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Impacts of Fall Armyworm, Groundnut Rosette, and Soybean Rust Diseases on Smallholder Welfare and the Effectiveness of Control Strategies

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Keywords: crop rotation | diseases | improved seeds | Malawi | pesticides | pests | Zambia

ABSTRACT

Smallholder farmers in Malawi and Zambia face significant challenges to their food security and welfare owing to the increasing prevalence of crop pests and diseases, such as the fall armyworm (FAW), groundnut rosette virus (GRV), and soybean rust. As climate change is projected to exacerbate these threats, understanding their impact and identifying effective control strategies is crucial. This study aims to determine the impact of these pests on crop yields, household income, and food security, as well as to evaluate the effectiveness of various control strategies using survey data from 1100 farmers in Malawi and Zambia. The descriptive results show that approximately 70% of the farmers experience FAW attacks in their maize fields, approximately 28% experience rosette in their groundnuts, and 40% of the farmers report soybean rust infestations. The econometric results show that FAW, rosette, and soybean rust result in 13.5%, 27.2%, and 25.2% yield loss in maize, groundnuts, and soybean, respectively. We also find that the FAW negatively affects income and food security. While rust, rosette, and their combination had no significant effect on income and food security, their combination with FAW led to a greater negative impact than the FAW alone. Although farmers employ multiple strategies to control these pests/diseases, we find evidence, albeit not robust to different estimation strategies, that pesticides, crop rotation, and the use of improved seeds aid in reducing the negative effect of pests/diseases on crop yields. These findings contribute to the growing body of evidence that can inform policies and interventions aimed at enhancing food security and supporting resilient farming systems in sub-Saharan Africa.

JEL Classification: Q16, Q12, Q18

1 | Introduction

Pests and diseases pose significant threats to agricultural productivity worldwide, causing substantial yield losses in various crops. A comprehensive study by Oerke (2006) estimated that pests and diseases are responsible for 20%–40% of global crop losses annually. In maize production, fall armyworm (FAW) (*Spodoptera frugiperda*) has been particularly devastating, with yield losses of 11.6% in small-scale farms across Africa (Baudron et al. 2019). A global assessment of crop health found that pests and pathogens reduced attainable yields by an average of 21.5% in wheat, 30.0% in rice, 22.6% in maize, 17.2% in potatoes, and 21.4% in soybeans (Savary et al. 2019). In a meta-analysis of yield losses due to plant pathogens, Newbery et al. (2016) concluded that, on average, diseases reduce crop yields by 10%–28%, with significant variations across crop types and geographical regions.

Climate change is increasing the emergence and exacerbating the spread of crop pests and diseases (Mafongoya et al. 2019). The effects of climate change on insect pests are especially pronounced because of their ectothermic physiology, making them highly sensitive to temperature variations (Lamichhane et al. 2015; Zhao et al. 2023). Changes in temperature not only affect the timing, reproduction, and development rates of insect pests but also influence their geographical distribution and population dynamics (Deutsch et al. 2018). Shifts in the timing and duration of growing seasons enable native polyvoltine species to produce more generations per year, leading to earlier crop colonization and increased crop damage (Yan et al. 2022).

In addition to reducing yields, pest infestations facilitate the transmission of viral pathogens, further compromising crop health and productivity (Zhao et al. 2023). Climate projections for Southern Africa indicate temperature increases ranging from 1.5°C to 3.5°C by 2050, which are likely to further exacerbate the prevalence and intensity of certain crop pests and diseases (Mupangwa et al. 2023).

Among the most significant climate-influenced pest and disease outbreaks are FAW, groundnut rosette virus (GRV), and soybean rust (Mafongoya et al. 2019). The FAW (*Spodoptera frugiperda*) poses a substantial threat to global agricultural productivity owing to its ability to migrate over long distances and reproduce rapidly (Nyamutukwa et al. 2022; Tambo, Day, et al. 2020; Tambo, Kansiime, et al. 2020). Since its first report in Africa in 2016, FAW has spread to over 40 sub-Saharan African countries, causing significant economic losses (Early et al. 2018). GRV, endemic to sub-Saharan Africa, has caused numerous devastating epidemics, leading to over 90% crop failure when plants are infected before flowering (Naidu et al. 1999). The virus is primarily spread by aphid vectors, whose behavior and population dynamics are highly sensitive to temperature changes (Hull 2014; Wu et al. 2020). Soybean rust, caused by *Phakopsora pachyrhizi*, is a major biotic constraint on soybean production, directly affecting grain yield and quality (Hartman et al. 2011). The fungus can cause explosive outbreaks owing to its ability to produce large amounts of airborne spores, and its spread is facilitated by changing climatic conditions.

Despite the known prevalence of these pests and diseases, there is a lack of comprehensive studies estimating their combined impact on yields and other livelihood outcomes for smallholder farmers in Africa. Most existing research (Kansiime et al. 2019; Tambo and Kirui 2021) focuses on individual pests or diseases, potentially underestimating their cumulative effects on food security and livelihoods. Furthermore, although farmers have employed various control strategies, their effectiveness in the context of smallholder farming systems remains inadequately assessed (Durocher-Granger et al. 2021).

This study aims to address these knowledge gaps by evaluating the individual and combined impacts of FAW, GRV, and soybean rust on crop yields, household income, and food security among smallholder farmers in Malawi and Zambia. Additionally, we assess the effectiveness of commonly used control measures, including chemical and cultural practices. By focusing on these two countries, where maize, groundnuts, and soybeans are crucial for both food security and livelihoods, we provide critical insights into the challenges faced by smallholder farmers in this region.

Our research contributes to the literature in several ways. First, we offer a comprehensive assessment of multiple pests and diseases affecting different crops within the same farming system across two countries, allowing for a more holistic understanding of their cumulative impacts. Second, we employ advanced econometric techniques, including Entropy Balancing and Double/Debiased Machine Learning, to address potential endogeneity issues in evaluating the effectiveness of control strategies. Finally, by examining both the direct effects on crop yields and the broader implications for household income and food security, we provide a nuanced understanding of how these pests and diseases affect smallholder welfare.

The findings of this study have important implications for food security policies and agricultural development strategies in sub-Saharan Africa. By identifying the most effective control measures and quantifying the economic impacts of these pests and diseases, we aim to inform targeted interventions that can enhance the resilience of smallholder farming systems against climate change and evolving pest pressures.

2 | Maize, Groundnuts, and Soybean Pests/Diseases in Zambia and Malawi

The three crop pests and diseases, FAW, rosette, and soybean rust, pose economic challenges as they impact strategic crops in many African countries, including Malawi and Zambia (Hartman 1991; Nyirenda et al. 2021; Stevens and Madani 2016). In Malawi, the agricultural sector is a cornerstone of the nation's socioeconomic stability and efforts toward poverty alleviation, contributing up to 27% of the gross domestic product (GDP) and employing 85% of the population, largely comprising smallholder farmers (Stevens and Madani 2016). Maize (*Zea mays L.*), which is affected by FAW, holds a paramount position as Malawi's staple and primary food crop, occupying approximately 80% of cultivated land and defining the country's food security landscape (Stevens and Madani 2016). The significance of maize extends to Zambia's central, southern, and eastern regions, where it serves as the main staple food, constituting 52% of the daily calorie intake of the local population. Recognized as an economic and political crop in Zambia, maize cultivation is practiced across the nation, involving approximately 90% of smallholder households and a notable fraction of commercial farmers (Alamu et al. 2021; Manda et al. 2018). While maize takes the lead, groundnut crops have begun to carve a niche within Malawi's predominantly cereal-based farming systems, contributing to improved soil fertility, human nutrition, productivity, and between 25% and 60% of household agricultural income (Simtowe 2009). Notably, the area planted with groundnuts witnessed a substantial increase

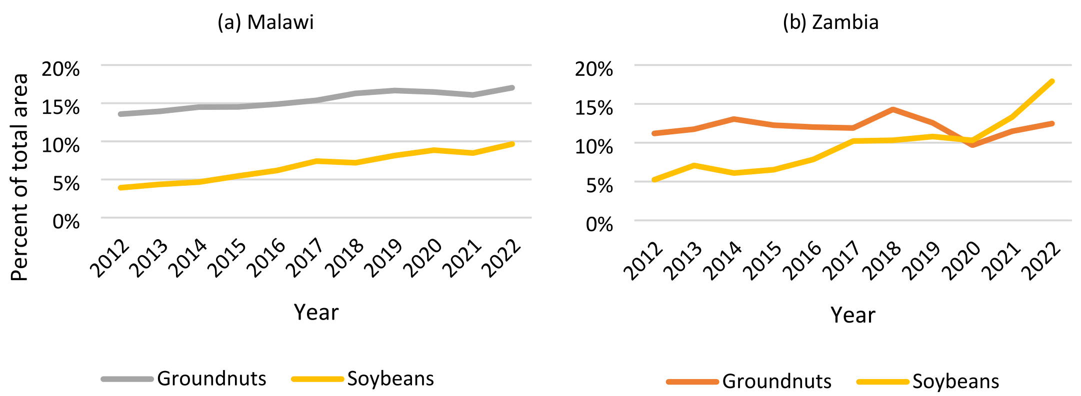

FIGURE 1 | Change in groundnut and soybean area cultivated to total cultivated area in Malawi and Zambia over the last 10 years. *Source:* FAOStat (2024).

of 54,000 ha between 2011 and 2017 (Gumma et al. 2019). In Zambia, groundnuts play a crucial role in rural livelihoods, as half of the households cultivate them, especially women (Mofya-Mukuka and Shipekesa 2013).

In Malawi, soybean is an important component of maize-based smallholder cropping systems and holds considerable potential for offsetting declining soil fertility in smallholder farming systems (Tufa et al. 2019; Van Vugt et al. 2017). However, current soybean yields on smallholder farmers' fields in Malawi are only approximately 1 ton per hectare, far below the African and global averages. The low productivity of soybean is partly due to the low adoption of improved varieties, use of poor-quality seeds, and inefficient and traditional production technologies (Tufa et al. 2019; Van Vugt et al. 2017). In Zambia, soybeans are promoted among small-scale farmers to improve agricultural diversity and income (Mubichi 2017). The increase in soybean cultivation in Zambia is largely driven by the expansion of the livestock and edible oil sectors (Kapulu et al. 2023). For instance, between 2006 and 2019, soybean production increased from 57,815 to 281,389 metric tons, representing a 320% increase. As Figure 1 shows, there has been a steady increase in the proportion of cultivated land allocated to groundnuts and soybeans in both Malawi and Zambia. Malawi has experienced an increase in both crops, while in Zambia, the groundnut proportion flattened between 2018 and 2022, but the soybean proportion has been rising from approximately 5% in 2012 to approximately 18% of the total cultivated area in 2022. These trends indicate that the importance of these two crops will become more pronounced in the coming years.

Numerous studies in Malawi and Zambia have highlighted the significant economic losses caused by FAW, Rosette, and Soybean rust. For example, Day et al.'s continent-wide study projected annual maize yield losses annually of between 21% and 53%; suggesting that the imminent spread of FAW in sub-Saharan Africa may exacerbate these losses (Day et al. 2017). It is also argued that FAW affects capital costs, labor, yields, and production expenses at the household level, directly influencing income (Kansiime et al. 2019).

Groundnut rosette virus is a devastating disease that can cause up to 100% yield loss in groundnut (*Arachis hypogaea* L.) crops (Naidu et al. 1999; Subrahmanyam et al. 2000). In a study conducted in Malawi, Minde et al. (2008) found that groundnut rosette disease (GRD) was a major constraint to groundnut production, with yield losses ranging from 30% to 100%. The study also highlighted the importance of resistant varieties and cultural practices, such as early planting and vector control, in managing the disease.

Similarly, Chintu (2013) investigated the distribution and incidence of GRD in Zambia. The study revealed that GRD was prevalent in all major groundnut-growing areas of the country, with incidence levels varying from 0.1% to 26%. The author emphasized the need for an integrated approach to disease management, including the use of resistant varieties, cultural practices, and chemical control of aphid vectors.

Soybean rust, caused by the fungus *P. pachyrhizi*, is another major disease affecting soybean production in Africa. Murithi et al. (2016) investigated the impact of soybean rust on yields across several African countries, including Malawi and Zambia. The study found that soybean rust caused yield losses of up to 80% in susceptible varieties, highlighting the need for resistant varieties and effective control strategies. In Malawi, Mhango et al. (2017) investigated the incidence and severity of soybean rust in farmers' fields. The study found that soybean rust was present at all surveyed sites, with incidence levels ranging from 10% to 100%. The authors recommend the use of resistant varieties, fungicides, and cultural practices to effectively manage the disease.

Although there are limited studies specifically focusing on the impact of the GRV and soybean rust in Zambia and Malawi, the available literature highlights the significant yield losses caused by these diseases and the need for an integrated approach to disease management. The development and adoption of resistant varieties, along with cultural practices and chemical control, are crucial for mitigating the impact of these diseases on smallholder farmers' livelihoods and food security in the region.

Given the ongoing trajectory of climate change and the consequent rise in crop pests and diseases, economically vital crops such as maize, groundnut, and soybean in nations such as Malawi and Zambia remain under threat. Existing studies underscore the limited adoption of control strategies by farmers in these countries (Chisonga et al. 2023; Day et al. 2017; Kansiime et al. 2019; Nyamutukwa et al. 2022; Tambo and Kirui 2021). This study complements prior research by offering estimates of the impact of three major crop stressors, broadening the analysis to encompass one pest and two diseases across three crops of economic importance in Malawi and Zambia.

Our methodological approach builds on previous studies that investigated the impact of pests and diseases on crop yields, household welfare, and the effectiveness of control strategies in sub-Saharan Africa (Tambo, Day, et al. 2020; Tambo, Kansiime, et al. 2020; Tambo et al. 2021; Kansiime et al. 2019; Tambo and Kirui 2021; Harrison et al. 2022; Tambo et al. 2023). By employing a combination of econometric techniques and considering multiple pests, diseases, and control strategies, our study provides a comprehensive assessment of the challenges faced by smallholder farmers in Malawi and Zambia and identifies potential solutions to enhance their resilience to these threats.

Specifically, this study contributes to the existing literature both empirically and methodologically. Empirically, this study provides a comprehensive assessment of the impact of three major crop stressors (FAW, GRV, and soybean rust) on smallholder farmer welfare in Malawi and Zambia. By considering the combined effect of these stressors on farmers' income and food security, this study offers a more holistic understanding of their impact on smallholder welfare. Moreover, the study evaluates the effectiveness of a broader range of control strategies used by farmers, including crop rotation and improved varieties, in addition to direct control methods such as the use of pesticides.

Methodologically, the paper employs advanced econometric techniques, such as Entropy Balancing and Double/Debiased Machine Learning, to address potential endogeneity issues arising from self-selection and unobserved confounding factors for the use of control strategies. These methods help isolate the causal effect of control strategies on crop yields, providing more reliable and robust estimates than traditional approaches. The application of these techniques to the study of crop pests and diseases in sub-Saharan Africa is a novel contribution to this field.

In summary, this study addresses important gaps in the literature by providing a comprehensive, multicrop, and multicountry analysis of the impact of crop pests and diseases on smallholder welfare in Southern Africa. The study's empirical findings and methodological innovations contribute to a better understanding of the challenges faced by smallholder farmers and inform the development of more effective and sustainable control strategies.

3 | Methods

3.1 | Farm Household Survey

To determine the impact of FAW, GRV, and soybean rust on smallholder farmers' welfare and evaluate the effectiveness of control strategies, we used data collected through a survey of 1100 randomely selected farming households in Malawi and Zambia. The survey was conducted using a structured questionnaire to gather information on household characteristics, crop production, pest and disease incidence, control strategies employed, and food security. The study gathered data from randomly selected households in Malawi ($n=600$) and Zambia ($n=500$) to gain comprehensive insights into the shift from maize to legume production by smallholder farmers. A multistage stratified sampling approach was used in both countries. After data cleaning, we were left with a sample of 1089 farmers.

In Malawi, districts were purposively selected in the first stage based on agricultural production estimates, indicating a transition from cereal to legume cultivation. The goal was to capture as many farmers as possible who grow the two legumes of concern—groundnuts and soybeans. The selected districts were Kasungu, Lilongwe, Salima, and Dowa. The second stage involved randomly selecting three Extension Planning Areas (EPAs) per district, resulting in 12 EPAs. In the third stage, two sections were purposively chosen from each EPA, yielding 24 sections for the entire study. Finally, 25 households were randomly sampled from each section, resulting in a total sample size of 600.

Similarly, in Zambia, the first stage involved purposively selecting the Central, Southern, and Eastern provinces based on agricultural production estimates data showing a shift from cereal to legume production. In the second stage, 10 districts with the highest observed shifts were chosen. The subsequent stages involved purposive selection of agricultural camps within each district, followed by the selection of one village per camp based on a growing trend in legume production. Finally, 25 households were randomly selected from each village, resulting in a total sample size of 500.

The generalizability of our findings should be considered in light of the sampling strategy. Our focus on areas experiencing shifts from cereals to legumes means that our results are most applicable to regions where legume cultivation is expanding and where conditions favor crop diversification. The incidence and impact of pests and diseases, as well as the effectiveness of control strategies, may differ in these areas. However, our findings remain relevant for agricultural policy because they capture the dynamics in areas where agricultural transformation is actively occurring. These areas represent potential future trajectories for other regions as crop diversification policies are expanded. Furthermore, the biological mechanisms through which these pests and diseases affect crops are likely consistent across regions, even if absolute impact magnitudes may vary.

3.2 | Key Variables

The key outcome variables are the yield of each crop (in kg/ha), annual household income (mainly farm income, in USD), food insecurity (measured as a binary variable), and the number of months a household is food insecure to measure the intensity of food insecurity. Table 1 presents the descriptive statistics of these variables. Crop yields are comparable across the two countries, whereas household income is higher in Zambia. We also evaluated two cultural practices that have been shown to reduce the effects of or prevalence of pests and diseases: the use of hybrid (maize) or improved seeds (legumes) and crop rotation. Improved seeds may be more tolerant to pests and diseases than local seeds (González Guzmán et al. 2022), whereas crop

TABLE 1 | Descriptive statistics for the variables used in the regressions.

	Malawi ($n = 599$)	Zambia ($n = 501$)	Difference
Outcome variables			
Maize yield (kg/ha)	1722.2	1659.8	62.38
Groundnut yield (kg/ha)[a]	1460.5	1522.4	−61.89
Soybean yield (kg/ha)	568.0	1002.0	−434.02***
Total annual household income, US$	264.8	353.0 (630.6)	−88*
Crop income, US$	164.9	87.7	77.19***
Households with inadequate food in the last 12 months (percent)	60.9	57.3%	3.65
Number of months HH was food insecure	1.5	1.2	0.33***
Key independent variables			
FAW infestation (1/0)	0.56	0.75	−0.18**
Rosette infestation (1/0)	0.32	0.40	−0.08*
Rust infestation (0/1)	0.41	0.40	−0.01
Maize plot crop rotation (1/0)	0.68	0.63	0.06*
Used hybrid maize seed (1/0)	0.66	0.81	−0.14***
Groundnuts crop rotation (1/0)	0.78	0.86	−0.08***
Used improved groundnut seed	0.26	0.15	0.11***
Soybean plot rotation (1/0)	0.78	0.86	−0.08***
Used improved soybean seed (1/0)	0.261	0.147	0.11***
Other controls			
Farm size (ha)	1.37	5.24	−3.86***
Tropical livestock units	0.08	5.69	−5.61***
Age of household head (years)	46.04	46.93	−0.89
Years of schooling of HH head	7.10	6.78	0.32
Female headed household (0/1)	0.28	0.23	0.05*
Access to extension (1/0)	0.54	0.27	0.27***
Number of years lived in the village	30.22	26.43	3.79***
Access to credit (1/0)	0.16	0.23	−0.07**
Member of farmer organization (1/0)	0.51	0.73	−0.23***
Basal fertilizer applied to maize (1/0)	0.76	0.82	−0.06**
Urea applied to maize (1/0)	0.70	0.83	−0.14***
Basal fertilizer applied to groundnuts (1/0)	0.01	0.00	0.01**
Basal fertilizer applied to soybean (1/0)	0.01	0.05	−0.03***

[a]Note that the groundnut yield is higher than the national average. We suspect this is a result of the study purposively selecting areas and farmers that grow more legumes than cereals, meaning these farmers could have specialized. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

rotation reduces the incidence of pests by breaking the life cycle of the pest (Ouda et al. 2018). Respondents were asked which crop they grew in the previous season in each plot. We defined the sequence as crop rotation if either a legume was grown where there was a cereal or vice versa in two successive seasons. The proportion of households that used improved seeds and practiced crop rotation with respect to each crop is also shown in Table 1 under key independent variables. There are significant differences between the two countries, with Zambia having a higher proportion of households using these cultural practices than Malawi, except for the use of improved groundnut seeds.

We also show the other controls included in the regressions. Overall, similar to the key variables, Zambia has higher values for these variables than Malawi, except for the proportion of households with access to extension and the number of years a respondent/household has lived in that village. For the yield regressions, we also controlled for fertilizer use.

For the key independent variable, pest attacks, we show the proportion of households reporting each attack in the results section in Figures 2 and 3. Farmers have employed different strategies to control these pests and diseases. For each farmer who reported an infestation in their plot, we asked what control measures they implemented, which are reported in Table 2. Local alternative refers to a collection of different practices that had too few farmers using them to be included on their own, such as the use of ash, spraying with soft drinks, spraying with washing detergents, and the use of certain herbs. Pesticides, scouting, and crashing are the most common control strategies for FAW, whereas local alternatives are used more against rosette virus and soybean rust. However, most farmers did not take any measures to control the pests/diseases.

3.3 | Econometric Approach

We employed several econometric models to analyze the data and address our research objectives, as follows. First, to estimate the effect of FAW, rosette virus, and soybean rust on crop yields, we used the following regression model:

$$\begin{aligned} yield_{ij} = \; & \beta_0 + \beta_1 \, FAW_{ij} + \beta_2 Rosette_{ij} + \beta_3 Rust_{ij} \\ & + \beta_X X_{ij} + \delta_j + \pi_j + \varepsilon_{ij} \end{aligned} \tag{1}$$

where $yield_{ij}$ represents the yield (kg/ha) of crop i (maize, groundnuts, or soybeans) for household j, while FAW_{ij}, $Rosette_{ij}$, and $Rust_{ij}$ are dummy variables indicating the presence of the respective pest or disease, X_{ij} is a vector of control variables (such as household characteristics and farm management practices), δ_j represents district fixed effects, π_j the country fixed effects, and ε_{ij} is the error term. The coefficients β_1, β_2, and β_3 capture the impact of each pest or disease on crop yield (Tambo, Day, et al. 2020; Tambo, Kansiime, et al. 2020; Harrison et al. 2022). We follow previous literature (Kassie et al. 2020; Tambo et al. 2023) in treating pest/disease infestation/attack as exogenous. This assumption is plausible for two reasons. First, once we control for district and country fixed effects that capture regional variation in climate, soils, and other agroecological factors, pest or disease infestation at the household level is largely driven by factors outside individual farmers' control, such as the migratory nature of FAW, the airborne transmission of soybean rust spores, the vector-based transmission of GRV through aphids, and weather patterns that affect pest/disease prevalence. However, we acknowledge the potential limitations of this assumption in this study. Unobserved farm management practices (such as planting dates or field sanitation) could influence pest susceptibility. Therefore, we do not interpret these results as causal.

We begin with a model without district fixed effects, as these may absolve most of the variation in pest attacks. We then add the district fixed effects to control for any district-specific differences, such as soils and climate, at the risk of losing variation; however, we find that the results are robust to this inclusion. Once we control for district and country fixed effects, pest or disease infestation at the household level is a result of factors outside the farmer's influence. Thus, it is not unreasonable to assume that infestation is exogenous and that control strategies are endogenous.

The multiple regression analysis may have several weaknesses. First, it relies on meeting several assumptions, including that the relationship between infestation and yield is linear. If this does not hold, the estimated coefficients may be biased. Furthermore, we plot the residuals of the yield regressions in Figure A1, which shows some levels of heteroscedasticity. To address these concerns regarding potential violations of OLS assumptions, particularly in the presence of measurement errors and nonlinear relationships, we employ generalized additive models (GAM) for robustness to check if the results still hold. GAMs are a powerful tool for analyzing the impact of pests on crop yield, as they can effectively handle nonlinear relationships, measurement errors, and violations of ordinary least squares (OLSs) assumptions (Wood 2017). Our choice of GAM was motivated by these factors. First, because our key independent variable (FAW infestation) is binary, the relationship with the continuous yield is nonlinear. Second, as shown in Figure A1, the residuals from our OLS models exhibit heteroscedasticity, particularly for (specific crop) yield. GAMs allow the modeling of complex, data-driven relationships without the need for prespecified functional forms, making them particularly suitable for capturing the intricate interactions between pests and yield (Wellington et al. 2023). Moreover, GAMs can accommodate measurement errors in both the predictor and response variables, providing more robust estimates than traditional regression methods (Carroll et al. 2006). Recent studies in agronomy have successfully applied GAMs to investigate the impact of various factors, including pests, on crop yield (Mosammam et al. 2015; Rosenheim and Meisner 2013; Varah et al. 2020). In all regressions, including those for OLS, we use robust standard errors to account for any potential heteroscedasticity.

Next, we assess the impact of pest and disease attacks on household income and food insecurity. When agricultural productivity is negatively affected, this directly leads to reductions in food security and income for rural households that depend on agriculture for food and income. Therefore, it is important to evaluate the effects of these pests and diseases on these outcomes. We use the log of annual household and crop income so that the coefficients are interpreted as percentage changes. We consider both household income and crop income, which contribute significantly (43%) to the total household income. For food insecurity, we consider both a qualitative measure and one that indicates the intensity of the food insecurity situation. Households were asked if they had ever not had enough food in the last 12 months, and those who did not were categorized as food insecure, which is a standard approach for eliciting a qualitative measure of food insecurity. Furthermore, to quantitatively measure the severity of food insecurity, respondents were asked how many months in the last 12 months they did not have enough food (Jones et al. 2013; Nicholson et al. 2021). Because these are household-level

TABLE 2 | Control strategies used against FAW, rosette virus, and soybean rust.

	FAW		Rosette virus		Soybean rust	
Control strategy	**Freq.**	**%**	**Freq.**	**%**	**Freq.**	**%**
Nothing	290	37.96	402	77.76	349	74.57
Pesticides	142	18.59	57	11.03	48	10.26
Local alternative	60	7.85	58	11.22	71	15.17
Scout and crash	138	18.06				
Use sand	134	17.54				
Total	764	100	517	100	468	100

Note: The table only reports a subsample of households that reported having any of their fields attacked by that pest/disease.

outcomes that are not crop specific, we consider the full factorial combinations of pest/disease infestation. As we have stated, this is one of the contributions of this study. Instead of merely focusing on one pest or disease, we consider the combined effects of these three stressors. We use the categories shown in Figure 3, with no attack as the reference category. We formally estimate the model as follows:

$$
\begin{aligned}
E\left(Y_{mj}\right) = \; & \eta_{m0} + \eta_{m1} FAW_{mj} + \eta_{m2} Rosette_{mj} + \eta_{m3} Rust_{mj} \\
& + \eta_{m4}\left(FAW_{mj} \times Rosette_{mj}\right) + \eta_{m5}\left(FAW_{mj} \times Rust_{mj}\right) + \eta_{m6}\left(Rosette_{mj} \times Rust_{mj}\right) \\
& + \eta_{m7}\left(FAW_{mj} \times Rosette_{mj} \times Rust_{mj}\right) + \eta_{mX} X_{mj} + \delta_{mj} + \pi_{mj} + \epsilon_{mj}
\end{aligned} \tag{2}
$$

where Y_{mj} is outcome $m =$ income, food insecurity, and intensity of food insecurity for household j, with the expectation operator $E\left(Y_{mj}\right)$ included to accommodate nonlinear models (more below). η_{m1} to η_{m7} are the parameters of interest for the associated variables that include the pests and their combinations. Specifically, the coefficients η_{m4} to η_{m7} capture the impact of combined pest and disease attacks on household welfare.

Finally, we evaluate the effectiveness of control strategies in reducing yield losses. We estimate each model separately for each crop. We evaluate the effectiveness of control strategies (Table 2) and cultural practices (improved seeds and crop rotation). For brevity, we refer to all of these as control strategies, even if the use of hybrids or crop rotation may not primarily be aimed at controlling pests or diseases. We begin with the following base OLS model:

$$
\begin{aligned}
yield_{ij} = \; & \theta_0 + \theta_1 Pesticides_{ij} + \theta_2 LocalAlternative_{ij} + \theta_3 ScoutCrash_{ij} \\
& + \theta_4 UseSand_{ij} + \theta_5 CropRotation_{ij} + \theta_6 HybridSeed_{ij} + \theta_X X_{ij} + \delta_j + \pi_j \\
& + \xi_{ij} \; iff \forall i: \; is \; attacked \; by \; a \; pest/disease
\end{aligned} \tag{3}
$$

where the variables *Pesticides*, *LocalAlternative*, *ScoutCrash*, *UseSand*, *CropRotation*, *HybridSeed* are dummy variables indicating the use of the respective control strategies with their corresponding parameters, $\theta_1 - \theta_6$, and the other variables are defined as before. This analysis is carried out only for a subset of farmers who had an attack of each respective pest/disease. The coefficients $\theta_1 - \theta_6$ measure the effectiveness of each control strategy in reducing yield losses (Kansiime et al. 2019; Tambo and Kirui 2021). As stated earlier, control strategies are potentially endogenous because farmers decide on what to use or adopt based on both observable and unobservable factors (i.e., self-selection).

While instrumental variable (IV) estimation would be an ideal approach to address potential endogeneity from unobserved confounders, our dataset lacks variables that meet the strict requirements for valid instruments, namely, variables that are correlated with the adoption of control strategies but affect yields only through their effect on adoption. In the absence of suitable instruments, we employ two complementary quasiexperimental approaches—Entropy Balancing and Double/Debiased Machine Learning—to address selection bias based on observable characteristics. However, we acknowledge that these methods cannot fully account for selection on unobservables; thus, we interpret our results on the effectiveness of control strategies with appropriate caution. To reduce clutter, we describe how these two methods address endogeneity and omit the mathematical equations.

Entropy balancing is a preprocessing method that aims to create balanced treatment and control groups by reweighting observations based on a set of predefined covariates (Hainmueller 2012; Hainmueller and Xu 2013). Entropy balancing addresses endogeneity by creating a weighted sample of the treatment and control groups, balanced on a set of observed covariates. The weights are calculated for each untreated individual such that differences in the distribution of covariates between the treatment and control groups are reduced. This is achieved by assigning weights to the units in the sample such that the weighted distributions of the covariates in the treatment and control groups are identical to each other. By ensuring that the treatment and control groups are comparable in terms of observed characteristics, entropy balancing reduces bias due to confounding variables. This technique helps mitigate selection bias and ensures that the treatment and control groups are comparable in terms of observable characteristics. The exact adjustment of covariate moments and its doubly robust property make it an appealing alternative to standard matching (e.g., propensity score matching [PSM]) or reweighting methods when estimating causal effects from observational studies (Zhao and Percival 2017). Compared to traditional matching approaches, such as PSM, entropy balancing has several advantages. When the number of covariates over which to balance or match increases, PSM faces challenges, whereas entropy balancing performs well (Meemken and Qaim 2018). In PSM, observations for which a proper match cannot be found have to be dropped from the analysis, sometimes resulting in small comparison groups that are no longer representative, while with entropy balancing, low levels of covariate balancing can be avoided, and information from all observations is used, because no observation is given a zero weight (Hainmueller 2012). By applying entropy balancing, we can isolate the effect of the treatment (in our case, the use of control strategies) on the outcome variable (crop yield) from the influence of the confounding factors. We consider the adopters of each control strategy as the treatment and those who do not use any as the control and estimate the models separately for each strategy versus control. This method has been increasingly used in agricultural economics research to improve the reliability of impact estimates (Rodrigues et al. 2023; Schader et al. 2021).

Double/debiased machine learning (DML), on the other hand, is a framework for estimating causal effects in observational studies while controlling for confounding variables. Similar to entropy balancing, DML is designed to address issues of endogeneity and confounding, but it does so by leveraging modern machine learning techniques to flexibly control for a potentially large number of covariates (Chernozhukov et al. 2018). The basic idea of DML is to use machine learning models to predict the outcome (maize yield) and treatment (adoption of control strategies) based on the observed covariates, and then use these predictions to adjust for the confounding effects in estimating the causal effect of the treatment on the outcome. This is performed in two steps. First, estimate the conditional expectation of $\boldsymbol{yield}_{ij}$ and of treatment (for notation, we call it D_{ij}, control strategies) given X_{ij} using appropriate nonparametric estimators (e.g., machine learners). Then, in the second stage, residualize $\boldsymbol{yield}_{ij}$ and D_{ij} by subtracting their respective conditional expectation function (CEF) estimates, and regress the resulting CEF residuals of $\boldsymbol{yield}_{ij}$ on the CEF residuals of D_{ij}. This approach works fairly well as long as the errors of the first step do not propagate excessively to the second step. According to Ahrens et al. (2024), double debiased machine learning leverages two key ingredients to control the effect of the first-step estimation error on the second-step estimate: (1) second-step estimation based on Neyman orthogonal scores and (2) cross-fitting. This approach involves four steps in the implementation of double/debiased machine learning. First, cross-fitting splits the data into K folds. In our case, we keep the K folds at 10, as it is recommended that they should be kept between 10 and 15 for small samples. Using 10 folds for cross-fitting is a common choice that balances the trade-off between bias and variance in the estimation process. More folds can lead to less bias but higher variance, whereas fewer folds can lead to more bias but lower variance. This is done to ensure that the predictions used for adjustment are not overfitted to the data. Second, the machine learning techniques are applied to each fold to train models to predict the outcome and the treatment based on the covariates using the other folds. We use the stacking regression (i.e., *pystacked*) for the machine learning program. We use the partial model specification, which means that we do not specify the full functional form of the relationship between the covariates and the outcome/treatment. The key identifying assumption in the partial model is that the error term from the outcome model and treatment, conditional on the covariates, are not correlated (Ahrens et al. 2024). Third, estimation uses the predictions from the machine learning models to adjust for confounding effects when estimating the causal effect. This is typically done by regressing the residuals from the outcome model on those from the treatment model. The fourth and final stage involves aggregation, where the estimates from each fold are averaged to obtain the final estimate of the causal effect, the average treatment effect. As before, we estimate for each control strategy versus control (no control strategy) pair separately.

In summary, the use of Entropy Balancing and Double/Debiased Machine Learning in our study improves the OLS estimates by addressing potential endogeneity issues arising from self-selection and unobserved confounding factors. These advanced econometric techniques help isolate the causal effect of control strategies on crop yields, providing more reliable and robust estimates compared to traditional methods. However, neither method can address unobserved confounders. Therefore, we interpret our results with caution.

4 | Results and Discussion

4.1 | Incidences of Fall Armyworm, Rosette, and Rust

Figure 2 illustrates the proportion (percent) of farmers in Malawi and Zambia who experienced pest and disease attacks in a mutually exclusive manner during the 2022/2023 season. In both countries, more than half of the farmers experienced FAW attacks, with more Zambian farmers reporting attacks than those in Malawi. Additionally, less than 41% of farmers in both countries experienced rosette virus and soybean rust attacks, with no significant difference between the two countries.

The high levels of infestation observed from FAW in this study are relatively higher than the proportions observed by Harrison et al., who reported varying infestation levels of about 57% overall in the two countries during the 2020/2021 farming season, implying that infestation levels may have increased since then (Harrison et al. 2022). However, this difference may be a result of differences in estimation methodologies; Harrison et al.'s rates are drawn from fields, while this study's estimations are drawn from household survey interviews with farmers, who may own multiple fields and may generalize that they were attacked.

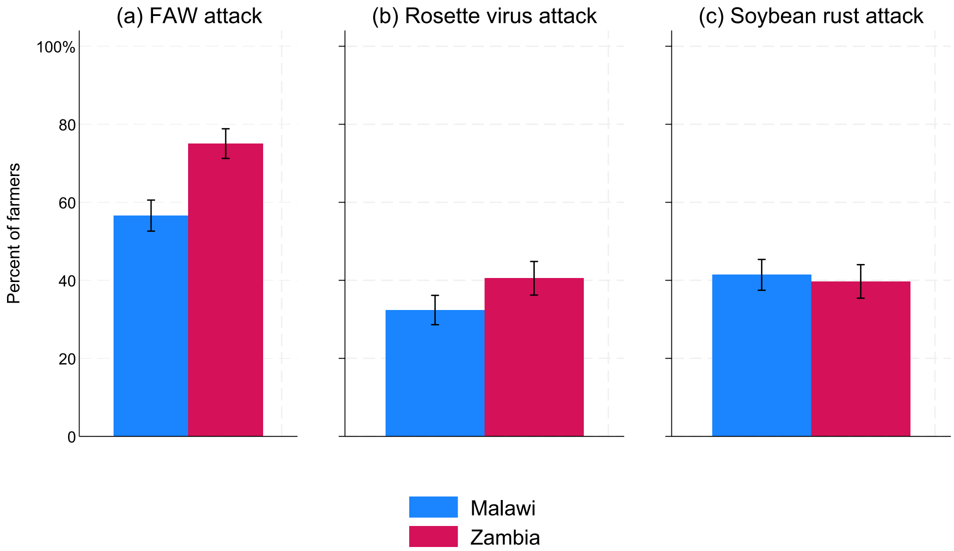

FIGURE 2 | Percentage of farmers affected by FAW, Rosette virus, and Soybean rust in Malawi and Zambia. The spikes on top of each bar represent the 95% confidence interval.

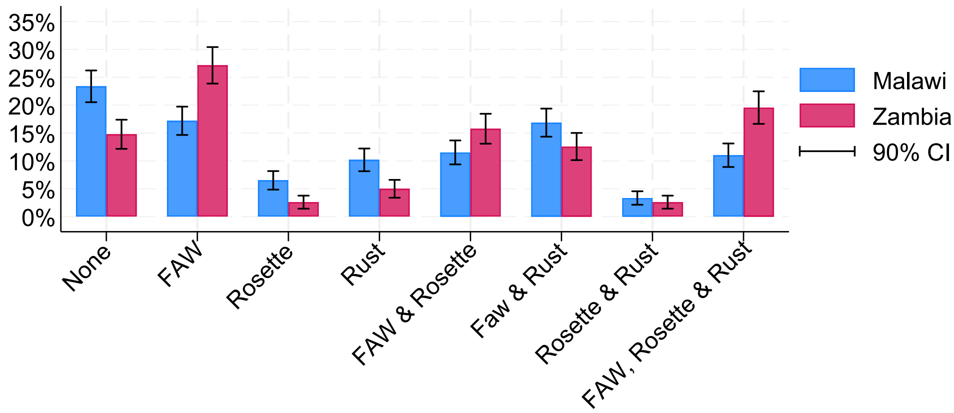

FIGURE 3 | Proportion of farmers reporting an attack from a given pest/disease, singly and in combination. The figure presents different mutually exclusive categories. The spikes at the top of each bar represent the 95% confidence interval.

Furthermore, considering the impact of the FAW on staple crops further necessitates the need to assess potential yield losses in the two countries and examine effective strategies. The lack of significant differences in Rosette and Rust attack rates between Zambia and Malawi highlights the fact that crop diseases know no borders. This underscores the importance of intervention strategies in both countries, given the economic significance of the crops affected by these diseases in both countries. Moreover, the similarity in attacks may justify aggregating observations from both countries for further analysis. Furthermore, the relatively low attacks observed in the two diseases (Rosette and Rust) are consistent with other studies conducted concurrently in both countries (Nachilima et al. 2020).

Figure 3 illustrates the proportion of farmers reporting attacks from the three stressors, including their combinations, in a mutually exclusive manner. The figure indicates a significant difference in all single pest or disease attacks between Malawian and Zambian farmers, but no major difference across the different combinations, except for the combination of all three.

4.2 | Impact of Fall Armyworm, Rosette, and Rust on Yield, Food Security, and Income

Table 3 shows the impact of FAW, Rosette, and Rust on the yield of maize, groundnuts, and soybeans. All regressions control for other variables such as household characteristics (farm size, age, household size, gender, tropical livestock units, and education), institutional (access to extension, number of years lived in the village, access to credit, and member of farmer organization), and input use (basal fertilizer application, use of improved seeds, urea fertilizer application, and crop rotation). Columns 1–3 present the model with these controls, while Columns 4–6 include controls and district fixed effects, and Columns 7–9 use the GAM that addresses some of the violations of the assumptions of OLS. The findings suggest that FAW infestation led to a reduction in maize yield by about 13.5% (230.7 kg/ha) (Table 4), with this effect remaining significant regardless of whether district fixed effects are applied (Columns 4–6). However, the effect size reduces slightly to about 200 kg/ha yield reduction when GAM is used (Column 7). This suggests that there is a reduction bias in

TABLE 3 | Effect of FAW, Rosette, and rust on yield of maize, groundnuts, and soybean, respectively.

	Ordinary least squares						Generalized additive models		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Maize yield (kg/ha)	Groundnuts yield (kg/ha)	Soybean yield (kg/ha)	Maize yield (kg/ha)	Groundnuts yield (kg/ha)	Soybean yield (kg/ha)	Maize yield (kg/ha)	Groundnuts yield (kg/ha)	Soybean yield (kg/ha)
FAW infestation	−230.7*			−232.5*			−197.9*		
	(132.9)			(133.1)			(103.8)		
Rosette virus infestation		−377.3**			−316.6			−310.4	
		(190.5)			(208.2)			(196.4)	
Rust infestation			−207.5***			−211.1***			−209.3***
			(53.62)			(52.01)			(48.9)
Constant	1361***	1800***	946.6***	1359***	2176***	965.7***	971.7***	1400***	623.5***
	(192.1)	(472.9)	(161.0)	(274.3)	(627.9)	(151.7)	(245.6)	(506.1)	(119.0)
Observations	1060	774	683	1060	774	683	1060	774	683
R^2	0.085	0.023	0.145	0.125	0.051	0.254	0.104	0.017	0.218
Other variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Allows nonlinearity	No	No	No	No	No	No	Yes	Yes	Yes

Note: Robust standard errors in parentheses. The other variables included as controls are farm size, tropical livestock units, age of the household head, education of the household head, gender of the household head, access to extension, number of years the household has lived in the village, access to credit, whether the farmer belong to an farmers' organization, whether they applied basal and top dressing fertilizer, and whether they used improved seeds. Average yield: Maize = 1693, Groundnut = 1493, Soybean = 764.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

TABLE 4 | Effect of FAW, groundnut rosette virus, and soybean rust on income and food security.

	(1)		(2)	(3)
Variables	**Log of annual HH income**	**Log of crop income**	**Food insecurity (0/1)**	**No. of months food insecure**
FAW	−0.528***	−0.144	0.0977**	0.0333**
	(0.191)	(0.191)	(0.0458)	(0.0134)
Rosette	−0.363	−0.480*	0.0473	0.0230
	(0.288)	(0.270)	(0.0754)	(0.0184)
Rust	−0.231	−0.500**	0.0788	−0.0222
	(0.243)	(0.240)	(0.0598)	(0.0186)
FAW and rosette	−0.585***	−0.771***	0.0685	0.0343**
	(0.226)	(0.197)	(0.0519)	(0.0147)
FAW and rust	−0.565***	−0.623***	0.149***	0.0763***
	(0.202)	(0.194)	(0.0489)	(0.0188)
Rosette and rust	−0.294	−0.298	0.0204	0.00987
	(0.338)	(0.334)	(0.0919)	(0.0235)
FAW, rosette, rust	−0.543**	−0.404**	0.202***	0.0601***
	(0.210)	(0.182)	(0.0482)	(0.0166)
Constant	4.411***	4.083***	−0.284***	−2.395***
	(0.381)	(0.364)	(0.0777)	(0.0274)
Observations	1100	1100	1100	1100
R^2	0.168	0.237	0.107	
Other variables	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses. Similar controls to those in Table 3 are included as controls. Column (1) and (2) are estimated using OLS and Column (3) using a linear probability model while Column (4) is estimated using Poisson model since number of months is a count variable.
***$p<0.01$; **$p<0.05$; *$p<0.1$.

accounting for nonlinear relationships. GRV decreased yields by 377 kg/ha, which is about 25% of the average yield. However, rosette virus infestation on groundnuts did not reduce yield significantly when district fixed effects were included and GAM was used. Similarly, Rust infestation resulted in a significant reduction in yield of approximately 27% (207–211 kg/ha), regardless of the estimation method used. This implies that after controlling for district-specific differences, such as average rainfall, temperature, soils, and other district-level policies, the Rosette virus infestation does not significantly affect groundnut productivity.

The 13.5% yield loss due to FAW estimated in this study is below the 22%–67% range estimated from farmer socioeconomic survey interviews from several African countries (Kansiime et al. 2019) but is closely aligned with the 11.5% estimate in Baudron et al. (2019) in Zimbabwe. However, the estimation for this study lies above other field scouting and harvesting of quadrant-based studies, whose yield loss estimate due to the FAW in Africa is approximately 9% (Kansiime et al. 2019). It is worth mentioning that some studies fail to find a significant relationship between FAW infestation and maize yield loss (e.g., Harrison et al. 2022; Tambo et al. 2023). The 27.2% soybean rust attributed yield loss for Malawi and Zambia established in this study falls within the 18%–55% range reported in Uganda and Zimbabwe (Nachilima et al. 2020). However, the results depart from the Malawi-specific mean yield loss of 32.5% across various soybean varieties, whose individual yield loss due to rust ranged from 8% to 89.4% (Guwela et al. 2013).

The estimation results of the effects of FAW, GRV, and soybean rust on income and food security are presented in Table 4. Households experiencing a FAW attack alone had 53% lower income. Additionally, a FAW attack increases the probability of being food insecure by about nine percentage points and extends the duration of food insecurity by 3 months.

In contrast, independent attacks by rosette and rust alone, or a combination of rosette and rust, had no significant effect on household income and food insecurity (Table 4). This is likely a result of food security defined by calories and the relatively less important role played by market purchases in food security for smallholder farmers (Mulungu et al. 2023). However, when we focus on crop income, we find that rosette and rust attacks on their own reduce crop income by about 50%, indicating the importance of these legumes as cash crops. Furthermore, Table 4 indicates that if a household is attacked by both fall army worms and rosettes, they have a 59% lower household income, a 78% lower crop income, a 12 percentage points increase in the likelihood of being food insecure, and a 28% increase in the months of being food insecure.

Results also suggest that households attacked by both FAW and rust (jointly) had a 57% lower household income, 62% lower crop income, a 16 percentage point higher chance of being food insecure, and a 7% increase in months of being food insecure. Overall, the combination of all three (FAW, Rosette, and Rust) attacks had a higher negative effect on livelihood outcomes than the individual attacks. Additionally, the FAW, rosette, and rust combination attack also suggests a 56% reduction in household income, a 40% reduction in crop income, a 20 percentage point increase in the likelihood of being food insecure (the highest), and a 47% increase in the duration of household food insecurity in months.

A key assumption in our analysis is the exogeneity of pest and disease infestation. Although this assumption is supported by the biological characteristics of these pests/diseases and previous literature, it has important implications for interpreting our results. If unobserved farm characteristics simultaneously affect both infestation likelihood and yields, then our yield loss estimates could be biased. For example, farmers with better management practices might be both less likely to experience severe infestations and more likely to achieve higher yields, potentially leading to overestimates of the infestation impacts. However, several factors suggest that this bias may not be severe. First, our inclusion of district fixed effects controls for many unobserved geographic factors that could affect both the infestation and yields. Second, the consistency of our results across different estimation methods, including those that account for selection on observables, suggests robustness to potential violations of the exogeneity assumption.

Overall, the results of this study highlight the impact of pests, such as FAW, and crop diseases, on household income and food security. Specifically, even on their own, and focusing on crop income, rust and rosette have a significant negative effect. Additionally, while rust and rosette on their own show no significant effect on income and food security, the results show that when combined with FAW, they (combinations) have a larger negative effect than FAW alone. This suggests that households affected by only one crop attack may temporarily rely on other crops for food. Otherwise, they are at risk of experiencing food insecurity for a longer period. It also shows that studies that study one pest or crop may miss the additional effect of a household experiencing multiple pests or diseases.

4.3 | Effectiveness of Control Strategies

Table 5 illustrates the impact of the control strategies on reducing the negative effects on yield. The results suggest that pesticides significantly reduce soybean losses by 230.2 kg/ha when district fixed effects are considered in the estimation; otherwise, the relationship is not significant. Furthermore, results indicate that hybrid/improved seed significantly reduces losses by 277.7 and 300.6 kg/ha in maize yield when estimated with and without district fixed effects, respectively.

In our study, we found that the use of pesticides had a significant negative impact on maize yield, but only when there were no district fixed effects, meaning that these differences are largely driven by differences across districts. A previous study conducted by Kansiime et al. in Zambia showed that approximately 60% of farmers used pesticides to control FAW infestation in maize during the 2016/2017 farming season (Kansiime et al. 2019). To the best of our knowledge, no study has specifically examined the effect of pesticides on soybean yield in Zambia and Malawi. This indicates the need for further research in this area. Nevertheless, several studies have expressed concerns about the use of pesticides as a control method because of their potential risks to human health and the environment and their lack of efficacy against pests (Kansiime et al. 2019; Nyamutukwa et al. 2022; Van Vugt et al. 2017).

Of all the control strategies tested in this study, the use of hybrid maize seeds significantly reduces the loss of maize by the largest margin (kg/ha). However, for the control of rosette and soybean rust, the OLS results show that most of the control strategies do not work, except for pesticides for soybean rust and rotation for rosette. As rosette is a virus, crop rotation may be a viable option for its control.

Table 6 presents a robustness check of the effect of control strategies on yield using entropy balancing. The check indicates consistent and significant results for pesticides in reducing losses in soybean productivity only when district fixed effects are included in the model, compared to the results in Table 5, despite the difference in magnitude. In addition, the robustness check in Table 4 for the crop rotation strategy shows a significant relationship in reducing yield loss in ground nuts and soybean, which contradicts the results observed in Table 3. Additionally, the robustness check for the use of hybrid/improved seeds shows consistent significant relationships for maize and soybean, though not significant under OLS. Similarly, the kg/ha in loss reduction varies across the estimation methods, that is, between those in Tables 5 and 6. Using entropy balancing, crop rotation shows benefits to groundnut resistance to rosette and soybean resistance to rust, as well as the use of improved seeds for maize and soybean. This differs from the OLS results. Furthermore, for strategies that are significant in buffering yield losses using entropy balancing, the effect size is larger, showing that endogeneity in OLS biases the results downwards.

Robustness checks of the effect of control strategies on yield using Double/Debiased Machine Learning are presented in Table 7. Similar to the entropy balancing results in Table 4, the results in Table 7 also indicate that the relationship between pesticide use and reduction in soybean yield loss is significant. These findings are consistent with those obtained using the entropy balancing method. Similar to the entropy balancing results, the double/biased machine learning-based results in Table 7 also show that pesticides, crop rotation, and the use of hybrids/improved seeds

TABLE 5 | Effects of control strategies in reducing the negative effects of FAW, rosette, and rust on crop yield (kg/ha).

	(1)		(2)		(3)	
	Maize yield	**Maize yield**	**Groundnut yield**	**Groundnut yield**	**Soybean yield**	**Soybean yield**
Pesticides	275.3**	168.1	294.3	322.8	151.6	230.2**
	(139.4)	(142.3)	(265.7)	(274.9)	(111.7)	(113.7)
Local alternative	41.31	1.603	−118.6	−137.1	203.3	173.2
	(162.8)	(164.5)	(218.4)	(232.9)	(125.3)	(116.6)
Scout and crash	18.21	−112.1				
	(115.9)	(125.7)				
Use sand	197.5	112.1				
	(135.6)	(140.0)				
Crop rotation	12.71	−56.09	373.1*	282.5	115.9	94.48
	(98.03)	(97.57)	(190.8)	(171.4)	(74.11)	(72.99)
Hybrid/improved seed	277.7***	300.6***	56.21	130.6	38.43	117.6
	(90.00)	(91.46)	(161.1)	(179.3)	(87.73)	(84.62)
Constant	1591***	1747***	1115***	1091***	353.1***	542.5***
	(264.3)	(302.0)	(273.5)	(326.9)	(134.2)	(152.6)
Observations	707	707	377	377	398	398
R^2	0.150	0.208	0.030	0.112	0.170	0.302
Other variables	Yes	Yes	Yes	Yes	Yes	Yes
District FE	No	Yes	No	Yes	No	Yes

Note: Results in this table are estimated for only households that experienced an attack of the respective pest/disease. Maize yield is 1621 kg/ha; 1306 for groundnuts, 692 for soybean for only those who experienced the respective pest/disease. Robust standard errors in parentheses. The other variables included as controls are farm size, tropical livestock units, age of the household head, education of the household head, gender of the household head, access to extension, number of years the household has lived in the village, access to credit, whether the farmer belong to an farmers' organization, whether they applied basal and top dressing fertilizer.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

protect against these pests/diseases. Surprisingly, under this estimation, we also find that local alternatives are marginally effective in protecting soybean yields from rust.

Overall, we find some differences in the adoption of control strategies between Malawi and Zambia. These contrasting patterns stem from differences in the agricultural policy environment and institutional frameworks. Zambia's Farm Input Support Programme has historically emphasized hybrid maize promotion (Mason and De Bello 2013), whereas Malawi's agricultural policies have recently prioritized legume diversification (Lunduka et al. 2013). The countries also differ markedly in extension service coverage, with 54% of farmers having access to extension services in Malawi compared to 27% in Zambia. These institutional differences are further reinforced by market structure variations, with Zambia having more developed private seed markets, particularly for maize (Mason et al. 2015), while Malawi has benefited from a stronger NGO presence in legume seed systems (Simtowe et al. 2016).

Our findings on pest and disease impacts show both similarities and notable differences compared to those of studies from other sub-Saharan African countries. The 13.5% maize yield loss to FAW we found aligns closely with Baudron et al.'s (2019) estimate of 11.5% in Zimbabwe but falls below the 22%–67% losses reported by Kansiime et al. (2019) across several African countries. These differences likely reflect variations in agroecological conditions and farming systems of the regions. In Ethiopia, Kassie et al. (2020) found that FAW reduced maize yields by 9.4%, suggesting potentially lower FAW pressure in East Africa's highland areas than in our study region.

Regarding the GRV, there are almost no recent studies estimating its effect on yield. Our findings align with those of Naidu et al. (1999) in Tanzania, who reported similar loss levels in comparable agroecological zones. For soybean rust, our observed 25.2% yield reduction falls within the range reported by Kumudini et al. (2008) in the USA of about 37%.

These comparisons suggest that, while broad patterns of pest and disease impacts are similar across sub-Saharan Africa, important regional variations exist in both impact magnitude and control strategy effectiveness. Such variations highlight the need for locally adapted pest management approaches, while also suggesting opportunities for cross-regional learning in developing effective control strategies.

TABLE 6 | Robustness check of the effect of control strategies on yield using entropy balancing.

Variables	(1) Maize yield	(2) Maize yield	(3) Maize yield	(4) Maize yield	(5) Maize yield	(6) Maize yield	(7) Groundnut yield	(8) Groundnut yield	(9) Groundnut yield	(10) Groundnut yield	(11) Soybean yield	(12) Soybean yield	(13) Soybean yield	(14) Soybean yield
Pesticides	205.7						133.9				384.4***			
	(149.5)						(242.9)				(122.7)			
Local alternative		14.3						−1.0				109.7		
		(208.8)						(233.7)				(84.73)		
Scout and crash			−51.3											
			(135.8)											
Use sand				160.8										
				(197.1)										
Crop rotation					−78.9				382.4**				160.0**	
					(104.5)				(150.7)				(72.39)	
Hybrid/improved seed						580.6***				150.7				166.5**
						(106.9)				(170.1)				(80.58)
Constant	2902***	2727***	2350***	2789***	2546***	2367***	1027	2148***	1500***	1575***	527.2**	698.4***	494.9***	597.2***
	(429.0)	(486.4)	(413.2)	(730.3)	(294.1)	(371.5)	(672.1)	(549.4)	(348.3)	(356.4)	(251.2)	(220.0)	(169.4)	(175.0)
Observations	378	298	370	372	692	692	334	343	377	377	372	351	398	398
R^2	0.162	0.267	0.190	0.148	0.137	0.250	0.320	0.144	0.477	0.125	0.532	0.375	0.334	0.328
Other variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses. The other variables included as controls are farm size, tropical livestock units, age of the household head, education of the household head, gender of the household head, access to extension, number of years the household has lived in the village, access to credit, whether the farmer belong to an farmers' organization, whether they applied basal and top dressing fertilizer, and whether they used improved seeds.
***$p<0.01$; **$p<0.05$; *$p<0.1$.

TABLE 7 | Robustness check of the effect of control strategies on yield using double/debiased machine learning.

Variables	(1) Maize yield	(2) Maize yield	(3) Maize yield	(4) Maize yield	(5) Maize yield	(6) Maize yield	(7) Groundnut yield	(8) Groundnut yield	(9) Groundnut yield	(10) Groundnut yield	(11) Soybean yield	(12) Soybean yield	(13) Soybean yield	(14) Soybean yield
Pesticides	167.7						−206.5				192.0*			
	(133.8)						(338.0)				(109.1)			
Local alternative		20.3						71.8				175.2**		
		(158.4)						(210.4)				(87.0)		
Scout and crash			−23.0											
			(113.9)											
Use sand				149.3										
				(134.0)										
Crop rotation					165.1*				144.5				−17.0	
					(96.8)				(170.0)				(61.2)	
Hybrid/improved seed						351.1***				−236.2				116.0**
						(102.3)				(268.3)				(58.6)
Constant	−26.1	−78.7	−94.8*	−47.5	−5.2	−0.505	−25.7	−70.5	12.9	59.9	−77.7***	−79.6***	5.4	−2.0
	(60.6)	(63.9)	(56.1)	(58.2)	(49.4)	(48.9)	(150.8)	(146.2)	(101.6)	(108.3)	(29.5)	(27.7)	(25.2)	(24.8)
Observations	424	343	414	415	1058	1058	374	392	772	772	408	407	682	682
Other variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses. The other variables included as controls are farm size, tropical livestock units, age of the household head, education of the household head, gender of the household head, access to extension, number of years the household has lived in the village, access to credit, whether the farmer belong to an farmers' organization, whether they applied basal and top dressing fertilizer, and whether they used improved seeds. Each model is estimated separately. The reference are those who did nothing to control the pest. In each regression, we control for several other household factors.
***$p<0.01$; **$p<0.05$; *$p<0.1$.

5 | Conclusion

Climate-induced pests and diseases have continued to be a menace, affecting smallholder agricultural production. However, evidence on the magnitudes of the effects on smallholder welfare and the efficacy of control strategies remains limited. This study provides a comprehensive assessment of the impact of three major crop stressors—FAW, GRV, and soybean rust—on the welfare of smallholder farmers in Malawi and Zambia, and assesses the efficacy of control strategies against these stressors. We specifically quantified the effects of these pests and diseases on crop yield, household income, and food security using survey data from 1100 farmers in Malawi and Zambia. This study makes a methodological contribution by applying advanced econometric techniques—Entropy Balancing and Double/Debiased Machine Learning—to address potential endogeneity issues and provide more reliable estimates of the effectiveness of control strategies.

Approximately 70% of the farmers experienced FAW attacks in their maize fields, and about 28% experienced rosette attacks in their groundnuts, and 40% of the farmers reported soybean rust infestations. The econometric results showed that FAW, rosette, and soybean rust resulted in 13.5%, 27.2%, and 25.2% yield loss in maize, groundnuts, and soybean, respectively. This further translated to reduced crop income and an increased likelihood of food insecurity among households. We also found that the FAW negatively affects income and food security. While rust, rosette, and their combination had no significant effect on household income and food security, their combination with FAW led to a greater negative impact than the FAW alone. Furthermore, we found that rosette and rust affected crop income on their own, while FAW did not, indicating the use of these crops as cash crops, while maize is mostly stored for home consumption. This is corroborated by the results on food insecurity, where FAW increases the likelihood of being food insecure, but rosette and rust do not. Although farmers employ multiple strategies to control these pests/diseases, we found evidence, albeit not robust to different estimation strategies, that pesticides, crop rotation, and the use of improved seeds aid in reducing the negative effect of pests/diseases on crop yields.

The study also highlights the limitations of pesticides as a sole control strategy, as they are not only costly for smallholder farmers but also pose health and environmental risks. Moreover, pesticides alone are not entirely effective in controlling multiple stressors, such as the FAW and rosette virus. These findings underscore the significant challenges posed by these pests and diseases, which threaten food security and livelihoods in the region. The limited effectiveness of pesticides may also stem from knowledge gaps in proper application techniques. Our data show that only 27% of Zambian and 54% of Malawian farmers had access to extension services, suggesting potentially suboptimal pesticide use in these countries. This aligns with the findings of Kansiime et al. (2019), who found that inadequate knowledge of proper pesticide application timing and methods significantly reduced their effectiveness against the FAW in Zambia. In addition, FAW resistance to common pesticides has been documented (Nyamutukwa et al. 2022). These findings have important implications for policymakers. Rather than broadly promoting pesticide use, interventions should focus on improving knowledge of application through enhanced extension services. Investment in farmer training programs that specifically address proper pesticide application techniques, timing, and safety measures could improve effectiveness.

To effectively adapt to the expected climate change, which is projected to increase the prevalence and severity of crop pests and diseases, this study advocates for investment in and further research on hybrid or improved seeds as a strategic control measure. This approach aligns with the principles of integrated pest management (IPM), which emphasizes the use of multiple, complementary control methods to reduce reliance on chemical pesticides and promote sustainable crop protection.

The observed cross-country differences in control strategy adoption suggest the need for contextually tailored interventions. Zambia would benefit from strengthening its extension services to match Malawi's higher coverage while building on its existing network of farmer organizations to promote IPM. Meanwhile, Malawi could focus on expanding credit access to match Zambian levels while leveraging its strong extension networks to promote improved varieties (Spielman and Smale 2017).

Despite these differences, both countries face common challenges that could benefit from their regional cooperation. Harmonizing pest management policies across borders could enhance their effectiveness, given the transboundary nature of these pests and diseases. Furthermore, facilitating cross-border learning about successful control strategies could accelerate the adoption of effective practices in both countries. Joint research programs focused on developing pest-resistant and disease-resistant varieties could also pool resources and expertise for a greater impact (Tambo, Day, et al. 2020; Tambo, Kansiime, et al. 2020).

Our findings offer several actionable insights for farmers and policymakers regarding pest and disease management. Given the substantial yield losses observed and their significant impact on household welfare, there is a clear economic justification for promoting control strategies. The effectiveness of improved seeds in reducing pest damage suggests that subsidizing improved variety adoption could be cost effective. However, the current differential adoption rates between Malawi and Zambia indicate that seed access alone is insufficient. The significant disparity in extension access between countries (54% in Malawi vs. 27% in Zambia) points to the need to strengthen agricultural advisory services, particularly in Zambia. Furthermore, the strong performance of farmer organizations in Zambia (73% membership vs. 51% in Malawi) suggests that promoting collective action through farmer groups can enhance technology adoption by reducing transaction costs and facilitating knowledge sharing.

For policymakers, our results call for a more holistic approach to agricultural support programs that address multiple crop stressors simultaneously, rather than focusing on single crops or specific pests. This could involve developing coordinated early warning systems and ensuring that input support programs cover a diverse range of crops. The observed differences in food security impacts between households with different crop portfolios suggest that crop diversification could be an effective risk management strategy, but it requires supportive market infrastructure, including market information systems, storage facilities, and rural roads. Success likely depends on coordinating multiple interventions—improving access to inputs, strengthening extension services, supporting farmer organizations, and developing market infrastructure—rather than relying on single solutions.

The study's methodological contributions, particularly the application of advanced econometric techniques such as Entropy Balancing and Double/Debiased Machine Learning, can inform future research on the impact of crop pests and diseases and the evaluation of control measures in sub-Saharan Africa and beyond. The findings of this study have important implications for policymakers, researchers, and development practitioners working to promote food security and sustainable agricultural practices in sub-Saharan Africa. Investing in the development and dissemination of improved seed varieties, along with promoting IPM strategies, can help smallholder farmers build resilience against the growing threat of crop pests and diseases in the face of climate change challenges. Furthermore, this study highlights the need for continued research to better understand the complex interactions between crop stressors, smallholder welfare, and control strategies to develop more targeted and effective interventions.

In light of projected climate change and the potential for increased crop pests and disease pressure, it is crucial to prioritize support for smallholder farmers in sub-Saharan Africa. This study contributes to the growing body of evidence that can inform the design and implementation of policies and programs aimed at enhancing food security, reducing poverty, and promoting sustainable agricultural practices in the region. For example, the development of improved tolerant cultivars will greatly benefit farmers in the future.

A limitation of our analysis is that, like many studies examining agricultural technology adoption, we lack instrumental variables that could help address the potential selection bias from unobserved factors. While our use of Entropy Balancing and Double/Debiased Machine Learning helps reduce selection bias on observables, future research would benefit from the collection of data on variables that could serve as valid instruments, such as randomized information provision about control strategies or geographic variation in the timing of extension programs promoting these strategies.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

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

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Appendix A

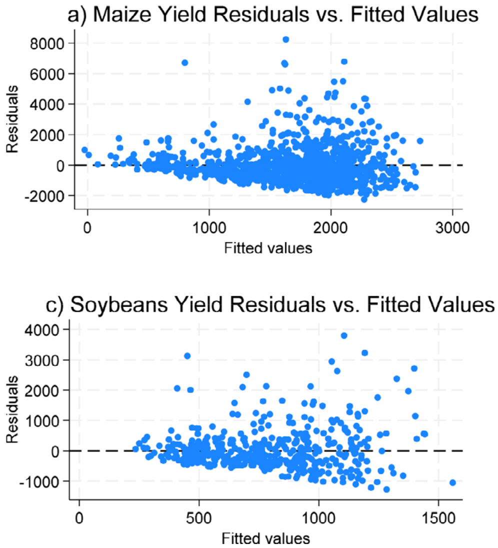

FIGURE A1 | Plot of yield residuals for (a) maize, (b) groundnuts, and (c) soybean against the fitted values of the regressions. The residuals are drawn from a model that does not include district fixed effects.