. *Proceedings of the National Academy of Sciences*, 112(22), 6931–6936.

Tack, J., Harri, A. & Coble, K. (2012) More than mean effects: modeling the effect of climate on the higher order moments of crop yields. *American Journal of Agricultural Economics*, 94(5), 1037–1054.

Taraz, V. (2023) Public works programmes and agricultural risk: evidence from India. *Australian Journal of Agricultural and Resource Economics*, 67(2), 198–223.

Urban, D.W., Roberts, M.J., Schlenker, W. & Lobell, D.B. (2015) The effects of extremely wet planting conditions on maize and soybean yields. *Climatic Change*, 130(2), 247–260.

Van der Velde, M., Tubiello, F.N., Vrieling, A. & Bouraoui, F. (2011) Impacts of extreme weather on wheat and maize in France: evaluating regional crop simulations against observed data. *Climatic Change*, 113(3–4), 751–765.

Verma, S. (2006) Impact of agricultural mechanization on production, productivity, cropping intensity income generation and employment of labour. *Status of Farm Mechanization in India*, 2006, 133–153.

Wang, R., Rejesus, R.M. & Aglasan, S. (2021) Warming temperatures, yield risk and crop insurance participation. *European Review of Agricultural Economics*, 48(5), 1109–1131.

Wang, X., Yamauchi, F. & Huang, J. (2016) Rising wages, mechanization, and the substitution between capital and labor: evidence from small scale farm system in China. *Agricultural Economics*, 47(3), 309–317.

Welch, J.R., Vincent, J.R., Auffhammer, M., Moya, P.F., Dobermann, A. & Dawe, D. (2010) Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures. *Proceedings of the National Academy of Sciences*, 107(33), 14562–14567.

Wing, I.S., De Cian, E. & Mistry, M.N. (2021) Global vulnerability of crop yields to climate change. *Journal of Environmental Economics and Management*, 109, 102462.

Won, S., Rejesus, R.M., Goodwin, B.K. & Aglasan, S. (2023) Understanding the effect of cover crop use on prevented planting losses. *American Journal of Agricultural Economics*, Early view. Available from: https://doi.org/10.1111/ajae.12396

Xue, C., Shi, X. & Zhou, H. (2020) Influence path of agricultural mechanization on total factor productivity growth in planting industry. *Journal of Agrotechnical Economics*, 10, 87–102.

Yang, J., Huang, Z., Zhang, X. & Reardon, T. (2013) The rapid rise of cross-regional agricultural mechanization services in China. *American Journal of Agricultural Economics*, 95(5), 1245–1251.

Yi, F., Jiang, F., Zhong, F., Zhou, X. & Ding, A. (2016) The impacts of surface ozone pollution on winter wheat productivity in China – an econometric approach. *Environmental Pollution*, 208, 326–335.

You, L., Spoor, M., Ulimwengu, J. & Zhang, S. (2011) Land use change and environmental stress of wheat, rice and corn production in China. *China Economic Review*, 22(4), 461–473.

Zampieri, M., Ceglar, A., Dentener, F. & Toreti, A. (2017) Wheat yield loss attributable to heat waves, drought and water excess at the global, national and subnational scales. *Environmental Research Letters*, 12(6), 064008.

Zhou, X., Ma, W., Li, G. & Qiu, H. (2020) Farm machinery use and maize yields in China: An analysis accounting for selection bias and heterogeneity. *Australian Journal of Agricultural and Resource Economics*, 64(4), 1282–1307.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Wang, T., Yi, F., Wu, X., Liu, H. & Zhang, Y.Y. (2023) Calamitous weather, yield risk and mitigation effect of harvest mechanisation: Evidence from China's winter wheat. *Australian Journal of Agricultural and Resource Economics*, 00, 1–27. Available from: https://doi.org/10.1111/1467-8489.12545