Research Article

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Economic analysis of crop protection strategies: comparing the value of increased fungicide inputs and crop genetic improvement in managing Ascochyta blight in Australian chickpeas

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Abstract

BACKGROUND: Genetic improvement of crop varieties requires significant investment. Therefore, varieties must be developed to suit a broad range of breeding targets, such as yield and suitability to rainfall zones, farm management practices and quality traits. In the case of breeding for disease resistance, breeders need to consider the value of genetic improvement relative to other disease management strategies and the dynamics of pathogen genetic and phenotypic diversity. This study uses a benefit–cost analysis framework to assess the economic value of fungicide management and crop genetic improvement in disease resistance for Australian chickpea varieties.

RESULTS: When assessing the likelihood of growers switching to new crop varieties with improved genetic resistance to disease, the simulation results reveal that adopting these varieties yielded higher net benefit values compared to implementing current fungicide strategies across all rainfall zones. On average, the increase in net benefit varied between 2.6% and 3.5%. Conversely, when we examined the scenario involving modifying the current fungicide strategy, we observed that, on average, switching from the current fungicide management strategy to one which involved additional fungicides was beneficial in about 73% of the cases.

CONCLUSION: Our analysis reveals the importance of factors such as commodity prices, production costs, disease-related variables and risk aversion in determining the economic benefits of adopting new crop protection strategies. Furthermore, the research reveals the need for accessible information and reliable data sources when evaluating the benefits of new agricultural technologies. This would assist growers in making informed and sustainable disease management decisions.

Keywords: agribusiness; breeding for resistance; chickpeas; crop protection; plant pathogen; utility theory

1 INTRODUCTION

The global population is projected to rise to 9.7 billion in 2050,[1] while the available arable land per person is likely to continue to decline steadily over the same period. Therefore, ensuring sustainable food production as well as supporting agribusinesses are essential, particularly in areas with high disease pressure. The impact of plant disease on agribusinesses and food security is a major concern worldwide.[2,3] Despite significant advancements in plant genetic improvement and the subsequent increase in yield potential, the occurrence of diseases and the propensity of pathogens to adapt in response to selection pressure from control measures continue to threaten overall production margins. For example, a study by Savary *et al*.[4] found that regions already struggling to produce sufficient food for their growing populations are experiencing significant yield losses. These regions are often characterized by rapidly growing populations and face additional threats from pests and diseases.

Plant disease can, therefore, be considered a 'stealer' of profit margins and a threat to food security and the sustainability of agribusinesses.[5] Diseases have a detrimental impact on crop performance because they limit the opportunity for varieties to reach their full potential. The extent of potential losses resulting from disease outbreaks is influenced by several factors. These include the presence and virulence of the pathogen, conducive environmental conditions that favor disease development and the disease resistance sensitivity of the host.[6–9] These factors impact

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the severity of diseases with financial implications resulting from yield losses and the cost of additional disease control inputs. For instance, when pathogens strike during the growing season, leading to substantial yield losses, the financial resources invested throughout the growing season become unrecoverable sunk costs.[10] As a result, the return on investment for all other inputs associated with production is compromised. Taking steps to ensure effective disease management is essential to reduce crop losses and enhance agricultural productivity.

The global pulse (legume grain) industry, vital for the global agricultural economy, is thriving with an annual production of 92–96 million tonnes from an area of 80 million hectares.[11] This robust pulse market aligns with consumer trends towards plant-based diets[11] and the growing demand for plant-based meat substitutes.[12–15] Subsequently, the demand for pulses is expected to increase and broadly adapted germplasm will enable grain producers to potentially address production risks and ensure that they are able to meet the growing demand while addressing sustainability concerns.

The top three pulses produced in Australia are chickpeas (*Cicer arietinum* L.), lupins (*Lupinus* spp) and lentils (*Lens culinaris* Medik.), with Australia being the leading global exporter of chickpeas, valued at USD 357 million in 2022.[16] Pulses account for about 10% of the total broadacre planted area in Australia, with some regions utilizing up to 25% of the production area. They are an important component of crop rotation strategies.[16] The pulse industry in Australia has a diverse and established value chain ensuring quality from farm to table, with pulses increasingly gaining recognition for their nutritional value and their role in enhancing cereal cropping systems amidst challenging pathogen pressures.[16,17]

Ascochyta blight disease in chickpeas is caused by the necrotrophic fungal pathogen *Ascochyta rabiei* (Pass.) Labrousse. The disease is economically significant to the Australian chickpea industry with reports of between 50% to 100% yield loss in cases where growers lose the ability to control the disease.[18–21] Rainfall remains a critical factor in the establishment of infection leading to Ascochyta blight, so early fungicide application needs to be considered to disrupt early infection and the ontogeny of disease development.[20] However, foliar fungicide sprays have been found to be generally inefficient in reducing disease during severe epidemics, with up to six sprays required to reduce the impact on yield in moderate disease epidemics.[22]

The most relevant economic impact study was undertaken by Bretag *et al.*[20] who reported that although some growers effectively managed Ascochyta blight using fungicides, there were significant costs associated with additional fungicide sprays, resulting in a reduction in net margins. The same experiment found that improving genetic resistance to Ascochyta blight yielded benefits without the need to use extra fungicide sprays. A study by Fanning *et al.*[21] highlighted the significance of varietal selection and timely fungicide use to reduce yield losses caused by Ascochyta blight, with preventative fungicide strategies decreasing yield losses. Investigations into the genetic diversity of Ascochyta *rabiei* have revealed multiple pathotypes, each with varying degrees of virulence, complicating disease management strategies.[8] Therefore, a combination of an effective fungicide regime and continued development of genetically improved varieties is an important strategy for the Australian chickpea industry. Unfortunately, crop genetic improvement has not kept up with pathogen evolution.

Efforts to combat Ascochyta blight have been centered around holistic disease management strategies that blend cultural practices such as strategic crop rotation, careful stubble management, judicious fungicide applications and host genetic resistance.[19,20,23] While early disease detection and prompt intervention remain critical in curbing the detrimental impact of diseases, advancements in molecular techniques and innovations in plant breeding research have revolutionized the identification of resistance genes in chickpea cultivars.[23,24] The integration of genetic resistance into chickpea breeding programs is essential in ensuring the viability of the industry.

Crop genetic improvement is considered one of the ways to reduce instances of Ascochyta blight in chickpea varieties.[25] Nevertheless, genetic improvement demands a substantial investment of both time and financial resources. Since new technologies are prone to risks, some adopters often delay adopting the new technology until the benefits of adoption are proven to yield economic benefits.[26] As a result, chickpea varieties must be developed to align with considerations such as breeding targets, farm management practices and market accessibility, while also ensuring that the varieties are economically viable for growers.

As growers continue to operate in an uncertain environment, there is a need to explore a variety of crop protection strategies to suit growers' current investment capacities. A seminal review by Mumford and Norton (1984)[27] introduced the economic damage theory, offering deeper insights into the economics of decision-making in pest management. Similarly, Bretag *et al.*[20] utilized field experiments trial data from various sites across Australia and provided an evaluation of the gross margin of different management options. On the other hand, Ghadim and Pannell[28] explored the influence of risk and uncertainty on a grower's willingness to adopt a new technology using a dynamic adoption model.

This study employs decision theory and the utility theory model framework to examine the net benefit of adopting different crop protection strategies. We utilize Monte Carlo numerical simulations to evaluate growers' net benefit in the presence of two main crop protection strategies: modified fungicide management strategies and the adoption of varieties with enhanced disease resistance. These strategies are assessed under epidemic and non-epidemic conditions and then compared to the baseline scenario, which involves using current fungicide management strategies. By considering factors such as the expected yield loss to disease, which is associated with the chosen crop protection strategies as well as quality impacts, growers would be able to make well-informed decisions about the most economically viable crop protection strategy.

2 MODEL SETTING

2.1 Model definition and assumptions

Consider a grower who wishes to assess the cost-effectiveness of adopting various crop protection strategies to safeguard their crops against plant diseases. To do so, we will consider four main variables likely to affect a grower's net benefit from planting a particular crop in a given growing season. These include: (i) the expected yield lost to disease and quality downgrade, (ii) the proportion of crop area affected by the disease, (iii) the total cost of production and (iv) the commodity price.

Let us examine a scenario with the following assumptions:

- The current disease resistance ratings (disease ratings) are classified as: susceptible (S), moderately susceptible (MS), moderately resistant (MR) and resistant (R). The intermediate classifications are denoted as MR-MS or R-MR.

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- Depending on seasonal conditions and disease management practices, any variety can shift down the disease resistance rating scale (*i.e.*, indicating loss of genetic resistance due to changes in the pathogen population).
- Each step down the disease resistance rating scale will require at least one extra fungicide spray in the absence of improved genetic resistance in normal seasonal conditions, to minimize the impact of disease on yield potential.
- The infection level is dependent on within-season weather conditions.
- There is a risk of increased disease severity in the existing variety due to shifts in the pathogen population leading to a breakdown of current resistance levels.
- There is no interaction between diseases in a given growing season. This restriction will allow us to independently evaluate the impact of each disease on growers' profitability.
- Fungicide efficacy declines over time due to fungicide resistance development.

In the next section, we will use the above assumptions to evaluate a grower's net benefit maximization problem when choosing between two crop protection strategies: (i) fungicide management and (ii) crop variety selection.

2.2 Model formulation

For ease of exposition, let us consider a scenario with varying levels of disease pressure; from low disease pressure (non-epidemic conditions) to moderate-high disease pressure (epidemic conditions). Let us also assume growers are likely to face quality impact issues, which may lead to commodity downgrade. A grower's decision to adopt a particular crop protection strategy under the specified disease pressure conditions is influenced by several factors. In this study, we focus on variety selection and fungicide management regime (see *e.g.*[25,29]). By comparing the net benefit associated with each alternative, a grower can determine which strategy is the most economically beneficial.

Suppose a grower has the option to either maintain their current fungicide regime, modify it or switch to a new crop variety (cultivar), which we assume to have better genetic resistance to disease. If a grower implements a fungicide management strategy, they will need to select either one or multiple fungicide modes of action groups to manage the disease. Let us further denote the proportion of farming area affected by disease in epidemic conditions as $\beta_t^e \in [0,1]$. Similarly, denote the proportion of farming area affected by disease in non-epidemic conditions as $\beta_t^{ne} \in [0,1]$, with the assumption that $\beta_t^e > \beta_t^{ne}$. The expected yield lost to disease ($\xi_{dt}^{(\cdot)}$) can be calculated as:

$$\begin{cases} \xi_{dt}^{e} = \lambda_t^e y_t\, \beta_t^e, & \text{In epidemic conditions} \\ \xi_{dt}^{ne} = \lambda_t^{ne} y_t\, \beta_t^{ne}, & \text{In non-epidemic conditions} \end{cases} \tag{1}$$

where $\lambda_t^{(\cdot)}$ denotes the proportion of yield lost to disease and y_t (tonnes per hectare, t/ha) represents the estimated yield potential in the absence of disease-induced yield loss risk. Mumford and Norton[27] and Cerda *et al.*[30] acknowledged the complexity of quantifying $\lambda_t^{(\cdot)}$, as it depends on the interaction of multiple factors, some of which can be difficult to obtain.

Let us also suppose a grower faces the risk of fungicide resistance developing over time.[31,32] As Mumford and Norton (1984)[27] noted, the effectiveness of the treatment will play a significant role in determining the losses incurred by growers. Given that the development of fungicide resistance is likely to decrease the effectiveness of fungicides, Eqn (1) can be modified to reflect the increased risk of yield loss. Hence, if we take into account the risk of fungicide resistance development in the model, Eqn (1) for yield loss can be re-written as:

$$\begin{cases} \xi_{dt}^{e} = \lambda_t^e(\psi)\, y_t\, \beta_t^e, & \text{in epidemic conditions} \\ \xi_{dt}^{ne} = \lambda_t^{ne}(\psi)\, y_t\, \beta_t^{ne}, & \text{in non-epidemic conditions} \end{cases} \tag{2}$$

where the yield loss factor $\lambda_t^{(\cdot)}(\psi)$ is a function of the fungicide efficacy factor (ψ) and is influenced by the effectiveness of the fungicide used. The value of $\lambda_t^{(\cdot)}(\psi)$ is assumed to decline as the fungicide efficacy improves. That is, when the fungicide mode of action group has a 100% effectiveness rate, we assume that the plant is completely protected against fungal pathogens. This results in yield losses below economic thresholds or those that do not adversely affect profitability. Conversely, if the fungicide mode of action group has a 0% effectiveness rate, we assume that the fungicide is ineffective at providing the plants with any protection against fungal pathogens. This implies that the grower is at increased risk of high yield losses above the economic thresholds. For the purpose of this study, we will assume that the value of $\lambda_t^{(\cdot)}(\psi)$ is uniformly distributed over a predefined range.

In addition, we assume that growers may face the risk of their commodity being downgraded due to quality-related issues. As highlighted by Wood and Scott (2021),[33] seed defects are common across all grain-producing countries and can have substantial impact on the prices, sometimes leading to the rejection of the grain. Therefore, let $\theta_t^{(\cdot)} \in [0,1]$ represent the proportion of yield that fails to meet the expected quality standards. We can then calculate the expected yield lost as a result of quality concerns in both epidemic and non-epidemic scenarios as:

$$\begin{cases} \xi_{qt}^{e} = \theta_t^e\left(y_t - \xi_{dt}^e\right), & \text{In epidemic conditions} \\ \xi_{qt}^{ne} = \theta_t^{ne}\left(y_t - \xi_{dt}^{ne}\right). & \text{In non-epidemic conditions} \end{cases} \tag{3}$$

We assume that $\theta_t^e > \theta_t^{ne}$, that is, during epidemic conditions, the disease severity is expected to be higher than in non-epidemic conditions, leading to a substantial impact on the quality of the commodity. Studies have shown that during high disease pressure conditions, as observed in epidemic conditions, the quality of the commodity is adversely affected.[33] In order to manage diseases and quality impact issues, suppose a grower uses at least one fungicide mode of action group in any growing season. The estimated total cost of production (c_t) is given by:

$$c_t = \begin{cases} c_t^s + \sum\limits_{N_t^e \in \mathfrak{R}^+} \left(c_t^f \times N_t^e\right) + c_t^q + c_t^0, & \text{In years with epidemic conditions} \\ c_t^s + \sum\limits_{N_t^{ne} \in \mathfrak{R}^+} \left(c_t^f \times N_t^{ne}\right) + c_t^q + c_t^0, & \text{In years with non-epidemic conditions} \end{cases} \tag{4}$$

where c_t^s represents the cost of seed for a particular variety, c_t^f denotes the cost of each fungicide treatment and also the application cost, $N_t^{(\cdot)}$ is the number of fungicide applications and $\sum\left(c_t^f \times N_t^{(\cdot)}\right)$ denotes the total fungicide treatment and application cost in a given season in year t. We assume that during epidemic conditions, growers incur additional expenses due to increased fungicide application costs $\left[\sum_{N_t^e \in \Re^+}\left(c_t^f \times N_t^e\right)\right]$, with $N_t^e > N_t^{ne}$. The term c_t^q denotes the extra cost associated with quality control measures, such as yield inspection and cleaning. Lastly, the term c_t^o denotes other production costs that are not directly related to disease management.

Let us now consider a scenario where a grower has a utility function represented by $U(\cdot)$. The utility function denotes a grower's set of preferences[34] and is assumed to be an increasing and concave von Neumann-Morgenstern utility function. Following Savage's[35] decision theory framework, suppose a grower's subjective probability of experiencing an epidemic condition in year t is $q_t \in [0,1]$ and the probability of having a non-epidemic condition is $1-q_t$. If we take into account the risk of yield loss due to disease and quality issues, the expected utility of wealth $\pi_t^{(\cdot)}$ can be expressed as:

$$\mathrm{EU}[\pi_t] = q_t\, U\left(\pi_t^e\right) + (1-q_t)\, U\left(\pi_t^{ne}\right), \tag{5}$$

where $U\left(\pi_t^{(\cdot)}\right)$ represents a grower's subjective satisfaction derived from wealth $\pi_t^{(\cdot)}$. Let us define the wealth levels under epidemic and non-epidemic conditions as:

$$\begin{cases} \pi_t^e = P_t\left(y_t - \xi_{dt}^e\right) - \left(P_t - P_t^\theta\right)\xi_{qt}^e - c_t, & \text{in epidemic conditions} \\ \pi_t^{ne} = P_t\left(y_t - \xi_{dt}^{ne}\right) - \left(P_t - P_t^\theta\right)\xi_{qt}^{ne} - c_t, & \text{in non–epidemic conditions} \end{cases}$$

where P_t denotes the commodity price (AU\$ per unit tonne, AU\$/tonne), while P_t^θ (AU\$/tonne) represents the commodity price of the downgraded yield. The term $\left(P_t - P_t^\theta\right)\xi_{qt}^{(\cdot)}$ denotes the value lost due to quality downgrade issues. In the absence of quality downgrade issues, the term $\xi_{qt}^{(\cdot)} = 0$. In order to determine a grower's net benefit from adopting a given crop protection strategy, let us assume that $U(\cdot)$ is characterised by a constant relative risk aversion (CRRA) utility function, taking the form (see *e.g.*[36,37]):

$$U(\omega) = \begin{cases} \dfrac{\omega^{1-\rho}}{1-\rho}, & \text{if } \rho \geq 0, \rho \neq 1 \\ \ln\omega, & \text{if } \rho = 1 \end{cases} \tag{6}$$

where ω denotes a grower's wealth while ρ represents the risk aversion parameter. A value of ($\rho = 0$) indicates risk neutrality, whereas values greater than 0 indicate varying degrees of risk aversion. A higher ρ value indicates a greater aversion to risk. Since growers often face significant risks, such as those related to production uncertainties, market volatility and regulatory changes, growers can prioritise investments in crop protection strategies to align with their risk tolerance and ultimately improve their chances of achieving favourable outcomes. If we substitute Eqns (6) into (5), the expected utility for a risk-averse grower adopting a given crop protection strategy is:

$$EU[\pi_t] = \begin{cases} \dfrac{q_t\left(\pi_t^e\right)^{1-\rho} + (1-q_t)\left(\pi_t^{ne}\right)^{1-\rho}}{1-\rho}, & \text{if } \rho \geq 0, \rho \neq 1 \\ q_t \ln \pi_t^e + (1-q_t)\ln \pi_t^{ne}, & \text{if } \rho = 1 \end{cases} \tag{7}$$

and the certainty equivalent profit which maximizes Eqn (7) is given by $U(CE(\pi_t)) = EU[\pi_t]$(see *e.g.*[36]):

$$CE[\pi_t] = \begin{cases} \left[q_t\left(\pi_t^e\right)^{1-\rho} + (1-q_t)\left(\pi_t^{ne}\right)^{1-\rho}\right]^{\frac{1}{1-\rho}}, & \text{if } \rho \geq 0, \rho \neq 1 \\ \left(\pi_t^e\right)^{q_t}\left(\pi_t^{ne}\right)^{1-q_t}. & \text{if } \rho = 1 \end{cases} \tag{8}$$

Let us consider a grower with a CRRA utility function who wishes to maximize the certainty equivalent profit derived from adopting a new crop protection strategy. To determine whether it would be beneficial to stay with the current crop protection strategy or switch to a new strategy in the presence of yield loss and quality downgrade risk, we can formulate the problem using a binary decision variable x; where $x = 1$ indicates switching to a new crop protection strategy and $x = 0$ indicates staying with the current strategy. The assumption of a binary decision variable simplifies the computational complexity and focuses our analysis on the impact of adoption *versus* non-adoption within the adoption decision continuum. The net benefit maximization problem for the grower in a given growing season can be formulated as:

$$\begin{aligned} &\text{maximize} && \mathrm{CE}_1(\pi_t)\, x + \mathrm{CE}_0(\pi_t)\,(1-x), \\ &\text{subject to} && P_t\left(y_t - \xi_{dt}^{(\cdot)}\right) - \left(P_t - P_t^\theta\right)\xi_{qt}^{(\cdot)} - c_t^o \geq c_t^s + \sum_{N_t^{(\cdot)} \in \Re^+}\left(c_t^f \times N_t^{(\cdot)}\right) + c_t^q, \end{aligned} \tag{9}$$

where,

$$\mathrm{CE}(\pi_t) = \begin{cases} \left[q_t\left(\pi_t^e\right)^{1-\rho} + (1-q_t)\left(\pi_t^{ne}\right)^{1-\rho}\right]^{\frac{1}{1-\rho}}, & \text{if } \rho \geq 0, \rho \neq 1 \\ \left(\pi_t^e\right)^{q_t}\left(\pi_t^{ne}\right)^{1-q_t}, & \text{if } \rho = 1 \end{cases}$$

$$\pi_t^{(\cdot)} = P_t\left(y_t - \xi_{dt}^{(\cdot)}\right) - \left(P_t - P_t^\theta\right)\xi_{qt}^{(\cdot)} - c_t,$$

$$\xi_{dt}^{(\cdot)} = \lambda_t^{(\cdot)}(\psi)\, y_t\, \beta_t^{(\cdot)},$$

$$\xi_{qt}^{(\cdot)} = \theta_t^{(\cdot)}\left(y_t - \xi_{dt}^{(\cdot)}\right),$$

$$c_t = c_t^s + \sum_{N_t^{(\cdot)} \in \Re^+}\left(c_t^f * N_t^{(\cdot)}\right) + c_t^q + c_t^0,$$

$$c_t^s, c_t^f, c_t^q, c_t^o, P_t, P_t^\theta, y_t, \theta_t^{(\cdot)}, \rho, \xi_{dt}^{(\cdot)}, \xi_{qt}^{(\cdot)} \geq 0,$$

$$t, N_t^{(\cdot)} \in \Re^+; 0 \leq q_t, \beta_t^{(\cdot)}, \lambda_t^{(\cdot)}(\psi) \leq 1; x \in \{0,1\}.$$

The objective function in Eqn (9) seeks to maximize the net benefit for a risk-averse grower in the presence of disease and quality downgrade risks. The constraint $P_t\left(y_t - \xi_{dt}^{(\cdot)}\right) - \left(P_t - P_t^\theta\right)\xi_{qt}^{(\cdot)} - c_t^o \geq c_t^s + \sum\left(c_t^f \times N_t^{(\cdot)}\right) + c_t^q$ ensures that the expected net benefit derived from adopting a given crop protection strategy (*i.e.*, a fungicide management strategy or switching to a new variety) offsets the cost of implementing the strategy.

Let $\mathrm{CE}_0^*(\pi_t)$ represent the certainty equivalent profit that maximises a grower's utility in the presence of the current crop protection strategy, while $\mathrm{CE}_1^*(\pi_t)$ represents the optimal certainty equivalent profit for a grower who adopts a new crop protection strategy. The change in net benefit value, $\Delta CE^{*}(\pi_t)$, can be determined as follows:

$$\Delta CE^{*}(\pi_t) = CE_1^{*}(\cdot) - CE_0^{*}(\cdot) \tag{10}$$

From expression (10), we can infer that if $\Delta CE^{*}(\pi_t) > 0$, it becomes economically beneficial for a grower to consider adopting an alternative crop protection strategy. This suggests that the economic benefits associated with implementing the new strategy outweigh the costs involved. Conversely, if $\Delta CE^{*}(\pi_t) < 0$, the potential benefits derived from adopting the new crop protection strategy may not sufficiently justify the associated costs.

Various studies have documented factors that significantly influence growers' willingness to adopt new technologies. These include social, economic and environmental factors, alongside the risks associated with adopting the technology.[38,39] Other studies have acknowledged the value of information in incentivizing growers to adopt new technologies. Notably, Ghadim *et al.*[38] stated that when growers have access to relevant farm management information, they are more likely to embrace new technologies, even in the face of potential short-term losses. However, growers would need to carefully assess the overall business landscape and weigh the additional benefits of adopting new technologies, such as the sustainability of their agribusinesses, to justify their decision for adoption. In the next section, we will examine the impact of disease and quality downgrade risk parameters on net benefit using Monte Carlo simulation.[40]

3 NUMERICAL SIMULATION EXPERIMENT

In this section, we will outline the experimental setup for a case study that focuses on managing Ascochyta blight in chickpeas using two main disease management strategies. These strategies include either (i) employing different fungicide modes of action groups to manage diseases or (ii) adopting improved varieties with varying disease resistance ratings. Suppose there is a risk of disease resistance in the existing variety, which can occur due to shifts in the pathogen population, leading to a breakdown of current disease resistance levels and higher expected yield losses. Consequently, depending on seasonal conditions, any variety has the potential to shift downwards on the disease rating scale.

The current disease resistance ratings are classified into different levels: S, MS, MR and R. There are also intermediate classifications denoted as MR-MS and R-MR. Additionally, we assume that a new variety with enhanced disease resistance is developed every 3 to 5 years, and each increment on the disease resistance rating scale corresponds to a reduced incidence of Ascochyta blight infection, resulting in lower yield losses.

In the absence of improved genetics, we assume that a grower applies at least one additional fungicide spray to reduce yield losses to an acceptable level. Since the decision regarding fungicide application depends on prevailing growing season conditions and the disease resistance rating, we assume that growers adopting varieties with higher disease resistance ratings would be more likely to use fewer fungicides in non-epidemic conditions compared to the baseline case (status quo).

3.1 Case study assumptions and parameters for the numerical simulation

Consider a case study involving the management of Ascochyta blight in chickpea. For the purpose of sensitivity analysis, we systematically vary each parameter within a predefined range and observe the corresponding impact on the net benefit. The numerical simulation experiment is conducted based on the following set of assumptions:

- Growers cultivate different chickpea varieties with varying disease resistance ratings and in diverse environmental conditions.
- In the absence of resistant varieties, growers use one unit of additional fungicide to minimize the impact of disease on yield.
- Growers use a unit less of fungicide during non-epidemic conditions in comparison to the baseline case, with a minimum of one unit of fungicide.
- Yield potential increases with high rainfall. For example, in low rainfall zones, the yield was assumed to be distributed between 1 to 2.4 t/ha; in the medium rainfall zone, the yield ranged from 1.8 to 3.2 t/ha and in the high rainfall zones, they varied between 2.2 to 4 t/ha.[41,42]
- Disease-induced yield loss varies across different varieties (see Table 1).
- Growers in low rainfall zones face lower disease risk. Consequently, fungicides are recommended if seasonal conditions favor disease development.

Table 1. A summary of the variables used in the simulation experiment: Disease resistance rating

				Fungicide applied			Scenarios: Genetic improvement
Commodity	Crop disease	Disease rating 2021	Yield loss (%)	Low rainfall zone	Medium rainfall zone	High rainfall zone	One-step genetic improvement
Chickpea	Ascochyta *blight*	S	20–50%	2	3–5	4–6	MS
		MS	10–20%	2	3–5	4–6	MR-MS
		MR-MS	5–10%	1	3	4	MR
		MR	2–5%	1	3	4	R-MR
		R-MR	0–2%	1	2–3	2–3	R
		R	0%	1	1	1	–

Note: Yield loss in non-epidemic conditions was assumed to be 25–50% lower than in the epidemic conditions.
Abbreviations: S, susceptible; MS, moderately susceptible; MR-MS, moderately resistant-moderately susceptible; MR, moderately resistant; R-MR, resistant-moderately resistant; R, resistant.

- The cost of fungicides is uniformly distributed between AU$6 and AU$30 per hectare, while the cost of fungicide application varies between AU$10 and AU$15 per hectare.
- The cost of seeds, whether farmer-retained or commercially sourced, depends on the selected variety and seeding rate. For chickpeas, we assume that the cost ranges from AU$56 to AU$120 per hectare.
- Other production costs vary between AU$150 and AU$250 per hectare, depending on farm operations.
- Commodity prices differ based on crop varieties and quality grades. For chickpeas, the prices range from AU$400 to AU $650 per tonne.
- The proportion of yield downgraded due to quality impacts $\theta_t^{(\cdot)}$, are assumed to be uniformly distributed between 0 and 0.4, with $\theta_t^{ne} \in [0, 0.1]$, and $\theta_t^{e} \in [0.1, 0.4]$. Growers incur additional costs associated with quality control measures, with costs varying between AU$30 and AU$45 per tonne, while the price penalty for the downgraded yield varied between AU$10 and AU $100 per tonne (see *e.g.*[33]).
- Growers are assumed to be risk-averse, with the risk aversion parameter varying between 0 and 3.5.[43]

Table 1 summarizes the parameter values for the numerical simulation experiment. To address the impact of crop disease risk on yield, our analysis assumes that a grower adopting a variety with a lower disease resistance rating would need to either use additional fungicides or switch to a more costly mode of action fungicide group to achieve equivalent disease risk mitigation benefits as a grower who chooses to adopt a genetically improved variety.

3.2 Model implementation

The simulation experiment was implemented within the R program.[44] To evaluate $CE^*(\pi_t)$ and to ensure the robustness of the results, the process was repeated 10 000 times with randomly drawn parameter values from the defined sample space. Random forest analysis[45,46] was used to evaluate key drivers influencing growers' gross margin values. Random forest is an ensemble learning method that combines the predictions of multiple decision trees to enhance accuracy and robustness, when addressing classification and regression problems.[45] This method has advantages over other statistical modelling methods, such as preventing overfitting, modelling nonlinear relationships and determining the relevance of the variables used.[47] Furthermore, it has also been successfully used in important agricultural applications (see *e.g.*[48–51]).

When formulating a random forest model, it is important to pay attention to certain hyper-parameters that can affect the performance of the model. One such parameter is the number of trees, denoted by *M*, which determines how many decision trees are built using a random subset of the data and features. While a higher *M* value can lead to more accurate predictions,[52] it can also increase computation time and memory requirements. Another essential parameter is the number of variables, denoted by *V*, which controls the number of randomly selected variables considered at each split when constructing a decision tree. It helps to ensure diversity and decorrelation among trees and prevents overfitting.[45,53–55] Although M and V are user-defined and depend on the dataset's properties, they can also be determined by calculating the mean squared error and out-of-bag error.[56] In the next section, we present the results obtained from the analyses of the data.

4 RESULTS

This section presents the results of numerical simulation experiments conducted to evaluate the benefit–cost of selected crop protection strategies, in the presence of disease and quality downgrade risks. Furthermore, we tested the sensitivity of the grower's net benefit to changes in the risk aversion parameter.

4.1 Impact of crop protection strategies on net benefit

The effect of crop genetic improvement and fungicide management on the net benefit was tested using Monte Carlo simulations. Table 2 reveals that, relative to the baseline case, enhancing genetics proved to be a more effective crop protection strategy than increasing fungicide sprays across all rainfall zones. In particular, in regions with low rainfall, characterized by relatively lower yields, growers who switched to improved genetics experienced an average increase of 3.5% in net benefit. However, growers who modified their current fungicide strategies by using additional fungicides experienced a net benefit rise of 2.1%. This trend remained consistent in moderate rainfall zones, where adopting improved genetics led to an average net benefit increase of 2.8%, while the average net benefit in the modified fungicide management strategies increased by 1.5%. Similarly, in high rainfall zones, switching to improved genetics resulted in an average net benefit rise of 2.6%. In comparison, using extra fungicides yielded a 1.6% increase in the average net benefit.

Moving to the impact of genetic improvement on growers' net benefits, Fig. 1 highlights the average change in net benefit resulting from a one-step improvement in genetic resistance across three rainfall zones. As shown in the graph, a one-step improvement in genetic resistance, relative to the baseline case, yielded positive average change in net benefit values across all the selected varieties. Additionally, we observe declining change in net benefits from genetic improvement as varieties become more resistant. Notably, varieties initially rated as S exhibited the most substantial improvement, where the change in average net benefit values varied between AU$60/ha – AU$96/ha across the three rainfall zones as the disease rating shifted from an S rating to an MS rating. Conversely, varieties with a rating of R-MR displayed very small improvement in the change in average net benefit as their classification moved from R-MR to R (*i.e.*, AU$1.20/ha – AU $2.20/ha). Overall, these results suggest that the size of incremental change is greater when starting from a low base resistance rating, as represented by S, compared to the step change for varieties that have higher disease rating.

When assessing the likelihood of growers switching to new crop varieties with improved genetic resistance to disease, the simulation results reveal that adopting varieties with improved genetic resistance to diseases yielded higher average net benefit values, compared to implementing current fungicide management strategies across all rainfall zones. On the other hand, when we examined the scenario involving modifying the current fungicide management strategy (*e.g.*, increasing the number of fungicide sprays), we observed that it was beneficial to switch from the current fungicide management strategy to one that involved additional fungicides in about 73% of the cases. This varied across rainfall zones, with probabilities varying between 69% and 80%.

The above results suggest that in some instances, the benefit derived from modifying current fungicide management strategies did not justify the associated costs. Surprisingly, when we

Table 2. Summary statistics of the numerical simulation experiment.

Panel A: Low rainfall zone	Mean	SD	Median	1Q	3Q	IQR
Net benefit (AU$/ha)						
Current practice: Baseline	469.60	225.52	446.13	299.79	624.88	325.09
Increasing number of fungicide sprays	479.37 (↑ 2.08%)†	225.34	456.16	307.54	633.64	326.10
One-step genetic improvement	485.79 (↑ 3.45%)†	224.55	462.19	314.04	639.43	325.40
Likelihood to switch						
$\mathrm{CE}^*_g(\pi_t) > \mathrm{CE}^*_f(\pi_t)$	100%					
$\mathrm{CE}^*_{fx}(\pi_t) > \mathrm{CE}^*_f(\pi_t)$	79.8%					
$\mathrm{CE}^*_g(\pi_t) > \mathrm{CE}^*_{fx}(\pi_t)$	51.4%					
Panel B: Moderate rainfall zone						
Net benefit (AU$/ha)						
Current practice: Baseline	800.34	267.78	781.63	603.06	978.08	375.03
Increasing number of fungicide sprays	812.46 (↑ 1.51%)†	265.42	792.39	617.53	989.80	372.27
One-step genetic improvement	822.88 (↑ 2.82%)†	264.40	803.03	625.56	997.44	371.88
Likelihood to switch						
$\mathrm{CE}^*_g(\pi_t) > \mathrm{CE}^*_f(\pi_t)$	100%					
$\mathrm{CE}^*_{fx}(\pi_t) > \mathrm{CE}^*_f(\pi_t)$	68.6%					
$\mathrm{CE}^*_g(\pi_t) > \mathrm{CE}^*_{fx}(\pi_t)$	65.6%					
Panel A: High rainfall zone						
Net benefit (AU$/ha)						
Current practice: Baseline	1044.18	338.14	1013.42	794.66	1267.98	473.32
Increasing number of fungicide sprays	1060.62 (↑ 1.57%)†	333.09	1028.77	812.91	1281.93	469.02
One-step genetic improvement	1070.82 (↑ 2.55%)†	332.00	1039.21	826.01	1289.96	463.95
Likelihood to switch						
$\mathrm{CE}^*_g(\pi_t) > \mathrm{CE}^*_f(\pi_t)$	100%					
$\mathrm{CE}^*_{fx}(\pi_t) > \mathrm{CE}^*_f(\pi_t)$	71.8%					
$\mathrm{CE}^*_g(\pi_t) > \mathrm{CE}^*_{fx}(\pi_t)$	65.5%					

Abbreviations: SD, standard deviation; 1Q, First quartile; 3Q, Third quartile; IQR, Inter-quartile range.
† Percentage change relative to the baseline; AU\$/ha represents dollar per hectare; $CE^*_f(\pi_t)$, certainty equivalent profit for the baseline scenario; $CE^*_g(\pi_t)$, certainty equivalent profit for the one-step genetic improvement scenario; $CE^*_{fx}(\pi_t)$, certainty equivalent profit for the modified fungicide scenario.

compared the average net benefit values between switching to crop varieties with improved genetic resistance to disease and modifying current fungicide strategies, we found that, on average, the likelihood of growers preferring crop varieties with improved genetic resistance to diseases was about 61%, with probabilities varying between 51% and 66%. These findings demonstrate that although switching to improved genetics offers enhanced protection against plant pathogens, the benefit of only disease protection may not be sufficient to cover the cost of intervention. Furthermore, these findings highlight the importance of considering additional benefits associated with crop genetic improvement beyond disease protection, and the risks associated with fungicide resistance to accurately assess the value of crop genetic improvement.

4.2 Key factors influencing net benefit

The random forests procedure was implemented using the *randomForest* function[45] in R. In our model, the value of M was set to 200 since increasing the number of trees did not reduce the value of the mean squared error (MSE). Additionally, this choice ensured a balance between computational efficiency and accuracy. The optimal number of selected variables V was determined by starting with the default value and increasing it by a factor of 1.5, until the out-of-bag error stopped improving by 1%. Subsequently, the optimal hyper-parameters were then incorporated into the random forest model.

The results from the random forest analysis reveal the variables with the highest importance across the three crop protection scenarios (refer to Fig. 2 for the top 10 important features). The average increase in MSE, denoted by '%IncMSE', indicates the reduction in prediction accuracy for out-of-bag samples when a particular variable is excluded from the model.[57] Market price emerged as the most important factor influencing the gross margin across all three scenarios. In the baseline scenario, the top four additional factors influencing the gross margin included the yield potential, total production cost, price penalty per tonne due to commodity downgrade and the probability of experiencing epidemic conditions. Similarly, in the modified fungicide management scenario, the other four important factors were price penalty per tonne due to commodity downgrade, yield potential, total production cost and the probability of an epidemic. Lastly, in the improved genetics scenario, yield potential, total cost of production, price penalty per tonne due to commodity downgrade and the probability of an epidemic emerged as the key variables impacting the gross margin.

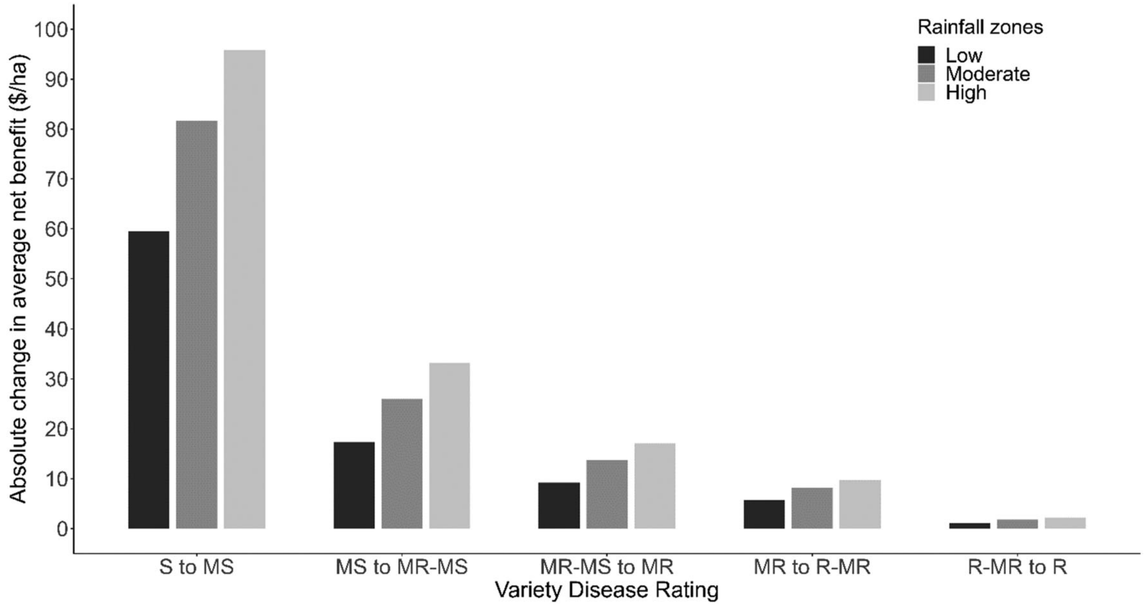

Figure 1. Projected change in net benefit from a one-step improvement in genetic resistance relative to the baseline scenario (current fungicide management). The plot compares the change in net benefit across three different rainfall zones. Disease resistance ratings for Ascochyta blight are defined as follows: S (Susceptible), MS (Moderately susceptible), MR-MS (Moderately Resistant – Moderately Susceptible), MR (Moderately Resistant), R-MR (Resistant – Moderately Resistant). One-step genetic improvement is denoted as: S to MS, MS to MR-MS, MR-MS to MR, MR to R-MR, R-MR to R.

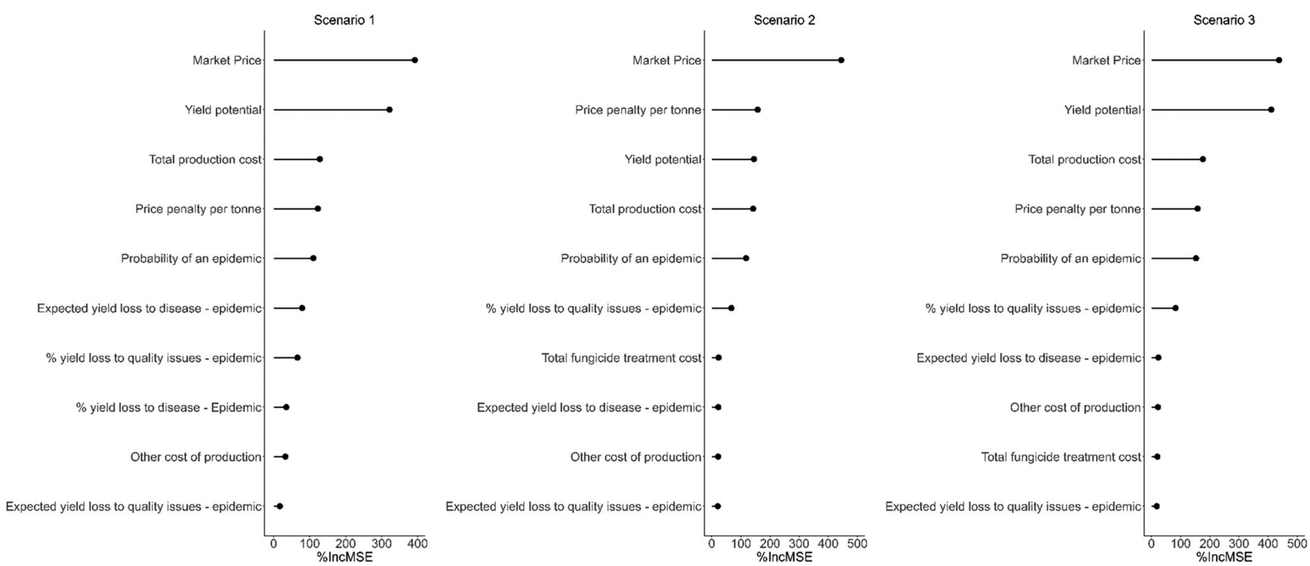

Figure 2. Feature importance plot for the top 10 drivers of gross margin across three scenarios: (1) Current fungicide management (baseline), (2) Modified fungicide management strategy and (3) improved genetics strategy. The variable with the highest score indicates the factor that has the greatest influence on gross margin values. '%IncMSE' denotes the percentage increase in Mean Squared Error.

4.3 Sensitivity analysis: impact of growers' risk aversion on net benefit

The results from the sensitivity analysis show variations in net benefit changes between improved genetic and baseline scenarios across three levels of risk aversion ($\rho = 0.8, 1.6, 3.2$) and varying probabilities of experiencing epidemic conditions (See Fig. 3). Notably, the change in net benefits increases as the probability of an epidemic rises across all three levels of risk aversion. Interestingly, at the highest level of risk aversion ($\rho = 3.2$), this change remains higher compared to those observed at low and moderate levels of risk aversion ($\rho = 0.8$ and 1.6, respectively). This indicates that, for highly risk-averse growers, the potential benefits of adopting improved genetics become more appealing as the likelihood of an epidemic increases, as shown by the greater change in net benefits. Conversely, at the lowest level of risk aversion ($\rho = 0.8$), the change in net benefits is lower compared to those observed at moderate and high levels of risk aversion ($\rho = 1.6$ and 3.2, respectively). These findings highlight the importance of developing and promoting effective crop protection strategies that align with the risk profiles of growers, especially as the benefits of such strategies become more pronounced under high risk conditions.

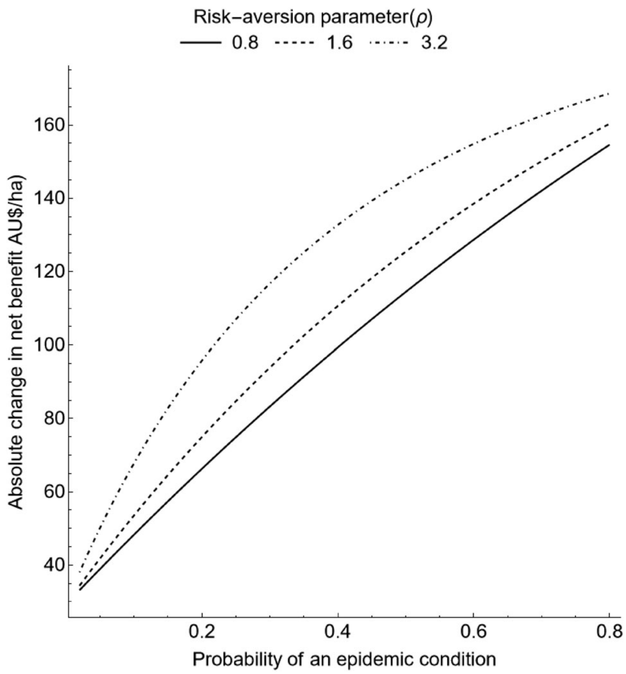

Figure 3. Impact of the probability of an epidemic on the absolute change in net benefit between improved genetic and baseline scenario across three risk aversion levels. This analysis compares change in net benefits at three levels of risk aversion (low = 0.8, moderate = 1.8 and high = 3.2), using average parameters values from Table 1. The calculations were performed using Mathematica v14.0.

5 DISCUSSION AND CONCLUSION

The decision of growers to either adopt or resist changes in their farm management practices is influenced by a range of socioeconomic factors along with their attitudes towards risk.[38,39,58,59] These factors can be broadly categorized into internal and external factors. Internal factors include those inherent within the agricultural system, such as farm size, experience of the grower and the profitability of farm operations. Conversely, external factors are those that are beyond the control of the growers, such as market conditions, government policies and social as well as cultural factors. The factors can either encourage change or create barriers that hinder the implementation of practices that could benefit the overall farm operations. This study aimed to provide insights into the benefit–cost analysis of adopting different crop protection strategies, while considering the risks associated with disease and the impacts on crop quality downgrade. Our analysis reveals several key insights.

First, the analysis of the impact of genetic improvement on growers' net benefits reveals important insights into the potential benefits of enhancing varieties with lower disease resistance ratings. Varieties initially rated as susceptible exhibited substantial improvements in net benefits with a one-step improvement in genetic resistance. This suggests that there is value in focusing genetic improvement efforts on susceptible or moderately susceptible varieties, as these have the highest potential for economic gains. However, we observed diminishing marginal returns as varieties become more resistant, highlighting the need for a balanced approach to crop genetic improvement efforts. Lüttringhaus *et al*.[60] found that increased resistance to diseases significantly boosted crop profitability while reducing the need for fungicides, which in turn lowered the overall production costs. Similarly, Geffersa *et al*.,[61] showed that the value of genetic resistance extended beyond direct benefits, offering both indirect and non-market value to farmers and society.

Moreover, the comparison between growers' likelihood of switching to new crop varieties with improved genetic resistance and modifying current fungicide strategies sheds light on the complex decision-making processes involved in disease management. The study found that adopting varieties with improved genetic resistance offers higher net benefits. However, the likelihood of growers preferring genetically improved crop varieties instead of modifying current fungicide strategies is about 61%. These findings suggest the importance of considering alternative disease management approaches in conjunction with crop genetic improvement efforts.

Second, the results derived from the random forest analysis further highlight the drivers of gross margin across the three scenarios. The importance of factors such as yield potential, production costs and disease-related variables highlight the complexity of crop protection decision-making. Therefore, in the presence of high disease pressure, an intervention such as modifying the current fungicide management strategy or switching to a variety with improved genetics needs to offer yield improvements to justify the cost of the intervention. Thus, this approach enables the appropriate assessment and recommendations of the benefits associated with adopting new technologies by considering each individual farm's unique characteristics and risk profile. These findings highlight the importance of considering a targeted approach to managing crop disease risk and making strategic investments in crop protection strategies.

Additionally, the results from our sensitivity analysis reveal important insights into the impact of growers' risk aversion levels on the net benefit under epidemic conditions. The analysis shows that, at a given probability of experiencing an epidemic, highly risk-averse growers have a relatively higher change in net benefit values compared to those with low and moderate risk aversion levels. This suggests that highly risk-averse growers are more likely to benefit from interventions that mitigate the financial impact of epidemics. These findings further emphasize the need for crop protection strategies tailored to different risk tolerance levels. Policies should support growers in adopting crop protection strategies that align with their propensity for risk. This approach would ensure that growers are able to effectively manage crop diseases during high epidemic conditions.

Third, our model highlighted the importance of integrating information on disease resistance ratings and quality impact into the crop protection decision-making process. Furthermore, the cost of purchasing a variety with improved disease resistance is not as prominent as the financial losses incurred due to reduced yield. The availability of accessible information and reliable data sources is essential in evaluating the economic impact of implementing different crop protection strategies. Extension services can play a crucial role in disseminating knowledge about the economic benefits and risks associated with different crop protection strategies. Growers accessing relevant information about the performance of crop varieties with different disease resistance ratings and the price penalty associated with quality downgrade will be better equipped to assess the economic benefits and risks associated with adopting alternative disease management strategies, thus leading to well-informed and sustainable management decisions.

Fourth, our study reveals the opportunities to reduce the risk of pesticide resistance using a plant breeding strategy. The

Australian agricultural sector heavily relies on fungicides to manage plant diseases,[21] which can be attributed to biotic and abiotic stresses. For example, Australia has experienced a consistent upward trend in average crop and pasture chemicals expenditure over the past three decades. In the 2021–2022 financial year, Australian farmers spent $5 billion on agricultural pesticides, with $496 million specifically allocated to fungicides.[62] While the use of fungicides may yield short-term benefits, neglecting the potential risk of fungicide resistance can lead to lasting economic and environmental impacts. Therefore, balancing short-term economic gains with long-term sustainability is essential. Providing growers with timely and accurate disease management information can help them make more informed decisions that appropriately balance risk and potential returns. This highlights the necessity for ongoing disease surveillance, information sharing and proactive crop protection management strategies to effectively mitigate the risk of fungicide resistance and ensure the resilience of agricultural systems.

Finally, it is important to acknowledge that obtaining precise estimates of disease severity, resistance levels, and other variables can be challenging due to the inherent variability in agricultural systems. To compare the net benefits of the three scenarios and to test the hypothesis, a future study could conduct an experiment using a randomized complete block design with three or four replicates in a small plot trial. Each of the three scenarios would be randomly allocated to replicate plots, with buffers placed between adjacent plots to prevent contamination from disease or treatment interventions. Additionally, our model assumes that growers make rational decisions and does not account for behavioral biases or external factors that may influence their disease management decisions. We also acknowledge the importance of crop rotation in long-term disease management, which merits further study beyond the annual crop protection decision-making framework addressed in this study. Exploring the potential trade-offs between fungicide management strategies, variety selection and crop rotation would complement our current findings by addressing the long-term impact of disease management strategies beyond the annual crop protection decisions. While enhancing varieties was found to be beneficial compared to the baseline case, the economic value of such improvements can vary depending on factors such as market competition, consumer preferences and the performance of alternative varieties. Moreover, our study does not account for yield penalty under disease-free conditions. Future research could explore these aspects to provide a more comprehensive understanding of the dynamics of decision-making processes in the context of adoption risks.

AUTHOR CONTRIBUTIONS

T.O.: Conceptualization, Data curation, Formal Analysis, Methodology, Visualization, Writing and Project administration. Z.C.: Conceptualization, Data curation, Formal Analysis, Methodology, Visualization and Writing. M.G.: Conceptualization, Formal Analysis, Methodology and Writing. All authors reviewed the manuscript.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

CONFLICT OF INTEREST

The authors declare no competing interests.

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