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Impact of new maize variety adoption on yield and fertilizer input in China: Implications for sustainable food and agriculture

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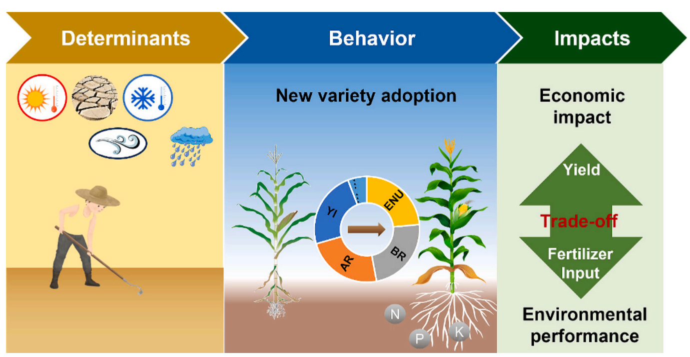
HIGHLIGHTS

- Crop variety adoption is considered as one of the main strategies for farmers to address climate change issues.
- Impact of new maize variety adoption on yield and fertilizer input, and the determinants of such adoption are examined.
- New maize varieties increase yield but fertilizer use as well. This trade-off is more pronounced among small-scale farmers.
- Different natural disaster experiences have varying impacts on the probability of adopting new maize varieties.
- Crop breeding needs to optimize resistance and nutrient use efficiency synergistically.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Crop variety adoption is considered as one of the main strategies for farmers to enhance productivity under stress brought by the climate change, with less environmental impacts. It holds an upstream position in the whole life cycle of agricultural clean production, compared to the field management and agricultural non-point source pollution treatment.
OBJECTIVE: This paper aims to (i) assess the impact of new maize variety adoption on maize yield and fertilizer input; (ii) analyze the main determinants of farmers' new maize variety choice in the context of climate change, and (iii) identify the heterogeneity of small-scale and large-scale farmers in maize variety choice and its impacts.
METHODS: Based on plot-level data collected from three major grain producing provinces in China, we employ a treatment effects model to correct the potential bias resulting from the farmers' self-selection and estimate the direct impacts of farmers' new maize variety adoption and the main determinants of such adoption.
RESULTS AND CONCLUSIONS: The empirical results indicate that the adoption of new maize varieties significantly increases maize yield by 9.4% but fertilizer use by 16.6 kg/mu (1 mu = 1/15 ha) as well, and this trade-off between economic impacts and environmental impacts is more pronounced among small-scale farmers. However, in the face of natural disasters, adopting new maize varieties results in a significant reduction in yield losses

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by 1.4% and a decrease in fertilizer input for natural disaster management by 2.45 kg/mu, as compared to the adoption of old varieties. What's more, our findings suggest that a higher frequency of pest and disease disasters significantly increases the probability of new maize variety adoption by farmers, while a higher frequency of climate disasters significantly decreases the probability.

SIGNIFICANCE: The estimated impacts of new maize varieties point out the need of synergistically optimized resistance and nutrient use efficiency for crop breeding, which have important policy implications for sustainable food and agriculture. Also, the significant factor analysis contributes to the proposal of feasible ways to promote the farmers' adoption behavior.

1. Introduction

- Climate change is threatening crop production by inducing more natural disasters such as extreme weather events and crop pests and diseases, posing great threats to food security and the agricultural sustainability. On the one hand, natural disasters cause significant losses in agricultural production (Liu et al., 2020; Chen and Hsu, 2014). In China, about 11.74 million hectares of crops were affected by natural disasters in 2021, causing direct economics losses of 334.02 billion yuan, which accounts for 3.8% of the total value of agriculture, forestry, animal husbandry, and fishery production in the same year (NBSC, 2022). On the other hand, certain climate adaptation and disaster remediation behavior of farmers, such as increased chemical inputs, may exacerbate environmental pollution and impede the Sustainable Food and Agriculture (SFA) (Chen et al., 2022b; Tang et al., 2018; Liu et al., 2022).
- Maize is the foremost staple crop grown in China. With the increasing environmental constraints and demand for food consumption, ensuring high and stable maize yield while minimizing environmental impacts has become a critical challenge (Zhao et al., 2024). Over the past two decades, Chinese maize production has witnessed continuous growth. However, the yield per unit and agricultural input intensity perform worse compared to developed countries. In 2022, the total maize production in China was 277.20 million metric tons (NBSC, 2023), while the total maize consumption reached 295.40 million metric tons, resulting in a net import of 20.62 million metric tons (JCI, 2023). In 2021, the average maize yield in China was 6291.20 kg per hectare, which was approximately 43% lower than the maize yield in the United States in the same year (FAOSTAT, 2022). In addition, China is among the highest countries in fertilizer-use intensity in the world. In 2021, Chinese farmers used fertilizer about 374.8 kg per hectare of cultivated land, which was about 1.7 times higher than the world average (World Bank, 2022). Therefore, Chinese maize production is facing the dual pressure of increasing grain output and reducing fertilizer input.

Due to technological progress and the continuous revision and improvement of the crop variety certification standards, China has witnessed a growing number of approved crop varieties in recent years. Taking maize as an example, 2562 new maize varieties were approved in 2020 in China, about 4.6 times more than those in 2016 (DSI, 2021), all of which are conventional varieties without genetic engineering technology. Introducing new crop varieties has become a prominent strategy for enhancing productivity and addressing climate and environmental challenges (Acevedo et al., 2020). It has both direct impacts on yield enhancement (Simtowe et al., 2019; Zeng et al., 2015; Villano et al., 2015; Zhou et al., 2018) and indirect impacts on yield stability (Emerick et al., 2016; Huang et al., 2015). Excessive fertilizer use may result in increased nitrogen (N) and phosphorus (P) loss to the environment, which contributes to environmental degradation (Zuo et al., 2018; Ju et al., 2009). Crop varieties with high nitrogen use efficiency can reduce the need of fertilizer input and nitrogen emission as well (Ma et al., 2022; Li et al., 2022). However, the effects of new maize variety adoption on maize yield and fertilizer input have not been systematically estimated, especially focusing on the commercialized conventional maize varieties in China. Farmers' choice of crop varieties is a crucial factor to achieve the effects of new maize varieties, some studies have identified several individual or household factors such as educational levels, plot size as the main determinants of farmers' adoption (Lunduka et al., 2019; Langyintuo and Mungoma, 2008; Khonje et al., 2015; Aryal et al., 2018a, 2018b; Bai et al., 2015), but none of them are linked to the effect of new variety adoption in actual production.

This paper aims to assess the impacts of farmers' new maize variety adoption on maize yield and fertilizer input simultaneously, and find the main determinants of farmers' choice in the context of climate change. The data used in this study were gathered from three major maize-producing provinces in China, namely Heilongjiang, Henan, and Sichuan, located in the northeast, central, and southwestern regions in China, respectively. The findings reveal a complex trade-off between increased yield and fertilizer input resulting from farmers' adoption of new maize varieties. These findings have significant implications for breeders and policymakers, not only within China but also other developing countries, as they strive to create and promote the new maize varieties of high and stable yield and efficient nutrient utilization.

The contributions of this study mainly include the following points: Firstly, we provide a more detailed analysis by using the quantity of fertilizer input instead of dummy variable used in previous study (Simtowe et al., 2019), filling a research gap in understanding the environmental effect of conventional maize variety adoption from the perspective of fertilizer input. Existing research on the environmental impacts of crop variety adoption has mainly focused on genetically modified varieties (Huang et al., 2002, 2005; Brookes and Dinh, 2021; Brookes, 2019; Coupe and Capel, 2016) or non-GM rice varieties (Emerick et al., 2016). Secondly, a treatment effects (TE) model is applied to address selection bias caused by both observable and unobservable factors, and estimate the direct impacts of new maize variety adoption on yield and fertilizer input. Some other methods have been used to solve the endogeneity issue of farmers' variety selection, such as two-stage least squares (2SLS), propensity score matching (PSM), and endogenous switching regression (ESR) (Simtowe et al., 2019; Bairagi et al., 2021; Khonje et al., 2015). However, 2SLS and PSM can only address selection bias caused by observable factors, and ESR is unable to assess the direct impacts. Lastly, we also analyze the heterogeneity of small-scale and large-scale farmers in variety choice and its impacts.

2. Model specification

The choice of new crop varieties by farmers is an endogenous behavior (Zhou et al., 2018; Bairagi et al., 2021). Farmers who choose to adopt new varieties may have systematically different characteristics compared to those who continue with old ones. Therefore, it is crucial to address the endogeneity issue caused by selection bias to obtain unbiased and consistent results. Previous studies have employed some methods, such as PSM, 2SLS, and ESR, to correct for selection bias (Simtowe et al., 2019; Bairagi et al., 2021; Khonje et al., 2015). However, PSM and 2SLS cannot address selection bias caused by unobservable variables, and the ESR model is unable to estimate direct impacts of new maize variety adoption on maize yield and fertilizer input. In this paper, a treatment effects (TE) model is employed to correct selection bias originating from both observable and unobservable variables.

Meanwhile, we can estimate the direct effects of new maize variety adoption on maize yield and fertilizer input.

The TE model is a two-stage estimation method. In the first stage, we model a farmer's behavior of new variety choice. Following the methodology employed in previous studies on crop variety adoption (Bairagi et al., 2021), the household's decision to adopt new varieties is modelled within the framework of random utility. Let V_{ij}^* represent the utility difference between adopting (V_{ij1}) and not adopting new maize varieties (V_{ij0}), where a household's choice to adopt a new maize variety is contingent upon $V_{ij}^* = V_{ij1} - V_{ij0} > 0$. However, the two utilities and their difference are not directly observable. Alternatively, we can use a latent variable model to express them as follows:

$$V_{ij}^* = Z_{ij}\alpha_{ij} + H_i\varphi_i + \varepsilon_{ij} \text{ with } V_{ij} = \begin{cases} 1 \text{ } if \text{ } V_{ij}^* > 0 \\ 0 \text{ } otherwise \end{cases} \quad (1)$$

where i and j denote households and plots, respectively; V_{ij}^* denotes a latent variable representing the likelihood of adopting new maize varieties; V_{ij} represents the actual adoption status of new maize varieties, where $V_{ij} = 1$ if household i adopts new maize varieties in plot j and $V_{ij} = 0$ otherwise; Z_{ij} comprises a vector of variables associated with plot-level characteristics (e.g., plot size, soil type, and land quality); H_i refers to a vector of household-level characteristics (e.g., education level of household head, household expenditure, and labor ratio); α_{ij} and φ_i are parameters to be estimated; and ε_{ij} is a random error term.

In the second-stage estimation of the TE model, we identify the impacts of adopting new maize varieties on maize yield and fertilizer input. For maize yield, we assume that a farmer's maize production adheres to the Cobb-Douglas production function. For fertilizer input, we assume that fertilizer input is a linear function of new maize variety adoption and other control variables. The empirical models can be written as:

$$log(Y_{ij}) = \beta_0 + \gamma_{ij}V_{ij} + log(X_{ij})\beta_{ij} + P_{ij}\theta_{ij} + H_i\delta_i + u_{ij} \quad (2)$$

$$F_{ij} = \beta_0 + \gamma_{ij}V_{ij} + P_{ij}\theta_{ij} + H_i\delta_i + u_{ij} \quad (3)$$

where Y_{ij} refers to maize yield in plot j of household i; F_{ij} represents fertilizer input; V_{ij} denotes the new maize variety adoption variable, which is defined in Eq. (1); X_{ij} comprises a set of plot-level input variables (e.g., labor input, fertilizer input, and machinery input); P_{ij} encompasses additional plot-level variables considered as controls, such as plot area, soil type, and land quality; H_i denotes a set of characteristics at the household level, such as education of household head, household expenditure, and labor rate; u_{ij} is a random error term; and γ is our parameter of interest.

The equations of the first and second stages are jointly estimated using a maximum likelihood estimator in TE model. The error term ε_{ij} and u_{ij} are assumed to follow a bivariate normal distribution with a mean of zero. During the process of this joint estimation, a correlation coefficient represented by $\rho_{\varepsilon u}$ between the error term ε_{ij} and u_{ij} is generated. A significant $\rho_{\varepsilon u}$ indicates a significant correlation between the error term ε_{ij} and u_{ij}, which would suggest that there exists selection bias caused by unobservable variables (Leng et al., 2020; Ma and Abdulai, 2017). Specifically, a negative and significant $\rho_{\varepsilon u}$ indicates a negative selection bias, suggesting that plots with lower-than-average yield and fertilizer input are more likely to be planted with new maize varieties by farmers.

For the identification of the TE model, Eq. (1) necessitates the inclusion of at least one instrumental variable (IV) within Z_{ij} or H_i, while ensuring its absence in X_{ij}, P_{ij}, and H_i in Eq. (2). The IV is considered valid if it influences the adoption of new maize varieties but does not have a direct impact on maize yield and fertilizer input. In this study, two variables representing the history of natural disasters in the past three years are used as IVs. Farmers' experience of natural disasters in previous seasons may affect their decision to adopt new varieties, but it should not affect maize yield and fertilizer input in the current season.

The estimated coefficients of the TE model signify only marginal impacts. To further ascertain the average effects of new maize variety adoption, we compute the average treatment effects (ATE) and the average treatment effects on the treated (ATT) by employing the following methodology:

$$ATE = E(log(Y_{1ij}) - log(Y_{0ij})) = E\{E(log(Y_{1ij}) - log(Y_{0ij}) |Z_{ij}, H_i)\} \quad (4)$$

$$\begin{aligned} ATT &= E(log(Y_{1ij}) - log(Y_{0ij}) |V_{ij} = 1) \\ &= E\{E(log(Y_{1ij}) - log(Y_{0ij}) |Z_{ij}, H_i, V_{ij}, V_{ij} = 1)|V_{ij} = 1\} \end{aligned} \quad (5)$$

$$ATE = E(F_{1ij} - F_{0ij}) = E\{E(F_{1ij} - F_{0ij}) |Z_{ij}, H_i)\} \quad (6)$$

$$ATT = E(F_{1ij} - F_{0ij}|V_{ij} = 1) = E\{E(F_{1ij} - F_{0ij}|Z_{ij}, H_i, V_{ij}, V_{ij} = 1)|V_{ij} = 1\} \quad (7)$$

where Eq. (4) and (6) are estimated using the full samples, including both new maize variety adopters and non-adopters. Conversely, Eq. (5) and (7) are estimated using only the sample of new maize varieties adopters in a counterfactual context.

3. Data, key variables measurement, and descriptive statistics

3.1. Data

The plot-level data used in this paper were gathered through surveys conducted in 2018 within three prominent grain provinces in China, namely Heilongjiang, Henan, and Sichuan, which respectively represent significant maize production regions in Northeast, Central, and Southwest China. Then, we proceeded with a stratified random sampling approach for sampling purposes. Four counties were randomly selected from each province and within each county, two towns were further randomly chosen. In each town, approximately 2–5 villages were randomly selected. Finally, three large-scale farmers and nine small-scale farmers were randomly selected.

The survey was conducted through face-to-face interviews. Given that some households cultivated only a single plot, we limited our information collection to no more than two plots per household. Through data cleaning, we dropped samples featuring missing information or lacking maize cultivation. The finalized dataset used in this study comprises 622 plots from 404 households. Among the 404 sampled households, 179 are classified as large-scale farmers, while 255 are categorized as small-scale farmers.[1] Of these, 186 households cultivated a single maize plot, whereas the remaining households cultivated two plots. Our survey questionnaire encompasses detailed information at both plot level and household level, such as detailed input-output data on maize production, adoption of crop varieties, occurrence of natural disasters in recent years, soil quality, household heads' education level, farming experience, and household's labor ratio.

The information on certified maize varieties in 2022 was retrieved from web page (www.a-seed.cn) using web scraping techniques. Then, we employed text analysis methods to organize and analyze the disclosed information on the traits of certified maize varieties.

3.2. Key variables measurement

The adoption status of new maize varieties serves as the dependent variable in the selection equation, denoted as Eq. (1), characterized by a binary outcome where the value is one if a farmer uses new maize varieties and zero otherwise. We utilize experience of natural disasters as IV variables in the selection equation, encompassing both climate

[1] Large-scale farmers were defined as that farm size is >3 times of the average farm size of the province or the county.

disaster experience and pest and disease disaster experience. The climate disaster experience is defined as the number of times that agricultural production was affected by climate disasters in the past 3 years (2014–2016), and pest and disease disaster experience is defined as the number of times that agricultural production was affected by pest and disease disasters in the past 3 years (2014–2016). According to Liu et al. (2021), we employed a falsification test to check the validity of the IVs. The results (see Supplementary Table S1) show that the chosen IVs have significant impacts on new maize variety adoption, but have no significant effects on maize yield and fertilizer input for the subsamples of non-adopters of new maize varieties, which implies that the IVs used in this paper are valid.

Maize yield and fertilizer input serve as the dependent variables in the outcome equations, corresponding to Eq. (2) and Eq. (3), respectively. Maize yield denotes the output of maize per unit area, standardized to a water content of 15%. Fertilizer input represents the amount of fertilizer applied per unit land area. The quantity of fertilizer input is converted to the quantity of the active ingredients of nitrogen, phosphorus, and potassium based on their proportion coefficients reported by farmers.

3.3. Descriptive statistics

Table 1 presents variable definitions and sample statistics. Within this table, it is demonstrated that the average maize yield was 464.36 kg/mu, which closely aligns with the average maize yield (479.2 kg/mu) in China reported by Chen et al. (2022a). The average fertilizer input was 27.35 kg/mu. Among the surveyed plots, 21% had sandy soil; 65% can be irrigated; and 78% were located on plain land. On average, household heads had 7.42 years of schooling and 31 years of farming experience. In our sample, the average frequency of agricultural production being affected by climate disasters and pest & disease disasters in the past 3 years (2014–2016) was 0.99 times and 0.09 times, respectively.

Figure 1a shows that approximately 51% of our surveyed plots suffered from natural disasters during maize production in 2017. Compared to the normal plots, the maize yields in the plots affected by natural disasters are significantly lower (Fig. 1b), accompanied by relatively higher fertilizer input (Fig. 1c). Furthermore, our survey revealed that 37% of the sample plots were planted with new maize varieties (Fig. 1d). The adopters of new maize varieties achieved higher maize yields (Fig. 1e and Supplementary Table S2) and, to a limited extent, used less fertilizer (Fig. 1f and Supplementary Table S2). Additionally, Table S2 of the Supplementary presents the mean difference in other plot- and household-level characteristics between individuals who have embraced new maize varieties and those who have not. This Table highlights systematic differences in observed characteristics between these two groups. For instance, new maize varieties were more likely to be cultivated on land with low quality and without sandy soil. Adopters of new maize varieties also experienced fewer climate-related disasters but more pest & disease disasters in the past 3 years. However, these simple descriptive statistics do not take various confounding variables into account, therefore a more rigorous econometric evaluation approach is required.

Table 1
Variable definitions and descriptive statistics.

Variables	Definition	Mean	S.D.
Dependent variables			
Maize yield	(kg/mu)	464.36	128.64
Fertilizer input	(kg/mu)	27.35	11.32
Independent variables			
Key independent variable			
New varieties	Whether the variety was used by the household for the first time (1 = Yes,0 = No)	0.37	0.48
Plot-level variables			
Natural disaster	1 = Maize production was impacted by climate disasters or pest and disease disasters, 0 = Others	0.51	0.50
Labor input	(Daily worker/mu)	2.64	5.54
Pesticide input	(yuan/mu)	22.89	22.09
Machine input	(yuan/mu)	73.06	89.53
Seed expenditure	(yuan/mu)	67.86	53.72
Other input	(yuan/mu)	3.77	16.58
Plot area	Area of maize plot (mu)	19.67	91.22
Distance	Distance from the plot to the homestead (0.5 km)	1.84	2.71
Sandy soil	Whether soil is sandy soil (1 = Yes, 0 = No)	0.21	0.41
Irrigation	Whether land can be irrigated (1 = Yes, 0 = No)	0.65	0.48
High quality	1 = High self-reported land quality, 0 = Others	0.41	0.49
Medium quality	1 = Medium self-reported land quality, 0 = Others	0.51	0.50
Low quality	1 = Low self-reported land quality, 0 = Others	0.07	0.26
Plain land	1 = Plain land, 0 = Others	0.78	0.41
household-level variables			
Education	Educational attainment of household head (years)	7.42	2.83
Cadre	1 = Household head is a village cadre, 0 = Others	0.28	0.45
Farming years	Years of household head's agricultural engagement (years)	31.44	12.80
Labor rate	The proportion of household labor force (%)	61.84	24.08
Number of plots	Number of land parcels	10.47	17.39
Climate disaster experience	Number of times that agricultural production was affected by climate disasters in the past 3 years (2014–2016)	0.99	1.19
Pest and disease disaster experience	Number of times that agricultural production was affected by pest and disease disasters in the past 3 years (2014–2016)	0.09	0.46
Expenditure	Household expenditure (10^4 yuan)	3.58	3.75
Heilongjiang	Residence of household (1 = Heilongjiang, 0 = Others)	0.41	0.49
Henan	Residence of household (1 = Henan, 0 = Others)	0.35	0.48
Sichuan	Residence of household (1 = Sichuan, 0 = Others)	0.24	0.43

6.75 Yuan =1 USD in 2017; 15 mu = 1 ha.

4. Empirical results and discussion

Main regression analysis results about the determinants of adopting new maize varieties, and its effects on maize yield and fertilizer input are presented in Fig. 2 and Fig. 3, respectively. Detailed information of regression results is included in Table 2 and Table 3. In terms of the impacts on maize yield, the estimated association between the selection error and the outcome error is −0.170, demonstrating statistical significance at the 5% level (Table 2), suggesting the existence of adverse selection bias. Concerning the impacts on fertilizer input, the estimated coefficient of correlation stands at −0.823, exhibiting statistical significance at the 1% level (Table 3), providing additional evidence indicative of the existence of adverse selection bias. Therefore, the selection bias issue cannot be neglected, and the TE model is more appropriate.

4.1. The factors affecting farmers' adoption behavior

Our results reveal that the experience of enduring natural disasters significantly influences farmers' new maize variety adoption, as demonstrated in Fig. 2, Table 2, and Table 3. More specifically, a history of climate disasters shows a negative and statistically significant effect on farmers' inclination toward adopting new maize varieties, whereas a history of pest and disease disasters has a positive and statistically significant impact. These findings imply a diminished likelihood of new

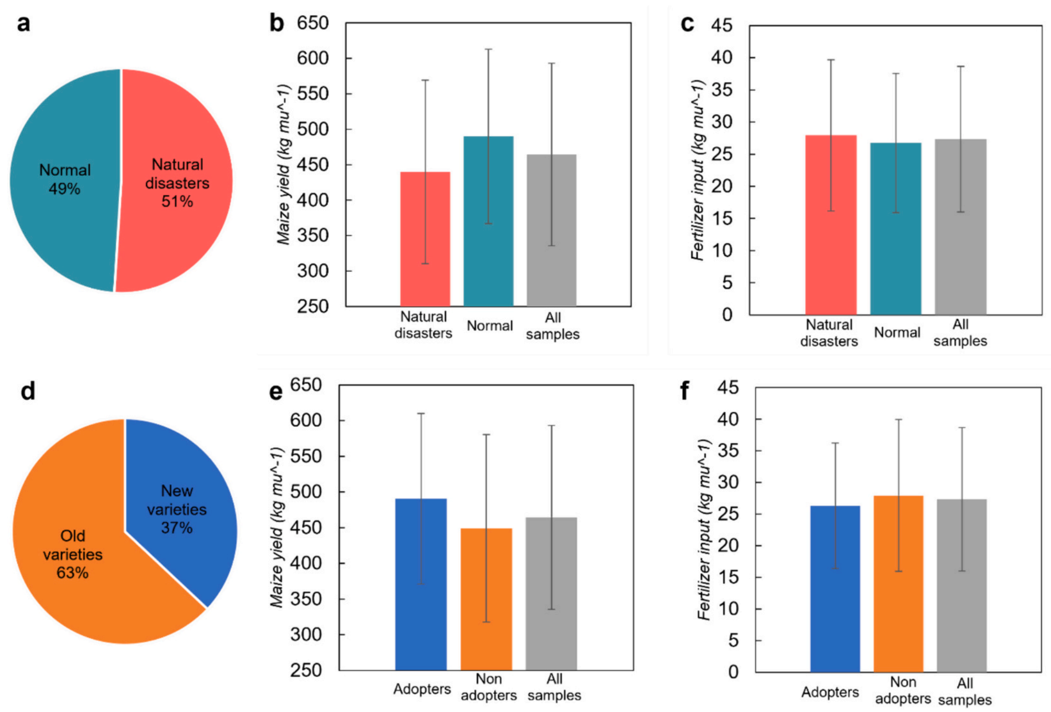

Fig. 1. Comparison of maize yield and fertilizer input among different groups. a, The proportion of plots affected by natural disasters. b, Average maize yield of climate disaster group, normal group, and all sample group. c, Average fertilizer input of climate disaster group, normal group, and all sample group. d, The proportion of plots cultivating new maize varieties. e, Average maize yield of new maize variety adopters, non-adopters, and all samples. f, Average fertilizer input of new maize variety adopters, non-adopters, and all samples.

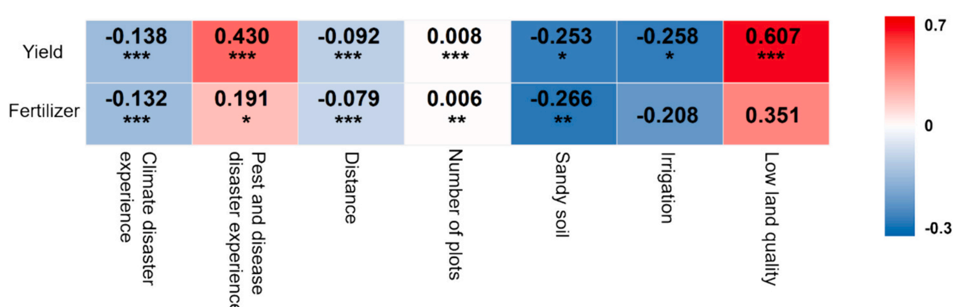

Fig. 2. Estimation of main factors affecting new maize variety adoption.
The first line presents the estimated results of maize yield selection equation (Detailed information can be found in Table 2). The second line presents the estimated results of fertilizer input selection equation (Detailed information can be found in Table 3). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

maize variety adoption in the current season among households that have experienced recurrent occurrences of climatic disasters in preceding seasons. Our finding aligns with the discoveries made by Bai et al. (2015), elucidating the adverse and statistically significant effect of unfavorable weather conditions in preceding seasons on the adoption rates of new maize varieties. However, our results indicate that there is a heightened likelihood of new maize variety usage in the current season among households previously affected by pest and disease calamities. One plausible explanation is that farmers have easier access to information about biotic-stress resistance of new maize varieties, whereas information about abiotic-stress resistance is lacking. Therefore, when facing anticipated climate risks, farmers tend to opt for familiar old varieties out of risk aversion, as they possess more knowledge about them (Bai et al., 2015).

In addition, our results suggest that land conditions have significant effects on the usage of new maize varieties (Fig. 2, Table 2, and Table 3). Specifically, the coefficient of distance is negative and statistically significant, which implies that household exhibit a decreased inclination to cultivate new maize varieties in plots situated at a greater distance from their homestead. Additionally, our estimation indicates an increased likelihood among farmers to opt new maize varieties in plots characterized by non-sandy soil, non-irrigation, and low land quality. Furthermore, an increase in the number of plots significantly enhances the likelihood of new maize variety adoption. Previous literature has also documented the influence of land conditions on new variety adoption (Bai et al., 2015; Aryal et al., 2018a, 2018b). For example, Aryal et al. (2018a) observed a reduced inclination among farmers to plant stress-tolerant varieties on plots characterized by good soil fertility, which is consistent with our results. Also, Bai et al. (2015) found a tendency among farmers to allocate a larger portion of land to old varieties specifically on sandy loam soil.

4.2. Impacts of adopting new maize varieties on maize yield

Figure 3a and the four to seven column of Table 2 present the effects of adopting new maize varieties on maize yield. The estimated results

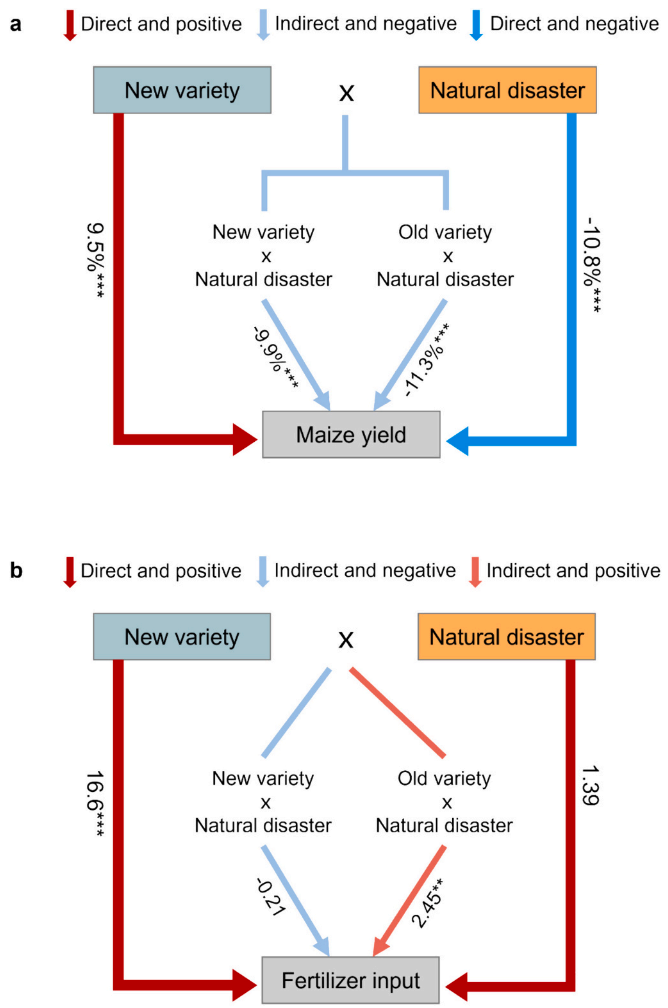

Fig. 3. Estimated impacts of new maize varieties adoption and natural disasters on maize yield and fertilizer input. a, Maize yield. b, Fertilizer input. Detailed information can be found in Table 2 and Table 3, respectively. Other plot- and household-level variables are controlled for. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

indicate a positive and statistically significant correlation between new maize variety adoption and maize yield. Specifically, adopting new maize varieties increases maize yield by an average of 9.5%. As excepted, the coefficient for natural disaster is negative and statistically significant, signifying an average reduction of maize yield by 10.8% following the incidence of such disasters. However, adopting new maize varieties can mitigate the negative impacts of natural disasters on maize yields. Compared to old maize varieties, adopting new maize varieties can reduce yield loss resulting from natural disasters by 1.4 percentage points (9.9% vs. 11.3%). Additionally, Table 4 shows that the estimated ATE of adopting new maize varieties on maize yield is 9.4%, which confirms the positive role of new maize varieties in increasing maize yield. Our results align with prior research (Yorobe Jr et al., 2016; Wossen et al., 2017; Simtowe et al., 2019), which found that the usage of new improved crop varieties has a positive effect on yield and reduces production risk.

The reminder of Table 2 confirms the necessity of controlling other variables that help explain households' maize production. Regarding the coefficients for different inputs, only seed input has a positive and significant effect on maize yield. Our finding reveals that further increases in maize output in China mainly depend on seed input, while further increases in other inputs will not necessarily lead to higher maize yields. Additionally, cultivating maize on plain plots exhibits a significant 5.9% increase in maize yield compared to cultivating maize on sloping plots, which aligns with the conclusions drawn by Chen et al. (2022a). The positively significant coefficient associated with the education variable indicates that as farmers possess higher levels of education, their maize cultivation yields also increase. This discovery echoes the observations made by Chen et al. (2022a), who demonstrate that education positively affects maize yield in China. Finally, household expenditure, which represents the wealth of a household, also contributes to the production of maize. The coefficient of household expenditure is 0.004, displaying statistical significance at the 5% level. This suggests that maize yield increases 0.4% when household expenditure increases by ten thousand yuan.

4.3. Impacts of adopting new maize varieties on fertilizer input

Figure 3b and Table 3 show that, when controlling all covariates, new maize variety adoption is positively associated with fertilizer input. To be specific, new maize variety adoption increases fertilizer input by 16.6 kg/mu. Similarly, the estimated ATE of new maize varieties on fertilizer input is 16.6 (Table 4). This finding is similar as that of Emerick et al. (2016), who found that the adoption of a new rice variety significantly increases farmers' fertilizer use.

The estimated coefficient for natural disaster is not significant (Fig. 3b and Table 3, column 4); however, the coefficient for the interaction between old maize varieties and the natural disaster variable exhibits statistical significance in a positive direction, which implies that farmers planting old maize varieties increase fertilizer input by 2.5 kg/mu when they suffer from natural disasters. The coefficient for the interaction between new maize varieties and the natural disaster variable is not statistically significant, indicating that farmers who adopt new maize varieties do not change their fertilizer input behavior when facing natural disasters. One possible explanation is that new maize varieties may have better stress resistance than old maize varieties, reducing the need for farmers to increase fertilizer input to combat natural disasters.

The estimated results of other control variables are also presented in Table 3. The coefficient associated with plot distance demonstrates both statistical significance and a positive direction, indicating an increased fertilizer application by farmers on plots located at a greater distance from their homestead. This discovery aligns with Tan et al. (2008), who found that fertilizer costs are higher on farms with greater average plot distance. In addition, our findings suggest a significant inverse relationship between the number of plots and fertilizer input, which aligns with the discovery of Tan et al. (2008), where fertilizer costs were found to decrease as plots became more fragmented. Furthermore, compared to plots with high land quality, plots with medium land quality require higher levels of fertilizer input. Lastly, the positively significant coefficient associated with plain land variable reveals that farmers use more fertilizer on plain plots than on sloping plots, likely because it is more challenging to apply fertilizer on sloping plots than on plain plots.

4.4. Household heterogeneity

Considering that households' adoption behaviors of new maize varieties and their impacts may vary across different farm scales, we conduct the above analysis separately for small- and large-scale farmers. Fig. 4 illustrates the outcomes derived from the estimation process (Detailed information can be found in Supplementary Table S3 and Supplementary Table S4). The results reveal that both climate disaster experience and pest & disease disaster experience significantly affect the usage of new maize varieties by small-scale farmers. Specifically, the experience of climate disasters diminishes the likelihood of small-scale farmers adopting new maize varieties, while the experience of pest and disease disasters increases it. However, for large-scale farmers, pest and disease disaster experience exerts a positive and significant influence on their inclination toward adopting new maize varieties, whereas

Table 2
The determinants of adopting new maize varieties and its impacts on maize yield.

	Selection equation		Outcome equation			
	New variety adoption		Ln (yield)		Ln (yield)	
	Coef.	Std. Err	Coef.	Std. Err	Coef.	Std. Err
New varieties			0.095***	0.028	0.086***	0.031
Natural disaster			−0.108***	0.019		
Old variety suffer from natural disasters					−0.113***	0.026
New variety suffer from natural disasters					−0.099***	0.027
Climate disaster experience	−0.138***	0.049				
Pest and disease disaster experience	0.430***	0.138				
Ln (labor)			−0.014	0.016	−0.014	0.016
Ln (fertilizer)			−0.002	0.005	−0.002	0.005
Ln (pesticide)			−0.000	0.004	−0.000	0.004
Ln (machinery)			0.002	0.001	0.001	0.001
Ln (seed)			0.033*	0.019	0.034*	0.019
Ln (other inputs)			−0.004	0.003	−0.004	0.003
Plot area	−0.001	0.001	−0.000	0.000	−0.000	0.000
Distance	−0.092***	0.028	0.003	0.003	0.003	0.003
Sandy soil	−0.253*	0.142	0.034	0.022	0.033	0.022
Irrigation	−0.258*	0.138	0.037	0.023	0.037	0.023
Land quality (base: land quality = High)						
medium	−0.192	0.118	0.008	0.024	0.008	0.024
Low	0.607***	0.227	−0.032	0.038	−0.032	0.038
Plain land	−0.175	0.146	0.059**	0.027	0.059**	0.027
Education	−0.015	0.022	0.009**	0.004	0.008**	0.004
Cadre	−0.083	0.127	0.002	0.020	0.002	0.020
Farming years	0.003	0.005	0.001	0.001	0.001	0.001
Labor rate	−0.001	0.002	−0.000	0.000	−0.000	0.000
Number of plots	0.008***	0.003	−0.000	0.001	−0.000	0.001
Expenditure	−0.020	0.016	0.004**	0.002	0.004**	0.002
Henan	−0.440***	0.147	−0.284***	0.032	−0.284***	0.032
Sichuan	−1.230***	0.174	−0.370***	0.058	−0.370***	0.058
Constant	0.837**	0.352	6.657***	0.111	6.660***	0.113
rho	−0.170 (0.065) **					
Wald test (rho = 0)	Chi^2 (1) =6.48, Prob>chi^2 = 0.011					
N	662					

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; The reference region is Heilongjiang.

the coefficient for climate disaster experience is not significant. One possible explanation is that, compared to small-scale farmers, large-scale farmers have better access to information on climate change and can adopt more targeted climate adaptation practices. Consequently, climate disasters have no significant impact on the adoption of new maize varieties among large-scale farmers.

In addition, Fig. 4 also indicates that for small-scale farmers, new maize variety adoption significantly increases maize yield by 12.7%, while the coefficient for large-scale farmers is not statistically significant. One reason could be the heightened engagement of large-scale farmers with seed vendors, with which large-scale farmers are more likely to possess up-to-date information on the latest maize varieties. Therefore, they may update their maize varieties more frequently, resulting in no significant difference in maize yield between new and old maize varieties for large-scale farmers. Additionally, the incidence of natural disasters significantly diminishes maize yield for both small- and large-scale farmers, with reductions of 12.1% and 7.2%, respectively (Supplementary Table S3). This finding implies that large-scale farmers possess enhanced capacities to cope with natural disasters and mitigate the risk associated with yield reduction during maize production.

The coefficients for new maize variety adoption on fertilizer input differ between small- and large-scale farmers (Fig. 4 and Supplementary Table S4). Specifically, small-scale farmers significantly increase fertilizer input by 12.38 kg/mu when planting new maize varieties, whereas large-scale farmers significantly reduce fertilizer input by 8.31 kg/mu. These findings indicate that the cultivation of new maize varieties by large-scale farmers can generate positive environmental benefits, but the risk of non-point source pollution may be increased due to the adoption of new maize varieties by small-scale farmers. Furthermore, the estimated results indicate that large-scale farmers significantly increase fertilizer input by 3.2 kg/mu to cope with natural disasters, while small-scale farmers do not change their behavior of fertilizer application (Supplementary Table S4).

4.5. Robustness analysis

To check the robustness of the TE model estimates, we also assess the impacts of new maize variety adoption on maize yield and fertilizer input using a 2SLS model. Supplementary Table S5 presents the results, which indicates a statistically significant positive influence of adopting new maize varieties on both maize yield and fertilizer input. Furthermore, Table S5 also demonstrates that climate disaster experience significantly decreases the likelihood of farmers planting new maize varieties, while pest and disease disaster experience significantly increases the likelihood of such adoption. These findings confirm our previous results. Besides, we replace the Cobb-Douglas production function with a Translog production function to further test the robustness of the effect of new maize variety adoption on maize yield, and the results (see Supplementary Table S6) further confirm the positive and significant effect of new maize variety adoption on yield.

4.6. Trade-off between economic and environmental impacts

The empirical results indicate that new maize variety adoption significantly increases maize yield by 9.4% but fertilizer input by 16.6 kg/mu. On the one hand, an increase in maize yield implies a positive economic impact in terms of increased efficiency of maize production by farmers, which contributes to food security. On the other hand, N use

Table 3
The determinants of adopting new maize varieties and its impacts on fertilizer input.

	Selection equation		Outcome equation			
	New variety adoption		Fertilizer input		Fertilizer input	
	Coef.	Std. Err	Coef.	Std. Err	Coef.	Std. Err
New varieties			16.607***	1.585	17.973***	1.951
Natural disaster			1.390	0.846		
Old variety suffer from natural disasters					2.452**	1.071
New variety suffer from natural disasters					−0.213	1.458
Climate disaster experience	−0.132***	0.039				
Pest and disease disaster experience	0.191*	0.113				
Plot area	−0.001	0.001	0.004	0.004	0.004	0.003
Distance	−0.079***	0.024	0.671***	0.197	0.668***	0.197
Sandy soil	−0.266**	0.128	−0.483	1.376	−0.417	1.370
Irrigation	−0.208	0.133	1.526	1.436	1.504	1.438
Land quality (base: land quality = High)						
medium	−0.178	0. 108	2.695**	1.219	2.715**	1.218
Low	0.351	0.263	2.320	2.882	2.365	2.868
Plain land	−0.183	0.139	4.427***	1.455	4.448***	1.449
Education	−0.043*	0.023	−0.149	0.281	−0.137	0.280
Cadre	−0.001	0.120	0.129	1.312	0.151	1.311
Farming years	−0.004	0.005	−0.001	0.052	0.001	0.052
Labor rate	−0.002	0.002	0.008	0.026	0.008	0.026
Number of plots	0.006**	0.003	−0.086***	0.028	−0.085***	0.028
Expenditure	−0.019	0.015	0.064	0.184	0.071	0.182
Henan	−0.416***	0.127	2.904**	1.376	3.037**	1.388
Sichuan	−1.118***	0.176	11.436***	2.005	11.419***	2.004
Constant	1.256***	0.364	10.788**	4.926	10.052**	4.991
rho	−0.823 (0.045) ***					
Wald test (rho = 0)			Chi^2 (1) =70.13, Prob>chi^2 = 0.000			
N			662			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; The reference region is Heilongjiang.

Table 4
Treatment effects of new maize varieties on maize yield and fertilizer input.

	ATE	z-value	ATT	z-value
Maize yield	0.094 (0.027)***	3.42	0.094 (0.028)***	3.42
Fertilizer input	16.606 (1.571)***	10.57	16.565 (1.572)***	10.53

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

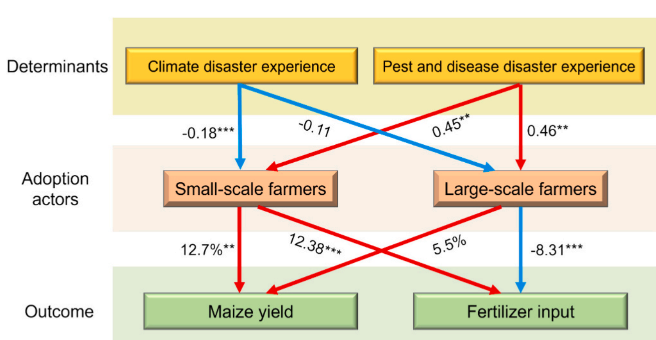

Fig. 4. Estimates of household heterogeneity. Detailed information can be found in Supplementary Table S3 and Table S4. Other plot- and household-level variables are controlled for. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

efficiency of grain production in China has declined significantly since the 1990s (Ju et al., 2009), so that increased fertilizer use will result in more N loss to the environment, which in turn will cause environmental degradation (Zuo et al., 2018; Ju et al., 2009). Therefore, it reveals a trade-off between the economic and environmental impacts of new maize variety adoption.

According to the results of Table 2, increased yields come from improved varieties, as the new maize varieties have significantly higher yields and are effective in reducing yield losses caused by natural disasters compared to the old varieties. Previous studies have also found that new crop varieties with traits of high yield and stress tolerance can effectively increase productivity (Villano et al., 2015; Zhou et al., 2018) and secure stable yield under natural disasters (Simtowe et al., 2019; Wossen et al., 2017; Kostandini et al., 2011; Katengeza and Holden, 2021). However, due to risk aversion and a lack of experience in planting new maize varieties, farmers tend to increase daily fertilizer input to ensure field performance and reduce the risk of yield losses. This mechanism is further validated by the results of heterogeneity analysis (see Fig. 4), which indicate that small-scale farmers, rather than large-scale farmers, significantly increase fertilizer input when planting new maize varieties, as small-scale farmers are more risk averse (Jin et al., 2015) and more likely to lack scientific cultivation information. The mechanisms behind the impacts of farmers' new maize variety adoption on yield and fertilizer input are summarized and displayed in Fig. 5.

5. Conclusion and policy implications

While numerous studies have focused on the determinants influencing crop variety adoption behavior, there has been a lack of systematic estimation regarding the economic and environmental impacts of adopting new crop varieties. This paper addresses this gap by examining the determinants influencing new maize variety adoption and assessing the impacts of such adoption on both maize yield and fertilizer input, using plot-level data collected from three major grain production provinces in China. Different from previous studies, we employ a TE model to correct selection bias and estimate the direct impacts of farmers' adoption of new maize varieties. Additionally, we investigate whether differences exist in maize yield and fertilizer usage between new and old maize varieties when faced with natural disasters. Furthermore, this study explores potential variations in the effects of new maize variety adoption between small- and large-scale farmers. Fig. 6 illustrates a graphical summary of our findings.

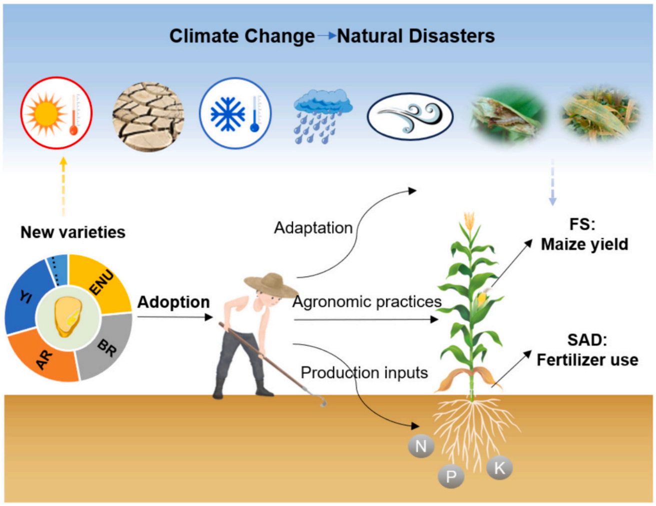

Fig. 5. The mechanisms underlying the impacts of farmers' new maize variety adoption.
YI, yield increase; AR, abiotic-stress resistance; BR, biotic- stress resistance; ENU, efficient nutrient utilization; FS, food security; SAD, sustainable agricultural development.

The results concerning the adoption of new maize varieties reveal that variables related to natural disaster experience, such as climate disaster experience and pest & disease disaster experience, as well as land characteristics including soil type, irrigation condition, land quality, number of plots, and distance from the homestead to the farmland, are identified as key factors influencing farmers' decisions to adopt new maize varieties. One interesting finding is that experiencing a higher frequency of pest and disease disasters significantly increases the likelihood of farmers adopting new maize varieties. Conversely, a higher frequency of climate disaster experiences significantly reduces such likelihood. One major reason may be that farmers often lack information about abiotic tolerance of new varieties, while information on insect and disease resistance is comparatively more accessible.

More notably, the empirical findings reveal a trade-off between the economic and environmental impacts of adopting new maize varieties. Our results indicate that the adoption of new maize varieties can significantly enhance maize yield by 9.4%. Simultaneously, new maize variety adopters use more fertilizer with 16.6 kg/mu on average than non-adopters. However, in the face of natural disasters, adopting new maize varieties results in a significant reduction in yield losses by 1.4% and a decrease in fertilizer input for natural disaster management by 2.45 kg/mu, as compared to the adoption of old varieties. These findings suggest that the adoption of new maize varieties may not necessarily result in both increased yields and enhanced sustainability in agricultural development. Nevertheless, it effectively addresses the challenges from natural disasters by mitigating yield losses and reducing the risk of excessive fertilizer application.

The results of the heterogeneity analysis indicate that, compared to the adoption of old varieties, small-scale farmers exhibit a more pronounced increase in maize yield when they adopt new varieties. However, when facing natural disasters, small-scale farmers suffer yield losses with 1.4 percentage points higher than those of large-scale farmers. In addition, planting new maize varieties by small-scale farmers leads to a significant increase in the use of fertilizer by 12.38 kg/mu, whereas that by large-scale farmers results in a significant reduction in fertilizer usage by 8.31 kg/mu. When confronted with natural disasters, large-scale farmers respond to these events by increasing fertilizer application, whereas small-scale farmers do not alter their fertilizer application behavior.

Our findings that adopting new maize varieties significantly increases both yield and fertilizer input, suggest that farmers planting new maize varieties in China cannot simultaneously achieve increased yield and reduced environmental pollution. One possible reason is a lack of information and cultivation experience of new maize varieties. Farmers, especially small-scale farmers, tend to be risk-averse (Jin et al., 2015). Therefore, they may increase fertilizer inputs to reduce the risk of yield reduction when cultivating new varieties. Another possible reason is that current breeding strategy does not effectively solve the problem of "trait trade-off" caused by linkage drag or gene pleiotropy, leading to the incompatible performance in yield and other aspects. Consequently, there are fewer crop varieties of synergistically optimized agronomic traits. It indicates the need of gene pyramiding and multiple character breeding for SFA. Moreover, our findings that the impacts of different experience with natural disasters on the adoption of new varieties vary, highlight the importance of variety traits resistant to abiotic stresses and the accessibility of variety information.

The revised national-level maize variety certification standards in 2021 emphasize the need for the identification of disease and pest resistance as well as lodging resistance in maize varieties. However,

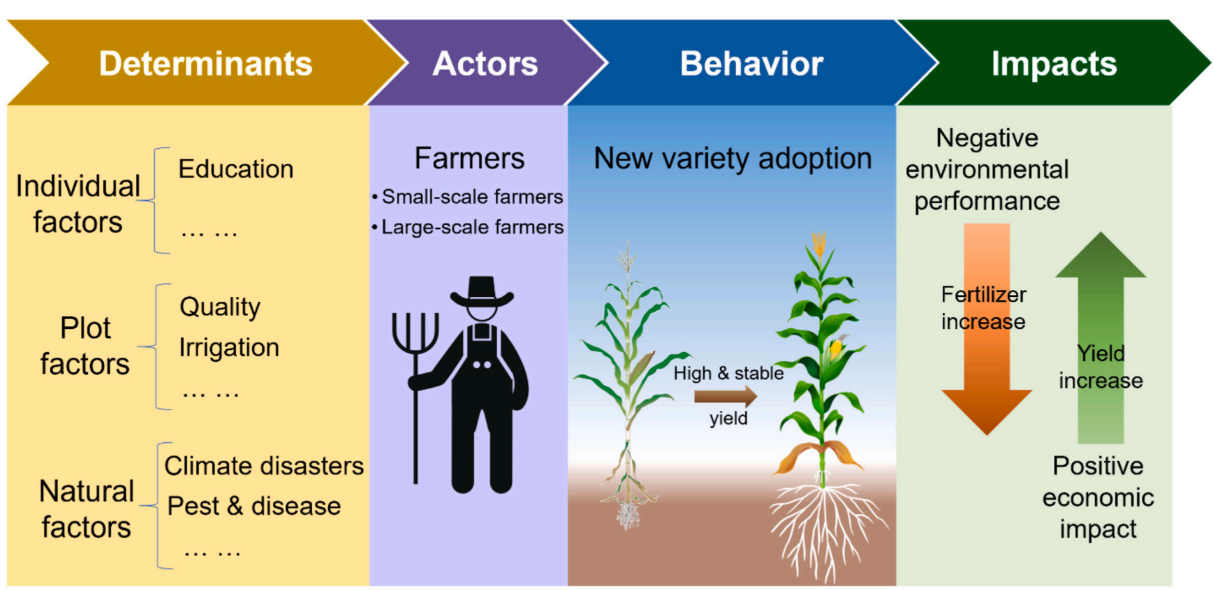

Fig. 6. Graphical summary of empirical results.

there is no explicit requirement for evaluating other traits related to resistance against abiotic stresses (NCVACC, 2021). In 2022, a total of 3028 maize varieties in China underwent certification, with 827 of them receiving national-level approval (MARA, 2022). Among these newly certified maize varieties, 89.70% disclosed information about their pest and disease resistance, 21.76% disclosed their lodging resistance status, while only 0.07% and 0.03% of these varieties disclosed their drought resistance and waterlogging tolerance status, respectively. Therefore, to promote the adoption of new crop varieties, ensure food security, and reduce agricultural non-point source pollution, policymakers could consider revising the criteria for crop variety validation. Such revisions would encourage breeding experts to develop more varieties with abiotic stress-tolerant traits. Additionally, the application of biotechnologies, such as gene editing, in biological breeding is crucial for ensuring food security (Wei et al., 2022a), which can significantly enhance breeding efficiency, shorten breeding cycles, and rapidly develop high-quality, environmentally friendly new varieties. China's application of biotechnologies in biological breeding has reached a level comparable to some developed countries (Wei et al., 2021). Nonetheless, its regulatory system for biotechnology crops maintains relatively strict, resulting in a limited variety, small-scale cultivation, and narrow application of commercially grown biotechnology crops (Wei et al., 2022b, 2022c). Therefore, there is a need for China to gradually open up the safety approval and commercial planting of biotechnology crops. Lastly, policymakers and researchers should accelerate the process of multiple desirable traits polymerizing such as broad resistance and high nutrient use efficiency during maize breeding.

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CRediT authorship contribution statement

Feifei Chen: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Huanguang Qiu:** Formal analysis, Data curation. **Yilin Zhao:** Writing – original draft. **Xun Wei:** Writing – review & editing, Conceptualization. **Xiangyuan Wan:** Writing – review & editing, Supervision.

Declaration of competing interest

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

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2024.104004.

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