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Assessing the environmental contribution of clustered regularly interspaced short palindromic repeats (CRISPR) rice in the presence of insect pest uncertainty

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Abstract
Adopting genome editing with the trait of pest resistance contributes to sustainable development by reducing pesticide use. Developed by Clustered Regularly Interspaced Short Palindromic Repeats (CRISPR) technology, CRISPR rice is resistant to two of its most destructive insect pests. However, there exists a trade-off between pest resistance and lower potential yield. In the presence of uncertainty of pest severity, adopting CRISPR rice demonstrates positive environmental benefits at its optimal planting ratio, estimated based on a microeconomic model extended with environmental externalities of rice cultivation. We estimate the optimal planting ratio to be 37%, with the environmental benefit of co-planting CRISPR rice to be 560 million US dollars annually in China. The environmental benefit accounts for 4–22% of the total value of co-planting CRISPR rice in the Monte Carlo simulations. Regional heterogeneity regarding optimal planting ratio and environmental benefit is studied for 12 major rice-cultivating provinces in China. We conclude with policy implications that policymakers need to consider the vast environmental benefit of CRISPR rice adoption to have a more comprehensive view of its economic and environmental market potential, contributing to the heated debate on regulating CRISPR technology in China and worldwide.

Keywords CRISPR rice · External cost · Environmental benefit · Uncertainty · China

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1 Introduction

The world is facing challenges in sustainable development. To achieve sustainable development, it is essential to harmonize economic growth, social inclusion, and environmental protection (Allen et al., 2018). The United Nations Member States in 2015 set 17 Sustainable Development Goals (SDGs) for sustainable development, including Zero Hunger, Good Health and Wellbeing, Clean Water and Sanitation, Climate Action, etc.. Fighting climate change, China targets sustainable development, as indicated by China's 14th *Five-Year Plan*, China's most crucial policy guideline since 1953. For the first time, the latest *Five-Year Plan* mentions that the economic growth should be within a reasonable interval but without mentioning an explicit growth target, which enables the flexibility to pursue the environmental goals and drive towards sustainable development (Guo et al., 2022; Sekar et al., 2021).

Agricultural production is critical in reaching sustainable development targets (Maroušek et al., 2022, 2023; Tanumihardjo et al., 2020; Viana et al., 2022). Reducing pesticide use in agricultural production has become a goal many countries share. In the United States, pesticides have been shown to pose a chronic threat to aquatic life in rivers (Stackpoole et al., 2021). Overuse of pesticides is one of the sources of emerging contaminants in agroecosystems and is linked to human health hazards, such as headaches, nausea, reproductive disorders, and even cancer (Poudel et al., 2020; Thakur et al., 2008). Bees, birds, and other non-targeted plants are affected by the contamination of air, water, and soil due to the overuse of pesticides (Mishra et al., 2021). 77% of farmers in Southeast Asia overuse pesticides and 77% of expenditures in pesticides are found to be overused (Schreinemachers et al., 2020). Overusing pesticides challenges developing countries without the institutional framework to manage potential risks efficiently. However, reducing pesticide use is complicated because most agri-food sectors still depend on it to control pests and reduce yield loss.

For more than half of the world's population, rice is the staple food (Fukagawa & Ziska, 2019); China consumes more rice than any other country, with 155 million metric tons in 2021 (NBSC, 2021). The world rice acreage has 165 million hectares, but rice production suffers from pest damage, with an estimated annual loss of 30 billion US dollars (Chintalapati et al., 2023). Thirty million hectares of rice are cultivated in China, and the pest damage is estimated to reach an annual loss of 1.8 billion US dollars (Li et al., 2020). Pesticides are applied to reduce pest damage; however, Chinese rice farmers overuse pesticides by 57% above the recommended amount (Huang et al., 2021; Zhang et al., 2015). One solution to the overuse of pesticides and the negative externalities of pesticide use is insect-resistant rice.

By suppressing the biosynthesis of serotonin (a neurotransmitter in mammals) induced by insect infestation, the recently developed CRISPR-Cas technology for rice—CRISPR rice—is resistant to stem borers and planthoppers, the two most destructive insect pests of rice (Lu et al., 2018). With the trait of pest resistance, farmers adopting CRISPR rice can reduce pesticide use and, meanwhile, reduce the level of yield loss, which has both economic and environmental benefits. CRISPR rice is an alternative to genetically modified (GM) insect-resistant rice. The classic GM rice variety is *Bacillus thuringiensis* (Bt) rice, developed in the 1990s. In 2009, Bt rice received biosafety certificates in China, indicating that it is not more dangerous than conventional rice. In 2018, Bt rice was approved by the United States Food and Drug Administration and Environmental Protection Agency for consumption and importation to the United States (but not being cultivated). However, GM rice has not been commercialized in any country worldwide (Jin et al., 2019a). Compared to GM rice, CRISPR rice has a greater chance of being commercialized because it is indistinguishable from the rice developed by traditional breeding techniques. Not only is no new gene added, but a mutation producing a gene structure similar to that of CRISPR rice can also occur in nature (Carlin, 2011; Lu et al., 2018), which has implications for regulation.

At this moment, the United States and Canada do not consider products developed by CRISPR-Cas technology as GM products, regulate them in the same limited way as conventional products, and therefore, no segregation or labeling in the supply chain will be compulsory once commercialization is permitted (US Department of Agriculture [USDA], 2018; Government of Canada, 2022). Research has shown that consumers' willingness to pay for CRISPR products is more than for GM products (Hu et al., 2022; McFadden et al., 2021; Muringai et al., 2020; Wang et al., 2023). China, however, has not yet issued specific regulations on genome editing, including CRISPR-Cas technology. Therefore, there is the possibility that CRISPR rice may be regulated as non-GM rice.

Different from GM rice without significant difference in yield compared to conventional rice (Huang et al., 2005), CRISPR rice, however, due to its trade-off between pest resistance and lower potential yield, there exists an optimal planting share. When there are few pests, in the extreme case, CRISPR rice with no pests in the lab produces over 30% lower yield; when there is a severe pest outbreak, pest-resistant CRISPR rice outperforms conventional rice (Lu et al., 2018). The relative yield between these two extreme pest scenarios is ambiguous, indicating that co-planting CRISPR rice would be advisable only if CRISPR rice could outperform conventional rice. This trade-off implies an optimal planting share for CRISPR rice with economic consequences (Jin & Drabik, 2022).

The external costs of pesticide use will also affect the optimal planting share. External costs are reflected in various forms, such as pesticide resistance, acute or chronic health problems for consumers taking in pesticide residues, water pollution, etc. (Thambhitaks & Kitchaicharoen, 2021; Prannetvatakul et al., 2013). External costs are not included in the price of pesticides that farmers pay for, nor in the food that consumers pay for. Due to the trait of pest resistance of CRISPR rice, its external costs are supposed to be less due to less pesticide application than conventional rice (Shew et al., 2018), and therefore, co-planting CRISPR rice may generate a positive environmental contribution. Although studies cover the environmental aspects of adopting insect-resistant GM crops (Brookes, 2019; Jin et al., 2019b), we are unaware of any study analyzing CRISPR rice from an environmental perspective.

To fill in the knowledge gap, we first extend the microeconomic model of CRISPR rice developed by Jin and Drabik (2022) by including the environmental externalities under uncertainty of pest severity. Our objective is to examine the environmental contribution of co-planting CRISPR rice of a representative farmer compared to cultivating conventional rice alone, considering the external costs of pesticide use and the uncertainty of pest severity. We hypothesize that adopting CRISPR rice under pest uncertainty has positive environmental benefits. This hypothesis is vital for policymakers to make informed decisions on the adoption of genome editing in general and the adoption of CRISPR rice in particular.

This study contributes to the literature by (i) investigating the optimal planting share of CRISPR rice considering the external cost of pesticide use and the uncertainty of pest severity; (ii) exploring the relationship between the environmental benefit and optimal planting share of CRISPR rice; and (iii) capturing the regional heterogeneity of the CRISPR rice adoption in China.

2 Model

Our model adopts the microeconomic framework of CRISPR rice (Jin & Drabik, 2022) and further extends the framework to analyze its environmental contribution. Following Jin and Drabik (2022), we define that a representative farmer cultivates both CRISPR rice (indexed by $i = C$) and conventional rice ($i = V$) on separate fields. Hence, the application of inputs is possible to distinguish. There is uncertainty over pest severity, so there are two states of nature: a severe state (indexed by j = S) indicating a pest outbreak and a less severe state (j = N) where the pest occurrence is weak. We define the uncertainty of pest severity with the probability of the severe state as q and the probability of the less severe state as $(1-q)$. The acreage of CRISPR rice and conventional rice is L_C and L_V, respectively. The total rice acreage $(\overline{L})$ is fixed in a given year, that is $L_C + L_V = \overline{L}$. The uncertainty of pest severity is revealed in the middle/late stage of the year. We assume that the representative farmer decides the pesticide quantity to use at the beginning of the year, similar to land allocation. The farmer will, therefore, choose the optimal pesticide application rate (X_i, in kilograms per hectare). X_i is the total amount of pesticide applied per hectare per year. Due to the trait of pest resistance for CRISPR rice, its intensity of pesticide use is lower than that of conventional rice ($X_C < X_V$). Y_i denotes the yield of rice type i in the absence of pest damage. The market experts we contacted argued that the farmers would only accept a maximum difference of 10% yield; therefore, in the baseline model, $Y_V = 0.9\, Y_C$.

After we introduce the yield of two rice types, the production function of rice type i in state j can be written as

$$Q_{ij} = \left[\alpha_i Y_i + G_j\left(X_i\right)\left(1 - \alpha_i\right) Y_i\right] L_i. \tag{1}$$

We follow Lichtenberg and Zilberman (1986) to denote $G_j\left(X_i\right)$ as the abatement function for rice type i in state j, which measures the percentage of the potential loss that can be averted. We denote $\alpha_i \in (0, 1)$ as the proportion of the maximum yield left after the severe pest damage if no damage abatement actions exist. Therefore, the yield loss equals to $\left(1 - \alpha_i\right) Y_i$. CRISPR rice has a higher percentage of yield left than conventional rice because it is insect-resistant, that is $0 < \alpha_V < \alpha_C < 1$. Therefore, the actual yield of rice type i in state j can be written as $\alpha_i Y_i + G_j\left(X_i\right)\left(1 - \alpha_i\right) Y_i$ where for example, when $G_j\left(X_i\right) = 1$, it denotes the complete eradication of the destructive capacity, and when $G_j\left(X_i\right) = 0$, it represents zero elimination of the loss.

The total production cost in state j (c_j) can then be expressed as

$$c_j = mX_C L_C + s_C L_C + A_j L_C^{\varepsilon} + \left(mX_V + s_V + \varphi^j\right) L_V. \tag{2}$$

Following the case of GM crops, we assume seed companies of CRISPR rice have the market power to decide the price. We model the monopolistic power for CRISPR seeds following Dillen et al. (2009). s_V is the cost of conventional seed per hectare and δ is a price premium (%) by which the monopolist charges more for CRISPR seed than the market price of conventional seed. The cost per hectare of CRISPR seed is $s_C = (1 + \delta) s_V$. This representation of monopolistic pricing of CRISPR seed is consistent with the price-taking behavior of the representative farmer.

m denotes the price of an aggregated pesticide (dollars per kilogram). The pesticide cost for CRISPR and conventional rice is proportional to the cultivated area: $mX_C L_C$ and $mX_V L_V$. The aggregated non-linear term AL_C^{ε} denotes other costs involved in the production of CRISPR rice, which can be desegregated into two parts: first, the cost of fertilizer, machinery, and other linear costs; second, strictly convex (in land) segregation cost. The latter part represents the strictness of regulation based on how the Chinese government regulates CRISPR rice. The strict convexity of the non-linear part of the CRISPR rice cost is represented by the parameter $\varepsilon > 1$, representing the elasticity of other costs with respect to the acreage of CRISPR rice (e.g., the more significant the acreage of CRISPR rice, the more efforts the farmer has to spend to disaggregate two rice varieties). The positive parameter A is determined at the calibration stage. The farmer does not incur segregation costs for conventional rice; therefore, all other costs are captured in the constant cost per hectare, φ. The values of parameters A and φ depend on the state of nature (e.g., more labor and energy costs are likely necessary in the severe pest state).

To include the external cost (EC) in the microeconomic framework summarized above (Jin & Drabik, 2022), we define $\mathrm{EC} = \left(L_C X_C + L_V X_V\right)\xi$, where ξ denotes the external cost of rice cultivation (dollars per kilogram). As the pest intensities X_C and X_V are predetermined before the pest severity of a given year is revealed, the external cost is assumed to be the same for each unit of pest intensity (kilogram per hectare). However, the external cost for CRISPR and conventional rice varies due to the land allocation for the two rice types. After constructing the external cost, we can calculate the environmental benefit (EB) (environmental value) of adopting CRISPR rice as the difference between the external cost of planting conventional rice alone (where total land is allocated to the cultivation of conventional rice) and external cost of co-planting two rice types.

$$EB = \overline{L} X_V \xi - (L_C X_C + L_V X_V)\xi \tag{3}$$

Denoting the market price of rice type i as p_i, together with Eq. (1) denoting the production quantity and Eq. (2) denoting the production cost, the farmer's profit in state j is

$$\pi_j = p_C Q_{Cj} + p_V Q_{Vj} - c_j - EC \tag{4}$$

We follow previous empirical studies (e.g., Chen et al., 2018; Jin et al., 2017; Liu, 2013) and consider the representative farmer a risk-averter. The expected utility (EU) is

$$\max_{\{L_C, X_C, X_V\}} EU = qu\left(\pi_S\right) + (1-q)u\left(\pi_N\right). \tag{5}$$

The Bernoulli utility function is assumed to take the exponential form, $u\left(\pi_j\right) = -e^{-r\pi_j}$, which is a popular functional form in the empirical literature (e.g., Jin & Drabik, 2022; Bodnar et al., 2018; Zuhair et al., 1992) with r indicating constant absolute risk aversion (Chen et al., 2018). The farmer maximizes the expected utility (EU) by choosing the optimal acreage for CRISPR rice L_C and pesticide intensity X_C and X_V.

The optimal values for L_C, X_C, and X_V satisfy the first-order conditions

$$\frac{\partial EU}{\partial L_C} = q\frac{du}{d\pi_S}\frac{\partial \pi_S}{\partial L_C} + (1-q)\frac{du}{d\pi_N}\frac{\partial \pi_N}{\partial L_C} = 0 \tag{6}$$

$$\frac{\partial EU}{\partial X_C} = q\frac{du}{d\pi_S}\frac{\partial \pi_S}{\partial X_C} + (1-q)\frac{du}{d\pi_N}\frac{\partial \pi_N}{\partial X_C} = 0 \tag{7}$$

$$\frac{\partial EU}{\partial X_V} = q\frac{du}{d\pi_S}\frac{\partial \pi_S}{\partial X_V} + (1-q)\frac{du}{d\pi_N}\frac{\partial \pi_N}{\partial X_V} = 0. \tag{8}$$

The necessary condition for a maximum problem is that the first-order partial derivatives are equal to zero. Therefore, we set the first-order conditions of the expected utility from Eq. (5) with respect to L_C, X_C, and X_V to be zero listed in Eqs. (6)–(8), and solve the equation system to obtain the optimal values for L_C, X_C, and X_V (Please see the specific equivalents presented by 13–15 in "Appendix 1" for details). Finally, based on the results of the first-order conditions, the optimal planting share of CRISPR rice (ρ) equals the optimal acreage of CRISPR rice divided by the total rice acreage, that is $\rho = L_C \big/ \overline{L}$.

3 Data and model calibration

The data in this study are based on the literature on CRISPR and conventional rice. Where the data on CRISPR rice are not available (e.g., pesticide application rate and cost because the field trial of CRISPR rice has not started yet), we use the data from the GM rice field trials (Huang et al., 2005) as an approximation, because both rice types are pest-resistant. Table 1 summarises the data together with the sources.

Previous literature (e.g., Brookes et al., 2010; Pray et al., 2001) has argued that farmers growing GM crops can afford to accept lower market prices because the cost of cultivating pest-resistant GM crops is lower compared to the conventional ones due to fewer inputs (e.g., pesticides or labor) and the benefit of reduced inputs outweighs the higher seed cost. Therefore, we set the price of CRISPR rice equal to 90% of the price of conventional rice in the baseline model. Later, in the Monte Carlo simulations, we relaxed this assumption and set the price of CRISPR rice below that of conventional rice (i.e., $p_C \le p_V$). We assume other costs per hectare of conventional rice are equal under both weak and severe pest damage in the baseline model ($\varphi_N = \varphi_S$), but we relax this assumption in the Monte Carlo simulations.

Based on Chen et al. (2018), we set the parameter r to be 0.09 in the exponential Bernoulli utility function in the baseline. The higher r, the more risk-averse the farmer is, ceteris paribus. Due to a lack of data, we simplify the model by reducing the number of calibrated parameters and set equal the calibrating constants A_S and A_N for other costs of rice cultivation. We assume that they do not depend on the state of nature to make the segregation cost of CRISPR rice less sensitive to pest severity. With these parameters, we calibrate four unknown parameters (λ_S, λ_N, A, and ε) and one variable (L_C) in the baseline model.

The first-order conditions (6–8) calculate λ_S, λ_N, and L_C. To calculate the parameters A and ε, we need two more equations. According to Eq. (2), the cost of cultivating CRISPR rice is

$$C_C = mX_C L_C + s_C L_C + AL_C^{\varepsilon}, \tag{9}$$

from which we calculate the corresponding marginal cost by dividing Eq. (9) by L_C. Therefore, $MC_C = mX_C + s_C + \varepsilon AL_C^{\varepsilon-1}$.

Let η be the elasticity of land use with respect to the marginal cost of CRISPR rice:

$$\eta = \frac{\partial L_C}{\partial MC_C}\frac{MC_C}{L_C} = \frac{mX_C + s_C + \varepsilon AL_C^{\varepsilon-1}}{\varepsilon(\varepsilon-1)AL_C^{\varepsilon-1}}. \tag{10}$$

We use Eq. (9) to calculate the production cost per hectare of CRISPR rice (UC_C) as $UC_C = C_C \big/ L_C = mX_C + s_C + AL_C^{\varepsilon-1}$, from which $AL_C^{\varepsilon-1} = UC_C - mX_C - s_C$. Substituting the right-hand side of the previous equation into (10) and rearranging, we obtain

Table 1 Data and sources

Parameter	Symbol	Baseline value	Source	Minimum	Maximum	Source of max./min
External costs of rice cultivation ($/kg)	ζ	0.868	Thambhitaks and Kitchaicharoen (2021)	0.608	1.13	30% variation
Price of CRISPR rice (1000 $/ton)	p_C	0.255	Index Mundi (2020)	0.164	0.356	Historical data from 1997–2020, Index Mundi (2020)
Price of conventional rice (1000 $/ton)	p_V	0.283	Assumed based on the literature	0.164	0.356	Historical data from 1997–2020, Index Mundi (2020)
Percentage of max. CRISPR rice yield after the most severe insect pest damage	α_C	0.810	The average of the interval provided by He et al. (2016)	0.650	0.970	He et al. (2016)
Percentage of max. conv. rice yield after the most severe insect pest damage	α_V	0.640	The average of the interval provided by Xu et al. (2017)	0.400	0.880	Xu et al. (2017)
Price of pesticide (100 $/kg)	m	0.001	Personal communication	0.001	0.002	30% variation
Max. yield of CRISPR rice (ton/hectare)	Y_C	6.975	$0.9 \times Y_V$ based on communication with experts	4.883	9.068	30% variation
Max. yield of conv. rice (ton/hectare)	Y_V	7.750	National Bureau of Statistics of China (NBSC) (2021)	7.625	7.875	Historical data from 1997–2006, NBSC (2021)
Total rice area (million hectares)	$\overline{L}$	28.50	NBSC (2021)	26.50	31.80	Historical data from 1997–2006, NBSC (2021)
The shape parameter of the abatement function under weak pests	λ_N	0.969	Calibrated	0.678	1.260	30% variation
The shape parameter of the abatement function under severe pests	λ_S	0.005	Calibrated	0.004	0.007	30% variation
Parameter of other costs of CRISPR rice	A	0.145	Calibrated	0.102	0.189	30% variation
Probability of severe insect pests	q	0.341	Jiaan Cheng (2009)	0	1	definition
Segregation cost parameter	ε	1.500	Calibrated	1.422	1.522	30% variation
Constant absolute risk aversion	r	0.090	Chen et al. (2018)	0.070	0.110	Chen et al. (2018)

Table 1 (continued)

Parameter	Symbol	Baseline value	Source	Minimum	Maximum	Source of max./min
Other costs per hectare of conventional rice under weak pest (1000 $/hectare)	φ_S	0.862	Personal communication (2018)	0.603	1.120	30% variation
Other costs per hectare of conventional rice under severe pest (1000 $/hectare)	φ_N	0.862	Personal communication (2018)	0.603	1.120	30% variation
Cost per hectare of CRISPR rice (1000 $/hectare)	UC_C	0.521	Assumed the same as for Bt rice; Personal communication (2018)	The confidence interval is not provided here because UC_C is not directly used in Monte Carlo simulations		
Elasticity of land used for CRISPR rice with respect to the marginal cost of CRISPR rice production	η	2.121	Assumed	The confidence interval is not provided here because η is not directly used in Monte Carlo simulations		
Monopoly surcharge in the CRISPR rice seed market compared to conventional seed (relative number)	δ	0.652	Calibrated	0.000 2.000 assumed		
Price of conventional rice seed (1000 $/hectare)	s_V	0.023	Personal communication (2018)	0.013 0.036 Personal communication (2018)		
Price of CRISPR rice seed proxied by GM rice seed (1000 $/hectare)	s_C	0.037	Personal communication (2018)	$s_C = (1 + \delta)s_V$		

1 USD = 7 RMB

$$\varepsilon^2 - \frac{1+\eta}{\eta}\varepsilon - \frac{mX_C + s_C}{\eta\left(UC_C - mX_C - s_C\right)} = 0, \tag{11}$$

which is a quadratic equation in ε. Finally, we calibrate the constant A by rearranging the unit cost function as

$$A = \left(UC_C - mX_C - s_C\right) / L_C^{\varepsilon-1}. \tag{12}$$

CRISPR rice is not yet approved for commercialization, so its production cost per hectare is unknown. However, the production cost is essential for technology adoption from the perspectives of both farmers and seed developers (Akbari et al., 2021; Pavolova et al., 2021). To overcome this information gap, we use the cost of GM rice in the field trial as an approximation and set $UC_C = 521.3$ US dollars per hectare (Private Communication, 2018).

The parameter ζ (US dollars per kilogram) captures the external cost of rice cultivation. According to Thambhitaks and Kitchaicharoen (2021), the external cost equals 0.608 US dollars per kilogram based on a life cycle analysis, quantifying five environmental impacts from the cradle-to-farm gate, which include climate change, terrestrial acidification, water depletion, eutrophication, and human health damage.

Finally, we determine the baseline value of the parameter δ via an iterative process. The price of conventional rice seed (s_V) is known. We keep adjusting the value of δ until the calculated value of CRISPR rice seed (s_C) (for which there are no historical observations yet) equals the price of GM rice seed, an approximation for the price of CRISPR rice seed.

To sum up, we obtain the four unknown parameters and one variable by simultaneously solving Eqs. (13), (14), (15) ("Appendix 1"), (11), and (12). Numerically solving the five equations, we can obtain $\lambda_S = 0.004$, $\lambda_N = 0.855$, $A = 0.155$, $\varepsilon = 1.500$, and $L_C = 9.5$ million hectares.

4 Baseline model results

For a given probability of pest outbreak, would the farmer be better off planting both rice types or sticking to CRISPR or conventional rice from an economic and environmental perspective? The optimal planting share of CRISPR rice in the baseline is 33% (=9.5/28.5). The difference in the expected profit values between co-planting CRISPR rice and cultivating conventional rice alone is 2.9 billion US dollars—the economic value of co-planting CRISPR rice. Similarly, 115 million US dollars of negative externalities could have been reduced if CRISPR rice were co-planted—the environmental value of co-planting CRISPR rice.

Table 2 presents the results decomposed by pest severity and rice type with the baseline data. The fourth and sixth rows present profits and external costs in billions of US dollars, respectively. By dividing the corresponding acreage, the second and fourth rows quantify the profit per hectare and the external cost per hectare, respectively.

The profits in the severe pest case are lower than those in the weak one. The relative difference in the co-planting scenario shows that the gap for CRISPR rice is -26% (8.74/11.83–1) but is much more pronounced for conventional rice by − 56% (10.71/24.48–1). This suggests that conventional rice is more sensitive to the uncertainty of pest outbreaks than pest-resistant CRISPR rice. The conclusion applies to all scenarios since the difference between the profits in the severe and weak pest cases for conventional rice alone is − 56% (16.05/36.70–1), decreases to − 46% [(8.74 + 10.71)/(11.83 + 24.48)–1]

Table 2 Profits and external costs from rice production under various scenarios

	Severe pest				Weak pest			
	Both types planted		One type planted		Both types planted		One type planted	
	CRISPR	Conv	Only CRISPR	Only conv	CRISPR	Conv	Only CRISPR	Only conv
Total profit from a rice type i (billion \$)	8.74	10.71	26.24	16.05	11.83	24.48	35.53	36.70
Profit per hectare (\$/ha)	920.64	563.21	920.64	563.21	1246.32	1287.67	1246.32	1287.67
External cost from a rice type i (billion \$)	0.04	0.33	0.12	0.49	0.04	0.33	0.12	0.49
External cost per hectare (\$/ha)	4.34	17.36	4.34	17.36	4.34	17.36	4.34	17.36

Table 3 Results of the Monte Carlo simulations (N = 13,076) (billion US dollars)

Co-planting CRISPR rice and conventional rice	Min	1st quartile	Median	Mean	3rd quartile	Max	SD
Optimal share (%)	0	20	34	37	52	100	0.22
Economic value	− 0.27	0.69	1.71	2.29	3.38	12.41	2.05
Environmental value	− 0.01	0.19	0.45	0.56	0.81	3.52	0.49
Total value	− 0.28	0.88	2.16	2.85	4.19	15.93	N.A
Share of environmental value in total value (%)	4	22	21	20	19	22	N.A

This table shows that the research hypothesis is confirmed that adopting CRISPR rice under pest uncertainty has positive environmental benefits

when both types are grown, and further decreases to -26% (26.24/35.53–1) when CRISPR rice is cultivated alone. When both rice types are co-planted, the external cost is lower than that of planting conventional rice alone, with a gap of − 24% ((0.04 + 0.33)/0.49–1). This suggests that adopting CRISPR rice can reduce the external cost. Therefore, from the perspective of profit and external cost, co-planting CRISPR rice benefits the farmer economically and environmentally.

Based on profits per hectare, we expect the farmer to favor CRISPR rice, as it can generate 3% more profit per hectare in the weak pest scenario (1246.32/1287.67–1) and 1.6 times more in the severe pest scenario (920.64/563.21). Based on the external cost per hectare, we also expect the farmer to favor CRISPR rice, as it generates 75% less external cost per hectare in both weak and severe pest scenarios (4.34/17.36–1). Therefore, from the perspective of unit profit and unit external cost, co-planting CRISPR rice benefits the farmer economically and environmentally.

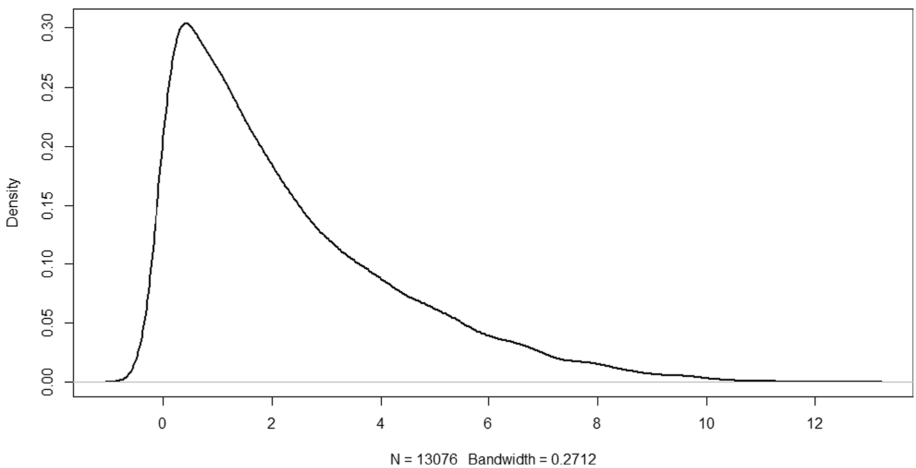

Fig. 1 Kernel density function of the economic value of co-planting CRISPR rice. *Note* The horizontal axis represents the economic value of co-planting CRISPR rice. The median, mean, and mode are 1.7, 2.3, and 0.4 billion US dollars, respectively; the standard deviation is 2.05

The baseline results depend on the chosen parameters. To check their robustness, we run Monte Carlo simulations with relaxed assumptions in the following section.

5 Sensitivity analysis of the baseline results

Based on a Project Evaluation and Review Technique (PERT) distribution for each parameter of interest (Table 1), we randomly draw the parameter values 100,000 times, and each time we run the model and record the results. We choose the PERT distribution because of its minimum prior information requirements: maximum, minimum, and mode. PERT distribution has advantages compared to other distributions, such as triangular distribution, because it constructs a smooth curve with the expectation that the resulting value will be around the most likely value.

Table 1 summarizes the baseline values of the parameters used as the mode of the PERT distribution and their confidence intervals. We use parameters with natural limits (e.g., probability of pest severity) for minimum and maximum. In the remaining cases, we depend on the previous literature (e.g., percentage of conventional yield left after severe pest damage), historical data (e.g., the market price of conventional rice per hectare), or in the absence of sources we set the lower (upper) bound to be 30% below (above) the baseline value (e.g., the parameter of the external cost ζ). We perform Monte Carlo simulations with the 'nleqslv' package in $R \times 64$ 4.0.5 (Fletcher, 2012; Hasselman, 2018; R Core Team, 2024).

Table 3 shows the results of Monte Carlo simulations for the optimal planting share, the total (economic and environmental) value of co-planting CRISPR rice, and the share of environmental value in the total value. We distinguish between cases where both rice types are cultivated and where the farmer cultivates conventional rice alone. Both scenarios are

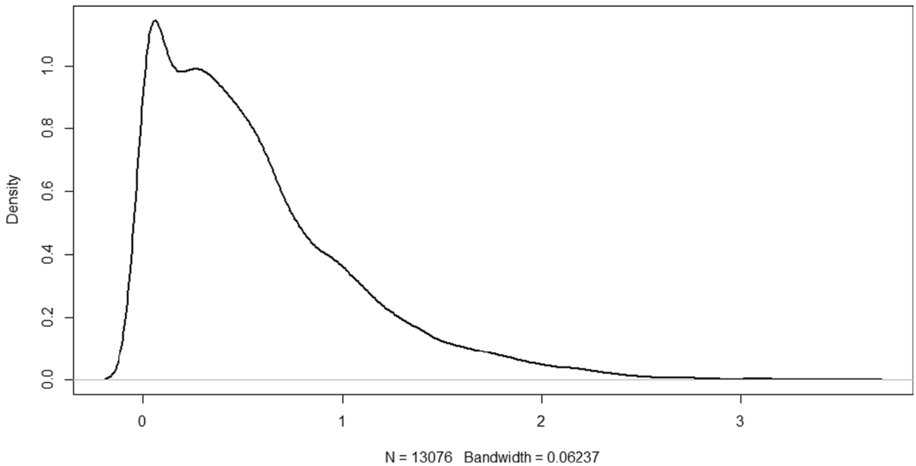

Fig. 2 Kernel density function of the environmental value of co-planting CRISPR rice. *Note 1* The horizontal axis represents the environmental value of co-planting CRISPR rice. The median, mean, and mode are 0.45, 0.56, and 0.07 billion US dollars, respectively; the standard deviation is 0.49. This figure shows that the research hypothesis is confirmed that adopting CRISPR rice under pest uncertainty has positive environmental benefits

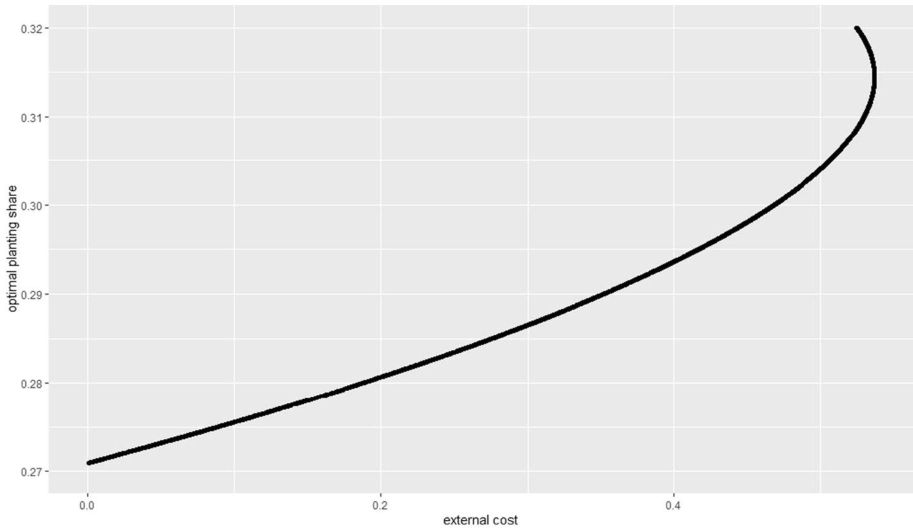

Fig. 3 Relationship between the external cost (1000 million US dollars) and the optimal planting share (%)

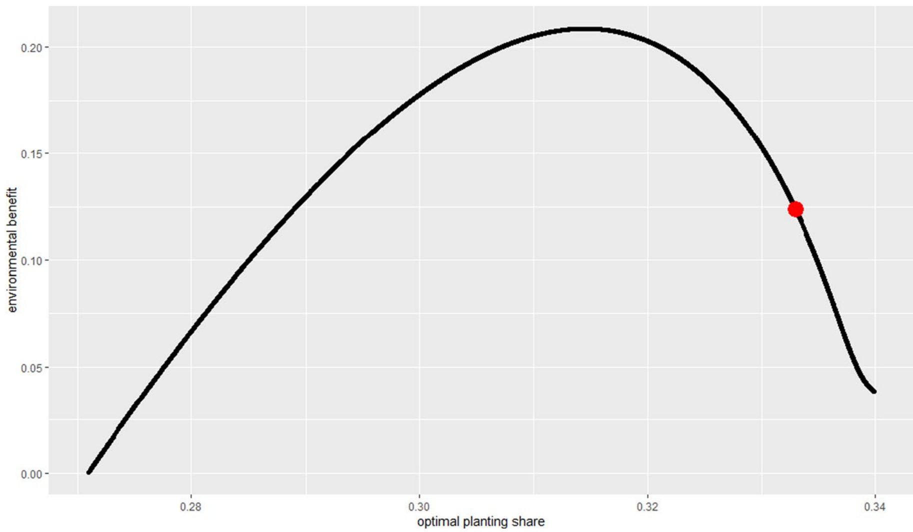

Fig. 4 Relationship between the optimal planting share (%) and the environmental benefit (1000 million US dollars). *Note* The red dot indicates the baseline with the optimal planting share and the environmental benefit equal to 33% and 115 million US dollars, respectively

run in one iteration, and the process is repeated 100,000 times. In each iteration, we randomly draw from the distributions of individual parameters. With those parameters, we calculate the variables of interest for both types of rice and conventional rice alone. It is essential to mention that not all results of the 100,000 model runs were considered. First, we excluded the infeasible solutions, those where the planting share was either negative or more significant than one. These solutions occur in numerical simulations due to some

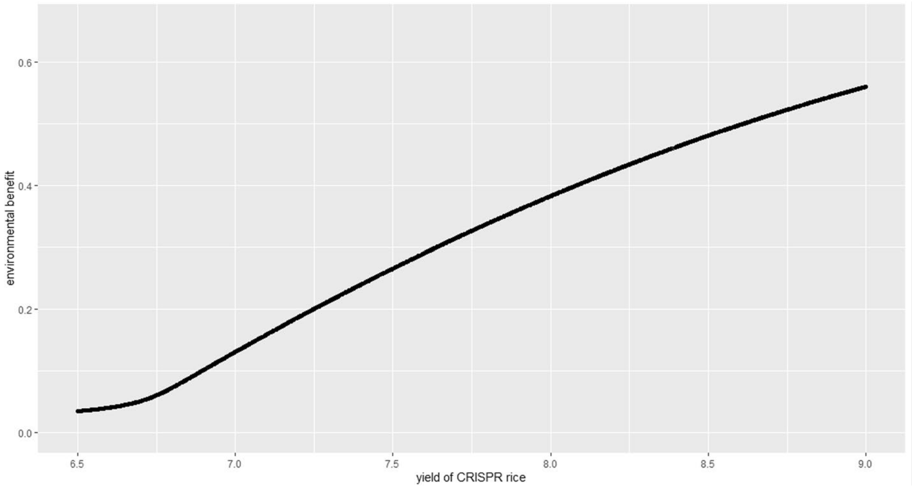

Fig. 5 Relationship between the yield of CRISPR rice (ton per hectare) and the environmental benefit (1000 million US dollars)

assemblages of model parameters. Second, for other constellations of exogenous parameters, the model could not converge due to the model's non-linearities and starting values that might not be close enough to the solution. In the end, we included the results of 13,076 model runs in the Monte Carlo simulation.

The last four rows in Table 3 estimate the economic, environmental, and total value of co-planting CRISPR rice and the share of environmental value in the total value of CRISPR rice adoption, respectively. The median of the economic value of co-planting CRISPR rice is 1.7 billion US dollars, and the mean is 2.3 billion US dollars, suggesting a distribution of the values skewed to the right. Overall, in 99% of the cases, we find a positive economic value in co-planting CRISPR rice. Our results are consistent with Jin and Drabik (2022) regarding the economic value of co-planting CRISPR rice with a mean of 2.3 billion US dollars, although the distribution is slightly different because our model also considers the external costs of pesticide use. Figure 1 depicts the kernel density function of the economic value of co-planting CRISPR rice.

For the environmental value of co-planting CRISPR rice, the median is 450 million US dollars, and the mean is 560 million US dollars. Overall, in 99% of the cases, we find a positive environmental value of co-planting CRISPR rice. Therefore, the research hypothesis is confirmed that adopting CRISPR rice under pest uncertainty has positive environmental benefits. The environmental value accounts for 4–22% of the total value of co-planting CRISPR rice. This is a moderate share of the total value not considered in previous studies. Figure 2 depicts the kernel density function of the environmental value of co-planting CRISPR rice.

6 Relationship between external cost, environmental benefit, potential yield and optimal planting share of crispr rice

It is consistent with the theoretical expectation that increasing the external cost of rice cultivation increases the optimal planting share. Maintaining all other parameters, we vary the parameter of external cost between 0 and 1.3 US dollars per kilogram, around a 50%

Table 4 Regional heterogeneity

Province	Hebei	Inner Mongolia	Liaoning	Jilin	Heilongjiang	Jiangsu
Pesticide intensity (kg/ha)	223	279	218	220	217	218
Pesticide cost (USD/ha)	295	369	289	291	288	289
Market price of japonica rice (USD/kg)	0.2	0.1	0.2	0.1	0.1	0.3
Environmental benefit (million $)	10	47	61	120	543	391
Optimal ratio (%)	69	100	66	81	80	100
Province	Zhejiang	Anhui	Shandong	Henan	Yunnan	Ningxia
Pesticide intensity (kg/ha)	219	207	207	231	252	208
Pesticide cost (USD/ha)	290	275	274	305	334	275
Market price of japonica rice (USD/kg)	0.4	0.2	0.3	0.3	0.2	0.2
Environmental benefit (million $)	92	251	15	75	119	5
Optimal ratio (%)	82	60	79	66	77	60

Source: The data on pesticide cost and market price of japonica rice are from the China National Development and Reform Commission (2021). Other data are calculated by the authors

1 USD = 7 RMB

increase from its baseline (0.868 US dollars per kilogram). The optimal planting share of CRISPR rice varies between 27 and 34% (baseline = 33%), and the external cost varies between 0 and 537 million US dollars (baseline = 371 million US dollars). In Fig. 3, the slope of the curve shows a positive relationship between the external cost and the optimal planting share of CRISPR rice. The increasing slope indicates that when the external cost increases, the optimal planting share not only increases but also increases with acceleration. This reflects the scale effect of environmental potential regarding adopting CRISPR rice. An inflection exists when the external cost equals 537 million US dollars, and the optimal planting ratio equals 31% because we manually set a range of the external cost in the simulation.

Figure 4 depicts a quadratic relationship between the optimal planting share and the environmental benefit. The red dot represents the baseline value. It is essential to notice that when the optimal planting share of CRISPR rice is chosen by maximizing the expected utility, it differs from the maximal environmental benefit as the baseline value is away from the vertex of the parabola. The maximal environmental benefit equals 209 million US dollars when the optimal planting share is 31%. This indicates a trade-off between maximizing the expected utility and the environmental benefit.

Figure 5 depicts a non-linear relationship between the yield of CRISPR rice and the environmental benefit. As expected, the higher the yield of CRISPR rice, the higher the environmental benefit of adopting CRISPR rice. This information is essential for the seed developers and other industrial stakeholders because increasing the potential yield of CRISPR rice can increase not only the profit of farmers but also its environmental contributions to society.

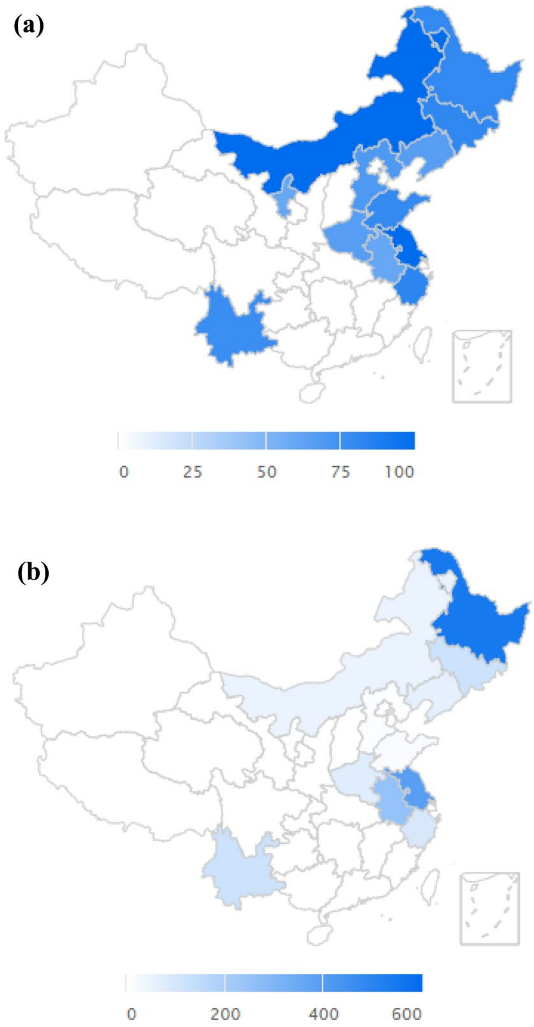

Fig. 6 **a**. Regional heterogeneity of the optimal planting share of CRISPR rice (%). *Note* We have the data on provincial pesticide usage for 12 major rice-cultivating provinces to study the heterogeneity of the optimal planting share of CRISPR rice. They are Anhui, Hebei, Heilongjiang, Henan, Inner Mongolia, Jiangsu, Jilin, Liaoning, Ningxia, Shandong, Yunnan, and Zhejiang. **b**. Regional heterogeneity of the environmental benefit of co-planting CRISPR rice (million US dollars). *Note* We have the data on provincial pesticide usage for 12 major rice-cultivating provinces to study the heterogeneity of the environmental benefit of co-planting CRISPR rice. They are Anhui, Hebei, Heilongjiang, Henan, Inner Mongolia, Jiangsu, Jilin, Liaoning, Ningxia, Shandong, Yunnan, and Zhejiang

7 Regional heterogeneity

The pesticide application of japonica rice in China is used to analyze the regional heterogeneity as a case study because more data are available compared to other rice varieties. The pesticide intensity (kilogram per hectare) for each province is estimated based on the pesticide cost (US dollar per hectare) divided by the market price of the pesticide (US dollar per kilogram) in 2021. Table 4 shows the estimated environmental benefit and the optimal planting share of CRISPR rice for 12 major rice-planting provinces in China.

Our model suggests adopting 100% CRISPR rice in Inner Mongolia and Jiangsu province so that the expected utility is maximized under the uncertainty of pest severity due to the relatively high pesticide costs and high market price of japonica rice, respectively. However, the optimal planting share of CRISPR rice for Ningxia and Anhui province is 60%, the lowest among those 12 provinces. Heilongjiang, Jiangsu, and Anhui province should gain the most environmental benefits, 543 million US dollars, 391 million US dollars, and 251 million US dollars, respectively. Although full adoption of CRISPR rice in Inner Mongolia is suggested, there does not seem to be an advantage in terms of environmental benefit due to the small acreage of rice cultivation (around 1% of the total rice acreage in China). For other provinces, their environmental benefits range between 5 and 120 million US dollars.

Figure 6a shows the regional difference in the optimal planting share. The pattern is that provinces in the northeast and major provinces of japonica rice cultivation and consumption are recommended to adopt a higher share of CRISPR rice. A different pattern is shown in Fig. 6b for the regional difference in the environmental benefit of co-planting CRISPR rice. Heilongjiang province will gain the most significant environmental benefit of 543 million US dollars due to its high optimal planting share and intensive rice cultivation.

It has been shown that regional heterogeneity exists regarding the optimal planting share of CRISPR rice and its environmental benefits. They would also likely differ depending on other factors not considered in our model, such as farmers' socioeconomic characteristics (Li & He, 2021) and their willingness to adopt CRISPR rice. Therefore, "one-size-fits-all" policies should be avoided.

8 Conclusion

Overusing pesticides and the external cost of pesticide use pose challenges to sustainable development. Insect-resistant rice developed with the CRISPR-Cas technology is a promising solution. The hypothesis that adopting CRISPR rice under pest uncertainty has positive environmental benefits is confirmed by this study. The environmental benefit of co-planting CRISPR rice is estimated to be 560 million US dollars annually. The study shows that it is essential to include the environmental contribution of CRISPR rice for a more comprehensive assessment as the environmental value accounts for 4–22% of the total value of co-planting CRISPR rice resulting from the Monte Carlo simulations. Results also show the regional heterogeneity regarding the optimal co-planting share of CRISPR rice and its environmental benefit.

The study has policy implications for various stakeholders. At the country level, considering the negative environmental externalities of pesticide use in the microeconomic framework can provide policymakers with a more comprehensive overview of CRISPR rice, which is essential for policymakers to make informed decisions on regulating genome editing. For public and private research institutions and plant-breeding companies focusing on advancing CRISPR-Cas technology, apart from the economic market potential of CRISPR rice, it is essential to emphasize and promote its environmental contribution, which is currently ignored. The study also sheds more light on individual farmers to better understand this new rice variety, which can provide economic and environmental value for them under the uncertainty of pest severity.

The results should be interpreted with caution because of the assumptions made in the model, including no spatial spillovers of pest outbreaks and fixed pesticide use of a given year without adjustment according to pest infestation. Limitations include lacking market data on CRISPR rice as it has not been commercialized. When the technical parameters for pest-resistant CRISPR rice are unavailable, those from pest-resistant GM rice are used as an approximation. That said, once more market data and parameters for CRISPR rice become available, the microeconomic model introduced in this article can be updated and used to generate more precise results. Future research is encouraged in the direction of a circular economy combining genome editing (e.g., Maroušek & Gavurová, 2022; Schilling & Weiss, 2021) and more consideration of the impact of soil fertility, water usage, and other essential input conditions (e.g., Maroušek et al., 2022; Qaim, 2020) for the potential adoption of CRISPR rice in various parts of the world.

Table 5 Regional data for rice cultivation (2021)

	Hebei	Inner Mongolia	Liaoning	Jilin	Heilongjiang	Jiangsu	Zhejiang	Anhui	Shandong	Henan	Yunnan	Ningxia
Pesticide costs (RMB/mu)	140	175	137	138	136	137	137	130	130	145	158	130
Pesticide costs (USD/ha)	295	369	289	291	288	289	290	275	274	305	334	275
Rice market price (yuan/50 kg)	58	50	67	35	38	109	149	80	98	103	53	79
Rice market price (USD/kg)	0.2	0.1	0.2	0.1	0.1	0.3	0.4	0.2	0.3	0.3	0.2	0.2
Pesticide intensity (kg/ha)	223	279	218	220	217	218	219	207	207	231	252	208

Source The data are from the China National Development and Reform Commission (2021)

1 ha = 15 mu; 1 USD = 7 RMB

Appendix 1: First-order conditions corresponding to the specific functional forms of the model

Using the functional forms specified earlier, first-order conditions (6)–(8) can be written as

$$\frac{\partial EU}{\partial L_C} = qre^{-r\pi_S}\left\{\begin{array}{l} p_C\left[\alpha_C Y_C + \left(1-e^{-\lambda_S X_C}\right)\left(1-\alpha_C\right)Y_C\right] - p_V\left[\alpha_V Y_V + \left(1-e^{-\lambda_S X_V}\right)\left(1-\alpha_V\right)Y_V\right] \\ -\left[mX_C + s_C + \varepsilon A L_C^{\varepsilon-1} - \left(mX_V + s_V + \varphi^S\right)\right] - \left(X_C - X_V\right)\xi \end{array}\right\}$$
$$+ (1-q)re^{-r\pi_N}\left\{\begin{array}{l} p_C\left[\alpha_C Y_C + \left(1-e^{-\lambda_N X_C}\right)\left(1-\alpha_C\right)Y_C\right] - p_V\left[\alpha_V Y_V + \left(1-e^{-\lambda_N X_V}\right)\left(1-\alpha_V\right)Y_V\right] \\ -\left[mX_C + s_C + \varepsilon A L_C^{\varepsilon-1} - \left(mX_V + s_V + \varphi^N\right)\right] - \left(X_C - X_V\right)\xi \end{array}\right\} = 0 \tag{13}$$

where

$$\pi_S = p_C Q_{CS} + p_V Q_{VS} - mX_C L_C - s_C L_C - AL_C^{\varepsilon} - \left(mX_V + s_V + \varphi^S\right)\left(\overline{L} - L_C\right) - \left[X_C L_C + X_V\left(\overline{L} - L_C\right)\right]\xi$$
$$\pi_N = p_C Q_{CN} + p_V Q_{VN} - mX_C L_C - s_C L_C - AL_C^{\varepsilon} - \left(mX_V + s_V + \varphi^N\right)\left(\overline{L} - L_C\right) - \left[X_C L_C + X_V\left(\overline{L} - L_C\right)\right]\xi$$

$$\begin{aligned} \frac{\partial EU}{\partial X_C} &= qre^{-r\pi_S}\left\{p_C\left(1-\alpha_C\right)Y_C L_C \lambda_S e^{-\lambda_S X_C} - mL_C - \xi L_C\right\} \\ &\quad + (1-q)re^{-r\pi_N}\left\{p_C\left(1-\alpha_C\right)Y_C L_C \lambda_N e^{-\lambda_N X_C} - mL_C - \xi L_C\right\} = 0 \end{aligned} \tag{14}$$

$$\begin{aligned} \frac{\partial EU}{\partial X_V} &= qre^{-r\pi_S}\left\{p_V\left(1-\alpha_V\right)Y_V\left(\overline{L} - L_C\right)\lambda_S e^{-\lambda_S X_V} - m\left(\overline{L} - L_C\right) - \xi\left(\overline{L} - L_C\right)\right\} \\ &\quad + (1-q)re^{-r\pi_N}\left\{p_V\left(1-\alpha_V\right)Y_V\left(\overline{L} - L_C\right)\lambda_N e^{-\lambda_N X_V} - m\left(\overline{L} - L_C\right) - \xi\left(\overline{L} - L_C\right)\right\} = 0 \end{aligned} \tag{15}$$

Notice that the term L_C can be canceled out in (14), as $L_V = \overline{L} - L_C$ can be in (15), such that the first-order conditions for X_C and X_V do not directly depend on land areas, which makes intuitive sense because X represents the application of pesticide per hectare. However, there is also an indirect effect via the profits π_S and π_N (in the exponents of 14 and 15) that depend on the allocation of the total land area to L_C and L_V.

See Table 5.

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Data availability Data is available on request from the authors.

Declarations

Conflict of interest We have no conflicts of interest to disclose.

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