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Can Agronomic and Cultural Strategic Practices Control Fall Armyworm, Boost Smallholder Productivity, and Strengthen Household Food Security in Malawi?

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ABSTRACT

Agronomic and Cultural Strategic (ACS) practices present sustainable solutions to the Fall Armyworm (FAW) outbreak in agrarian economies. FAW (*Spodoptera frugiperda*), an invasive lepidopteran pest, has caused severe yield losses since its first detection in 2016. Its rapid spread, intensified by rising temperatures, threatens food security in Sub-Saharan African countries such as Malawi. While synthetic pesticides are commonly promoted for FAW control, their high cost and environmental risks limit their acceptability, accessibility, and sustainability. Using nationally representative data, this study evaluates the impact of ACS practices on sustained smallholder farm productivity and food security in Malawi. We find that FAW significantly reduces farm productivity by 13%. However, the adoption of ACS practices increased farm productivity by 28% and household food security by 14%, highlighting the effectiveness of ACS practices in managing FAW and enhancing household food security. Key land characteristics, particularly soil type and slope, also significantly influence farm productivity outcomes by at least 30%. Among ACS practices, sustainable land management measures proved to be the most effective strategy for enhancing household food security, yielding an average treatment effect on the treated (ATT) of 14.99 percentage points, with manure application (ATT = 4.89), agroforestry (ATT = 4.18), and mulching (ATT = 3.68) contributing the most. Agricultural extension advisory services and input subsidies were key complementary interventions to enhance the adoption and effectiveness of ACS practices as viable and sustainable pathways for managing FAW, improving farm productivity, and enhancing food security among farming households in Malawi.

Keywords: Invasive Fall Armyworms; Agronomic and Cultural Strategic Practices; Farm Productivity; Food Security; Complementary Interventions

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1. Introduction

The Fall Armyworm (*Spodoptera frugiperda*), an invasive lepidopteran pest native to the Americas, is one of the most destructive pests in Sub-Saharan Africa (SSA), attacking over 80 plant species [1]. Since its first detection in Central and Western Africa in 2016, FAW has rapidly spread across SSA, facilitated by its natural migration capacity, international trade, and improved transportation networks [2]. It travels an estimated 1,600–2,000 km annually, reaching all SSA countries within a short period [3]. Climate plays a crucial role in FAW distribution and population dynamics, with rising temperatures accelerating its spread and increasing severity. Warmer conditions exceeding 20°C have intensified outbreaks, further threatening food security [4]. FAW poses severe economic risks, feeding on 353 plant species, including key staple crops. Maize, its preferred host, suffers the greatest losses, leading to widespread crop failures [5].

FAW outbreak causes significant economic and yield losses across Sub-Saharan Africa (SSA) countries like Kenya, Ghana, and Ethiopia, FAW has reduced yields by 15%–73% [6]. Zimbabwean households have suffered losses of approximately 58%, while in Zambia; FAW has affected 35% of cultivated crops [7]. Climate models predict that FAW outbreak will intensify in both magnitude and frequency, potentially reducing current yields by 40%. Without a comprehensive understanding of FAW development, survival, and control strategies, achieving the Sustainable Development Goal (SDG) of ending chronic hunger by 2030 in SSA will remain out of reach. Meanwhile, FAW-related economic losses are estimated at $2.5 billion to $6.3 billion annually [8].

Over 90% of Malawi's population depends on subsistence farming for their livelihood [9], making them highly vulnerable to Fall Armyworm (FAW) attack. The country recorded its first FAW outbreak in September 2016, causing severe damage to crop vegetative and reproductive structures [10]. The FAW outbreak led to a 42% decline in crop production, resulting in economic losses estimated at $0.23 million to $0.56 million. As a consequence, approximately 6.5 million people faced food insecurity. The rapid spread and severity of FAW in Malawi have been exacerbated by limited adoption of control measures, suboptimal agricultural practices, and rising temperatures [11]. Temperature ranges between 20 °C and 35 °C have been shown to accelerate FAW development, survival, and proliferation [12]. Without effective control strategies targeting FAW at its developmental stages, household farm productivity and food security will remain at risk [13].

Several strategies have been recommended for managing FAW, including cultural, biochemical, and agronomic controls such as sanding, ashes, soap application, manual killing, mulching, and synthetic pesticides [14]. However, these methods are most effective when households receive proper training and implement control measures promptly. Chemical controls, while widely used, pose environmental and human health risks [15]. Additionally, FAW has developed resistance to over 30 active insecticides, and literature on this dates back to the 1990s [16], further reducing their effectiveness. Limited availability, high costs, and information gaps also hinder access to chemical pesticides, making them unaffordable for many rural households [17].

Agronomic and cultural strategic (ACS) practices provide a viable and sustainable option for managing Fall Armyworm (FAW) [18]. These methods are cost-effective, widely accessible, and pose fewer environmental risks compared to chemical controls [19]. ACS practices are not new and combine multiple pest suppression techniques such as mulching, handpicking, dusting, intercropping, timely planting, and the use of improved crop varieties. They help prevent pest outbreaks while minimizing environmental and human health risks. However, many ACS recommendations are largely anecdotal, making their adoption and localization challenging [20]. Additionally, there is limited empirical data on the effectiveness of ACS practices in managing FAW outbreak [21]. Basically, few studies have examined household experiences with FAW and ACS effectiveness in Malawi, despite the country's heavy reliance on maize, a staple crop highly susceptible to FAW [22]. Frequent cross-country movements from FAW-affected countries may also contribute to its continued spread if ACS practices are not effectively mainstreamed at the farm level [23]. Understanding the effectiveness of ACS practices is pivotal as FAW heavily attacks the maize crop which is the main staple for agrarian economies like Malawi, where over nine out of ten farm households depend on maize for food, nutrition, and food security [9].

This paper makes three key contributions to the existing literature on Fall Armyworm (FAW). First, it examines the impact of FAW and agronomic and cultural control strategies (ACS) on household farm productivity. Second, while accounting for the potential endogeneity of ACS practices' adoption, it assesses the effects of various ACS methods on household food security. These findings are particularly relevant for achieving the Sustainable Development Goals (SDGs) and Malawi Vision 2063, which prioritize ending hunger and promoting environmentally sustainable agricultural practices [24,25]. Third, this study captures household feedback on the technical efficiency of ACS practices. Unlike previous research that primarily identifies factors influencing ACS adoption, this paper takes a step further by using farm productivity as the central measure of interest. Prior studies have largely focused on a single crop [23,26,27]. Moreover, existing research has examined the negative effects of synthetic pesticides without evaluating their broader impact on farm productivity [12,13,15,28,29]. To address these gaps, this paper utilizes nationally representative household survey data from 2010 to 2020, compiled by the Malawi National Statistics Office (NSO) [30].

2. Methods

2.1. Study Area, Sampling, and Data

This study used household survey data from the Malawi National Statistics Office (NSO), collected from rural communities across the country (see **Figure 1**), where crop production is vital to both livelihoods and food security [10,30]. Covering an area of 118,480 square kilometers, Malawi is home to Lake Malawi, which occupies about one-third of its total land area. The country is divided into districts, with elevations ranging from below 500 meters to 1,500 meters above sea level. Malawi experiences a single rainy season from November to April, with average precipitation varying between 725 mm and 2,500 mm. FAW outbreak has a significant impact on households, particularly in districts such as Chikwawa, Chiradzulu, Karonga, Mulanje, Nsanje, Lilongwe, Mzimba, and Phalombe, which are among the most affected. Figure 1 also shows cities in the Northern (i.e., Mzuzu City), Central (i.e., Lilongwe City), Southern (i.e., Blantyre City), and Eastern (i.e., Zomba City) regions, highlighted in yellow. In 2018, FAW outbreaks caused damage to more than 21% of household crop production. Climate models predict increasing vulnerability to pests and extreme weather events, including FAW outbreak, which are expected to intensify in both magnitude and frequency [30,31]. In addition to limited adaptive capacity, the El Niño and La Niña phenomena have further heightened the country's exposure to FAW outbreaks [10,32].

The NSO household survey utilized a multi-stage sampling approach and featured a robust agricultural component [30]. The survey traced households in 2010, 2013, 2016 and 2019, with the sample size expanding from 1,600 in 2010 to 2,500 in 2019/2020 following split-up households. It gathered demographic data, including age, gender, education, income, and agricultural variables such as farm size, seed usage, fertilizer application, pesticide use, organic manure application, and the adoption of improved crop varieties. In addition, the survey included a module on agricultural shocks, where households were asked whether they had experienced a FAW outbreak on their farms. For the purposes of this study, households that reported experiencing FAW outbreaks are classified as FAW-affected households (FAH), while those that did not are categorized as non-FAW-affected households (NFAH). Similarly, households that adopted any form of agronomic and cultural strategies (ACS) are identified as adopters (FMH), while those that did not adopt ACS are categorized as non-adopters (NFMH).

Figure 1. The map of Malawi, showing Lilongwe, the Capital City and Bunda College of agriculture.

2.2. Theoretical and Empirical Strategy

This paper examines the impact of Fall Armyworm (FAW) and integrated pest management (IPM) practices on farm productivity and food security. Specifically, it compares the effects of FAW on farm productivity and food security between households that adopt agronomic and cultural strategies (ACS) practices (FMH) and those that do not (NFMH). According to Tambo et al. [26], FAW adaptation is defined as the implementation of any Agronomic and Cultural Strategies (ACS practices, such as mulching, dusting, intercropping, the use of improved crop varieties, synthetic pesticides, landscape management strategies, and agroforestry. The study primarily measures farm productivity by converting yield per hectare into a common monetary value for each crop, which allows for the aggregation of farm-level output values. In Malawi, where households heavily depend on farm production for both livelihoods and food security [9,33,34], the value of output from the farm directly influences household food consumption [35].

Endogeneity due to the non-random nature of household decisions is common among most ACS practices adoption studies [36]. Most households adopt ACS practices through the influence of unobserved household factors, such as management ability and risk aversion. Failure to account for these unobservable factors could result in misleading estimates [37,38]. Several methods exist to address selection bias [38]. One such method is the Difference-in-Differences (DiD) approach, which estimates the causal effect of a treatment by comparing pre- and post-treatment outcomes between a treatment and a control group [39]. The DiD method helps control confounding factors that remain constant over time, leading to more accurate treatment effect estimates [40,41]. However, the DiD framework requires random assignment of survey participants, which was not possible with the NSO household survey design. An alternative is Propensity Score Matching (PSM), which estimates the causal effect by matching treated units with untreated units based on observable characteristics [42]. However, PSM relies on observable rather than unobservable characteristics. This paper adapts the Endogenous Switching Regression (ESR) model, which addresses the endogeneity issue by simultaneously accounting for selection bias [43] as subsequently discussed.

Adaptation to FAW is informed by the random utility theory, where a household adopts any ACS practices that provide higher utility than the alternatives [44–46]. Similarly, a household adopts the ACS practices when the utility derived from the adoption exceeds that of non-adoption. Let A_i^* represents the latent difference between utility derived from ACS practices' adoption (U_{iA}) and the utility from non-adoption (U_{iN}). The latent variable A_i^* can be specified as follows in the Equation (1):

$$A_i = \begin{cases} 1 \; if \; \vartheta_i Z_i + \mu_i > 0 \\ 0 \; if \; \vartheta_i Z_i + \mu_i < 0 \end{cases} \tag{1}$$

where A_i denotes adoption status of ACS practices, taking the value of one (1) if an individual household adopts any ACS practices, and otherwise, zero. We assume that the adoption decision is directly influenced by the extent of FAW crop damage. The Z_i is a vector of socioeconomic characteristics that influence household adoption decisions. The ϑ_i represents the vector of unknown parameters to be estimated, and the μ_i is the error term, capturing unobserved factors affecting the adoption decision.

The ACS practices (A_i) enhance the household farm productivity, thus improving food security. We assume the decision status results in the two outcome regimes [47] of farm productivity (y_{ji}) and can be specified as in Equation (2):

$$\hat{\kappa}_{ji} = \begin{cases} \hat{\kappa}_{1i} = \emptyset_1 x_{1i} + \omega_1 A_{1i} + \varepsilon_{1i} \; if \; \vartheta_i Z_i + \mu_i > 0 \rightleftarrows A_i = 1 \\ \hat{\kappa}_{2i} = \emptyset_2 x_{2i} + \omega_2 A_{2i} + \varepsilon_{2i} \; if \; \vartheta_i Z_i + \mu_i \leq 0 \rightleftarrows A_i = 0 \end{cases} \tag{2}$$

where $\hat{\kappa}_{ji}$ is the household farm productivity. The x_{ji} represents household and farm level characteristics. The $\emptyset_j$ is the vector of the unknown parameters to be estimated. The ε_{ji} is the error term. The ε_{ji} and μ_i have a trivariate normal distribution, with mean vector zero and the covariance matrix (Ω) as in Equation (3):

$$\Omega = \text{covariance}\ (\mu, \varepsilon_1, \varepsilon_2) = \begin{bmatrix} \sigma_\mu^2 & \sigma_{\mu 1} & \sigma_{\mu 2} \\ \sigma_{\mu 1} & \sigma_1^2 & . \\ \sigma_{2\mu} & . & \sigma_2^2 \end{bmatrix} \tag{3}$$

where σ_μ^2 = variance (μ), σ_1^2 = var (ε_1), σ_2^2= variance (ε_2), $\sigma_{\mu 1}$ = covariance (μ, ε_1), and $\sigma_{\mu 2}$ = covariance (μ, ε_2). We accept that σ_μ^2 equal to one and is estimable only up to a scalar factor [44]. Since $\hat{\kappa}_{1i}$ and $\hat{\kappa}_{2i}$ are never observed simultaneously, the covariance between ε_1 and ε_2 is hardly defined and never observed simultaneously. The error terms of ε_{1i} and ε_{2i} of the outcome equation are non-zero, resulting in inefficient estimates when using any ordinary least square estimation procedure [47].

Thus, the expected values of the truncated error terms (ε_1 and ε_2) are as given in Equations (4) and (5):

$$E(\varepsilon_1 | A = 1) = \sigma_{\mu 1} \frac{\phi(\vartheta_i Z_i)}{\Phi(\vartheta_i Z_i)} \equiv \sigma_{A\mu} \gamma_{Ai} \tag{4}$$

$$E(\varepsilon_2 | A = 0) = \sigma_{\mu 2} \frac{\phi(\vartheta_i Z_i)}{(1 - \Phi)(\vartheta_i Z_i)} \equiv \sigma_{N\mu} \gamma_{Ni} \tag{5}$$

where ϕ is the standard normal probability density function, Φ the standard normal cumulative density function. The γ is a vector of the inverse mills' ratio computed to control for self-selection [26,46].

The study extends the analysis to examine the effect of ACS practices on food security through averaging the treatment effect on the treatment (ATET), which measures the difference in food security between adopters and non-adopters. The PSM is commonly applied as a quasi-experimental technique [39]. However, PSM ignores the likely effect of unobservable characteristics on both household adoption and food security. Moreover, they only use a sub-sample, which meets the balancing property rule [42]. Thus, this study examines the ATET using the pooled ESR model, which accounts for the unobservable and observable characteristics as previously discussed. Thus, the heterogeneity effects can be computed from the difference between ATET and ATU. The study calculates the ATET and ATU on the untreated (U) as in equations for flood risk adapters (Equations (6) and (8)) and non-adopters (Equations (7) and (9)):

$$E[\hat{\kappa}_{Ai}|A_i = 1] = x_{Ai}B_A + \sigma_{A\mu}\gamma_{Ai} \quad (6)$$

$$E[\hat{\kappa}_{Ni}|A_i = 0] = x_{Ni}B_A + \sigma_{N\mu}\gamma_{Ni} \quad (7)$$

$$E[\hat{\kappa}_{Ni}|A_i = 1] = x_{Ai}B_A + \sigma_{N\mu}\gamma_{Ai} \quad (8)$$

$$E[\hat{\kappa}_{Ai}|A_i = 0] = x_{Ni}B_A + \sigma_{A\mu}\gamma_{Ni} \quad (9)$$

where $\hat{\kappa}$ denotes the household farm productivity and food security as previously discussed. The γ is the selection term that captures all potential effects of the difference in unobservable characteristics. The study computes the ATET as the difference between Equations (6) and (8), while ATU as the difference between Equations (7) and (9), and as can be presented in Equations (10) and (11):

$$ATT = x_{Ai}B_A + \sigma_{A\mu}\gamma_{Ai} - x_{Ai}B_A + \sigma_{N\mu}\gamma_{Ai} \quad (10)$$

$$ATU = x_{Ni}B_A + \sigma_{N\mu}\gamma_{Ni} - x_{Ni}B_A + \sigma_{A\mu}\gamma_{Ni} \quad (11)$$

We can estimate the ESR model using several methods, including two-step least squares, control function, or full-information maximum likelihood (FIML). However, the first two methods typically result in heteroskedastic residuals, requiring complex adjustments to derive consistent standard errors [48]. To overcome this issue, this study adopts the FIML method, which leverages the joint normality of the error terms to simultaneously estimate both the binary and continuous parts of the model, ensuring consistent standard errors. The presence of endogenous switching is identified by examining the signs and significance levels of the correlation coefficients in the outcome equations. For proper identification of the ESR model, the selection equation must include at least one variable that is excluded from the outcome equations, in addition to those arising from the non-linearities of $\emptyset$ and γ.

Empirically, the model specification for this study is informed by a review of similar research [41,44,47,48]. Literature suggests that various factors influence the adoption of Agronomic and Cultural Strategies (ACS), which, in turn, affect household farm productivity and food security. Consequently, this study includes a range of variables: farm characteristics (such as soil type, quality, and slope), self-reported rainfall shocks, farm size, use of inorganic fertilizers, labor, and access to credit; household characteristics (including family size, education, gender, and age); and geographic location. These factors are examined to assess their impact on FAW management adoption and farm productivity.

3. Results and Discussions

3.1. Household Characteristics

A summary of the socio-economic characteristics of households affected (FAH) and not affected (NFAH) by Fall Armyworm (FAW) in Malawi is presented in **Table 1**. The study found that the majority of households (70%) are headed by males, with an average age of 43 years and a standard deviation (SD) of 15 years. Additionally, 80% of FAH and NFAH household heads attended formal education, whereas only 60% were literate in their local language. On average, household heads have attended formal education for about 5 years, with an SD of 2.8 years where some have even been in school for just 2 years. Nearly 70% of household heads, regardless of FAW status, owned a cell phone, which facilitated access to climate-related information, including ACS practices. Similarly, both FAH and NFAH households had relatively high access to FAW-related extension services. Households in both categories reported applying barely above 50 kg bags of inorganic fertilizer, with a SD of 18.3 kg. FAH households dedicated approximately 64 personal working days to farming, while NFAH households allocated about 63 days, with an SD of 16 personal working days. The average household size in the study areas was 5 members, with an SD of 2.3 persons, and similar household sizes were observed among households adopting and not adopting ACS practices. These findings are consistent with previous studies [29,30,34], where household sizes do not differ among households in Malawi.

Table 1. Summary of socioeconomic characteristics between FAH and NFAH as well as FMH and NFMH.

	HH Affected by FAW			HH FAW Adaptation		
	NFAH	FAH	Difference	NFMH	FMH	Difference
Gender (Male = 1; Female = 0)	71.80%	74.10%	−0.023	73.80%	70.90%	0.029**
Age (Years)	43.01	43.76	−0.747	41.67	44.55	−2.882***
Education attendance (Yes = 1)	81.50%	84.90%	−0.034**	81.00%	83.30%	−0.023*
Literacy (Yes = 1)	66.60%	69.30%	−0.027	67.20%	67.10%	0.001
Education class (Years)	5.309	5.274	0.036	5.529	5.091	0.438***
Cell-phone ownership (Yes = 1)	70.70%	72.90%	−0.022	70.10%	72.10%	−0.02
Credit accessibility (Yes = 1)	19.70%	27.00%	−0.073***	17.60%	24.50%	−0.069***
Extension accessibility (Yes = 1)	60.30%	63.70%	−0.034*	53.30%	68.00%	−0.147***

Table 1. *Cont.*

	HH Affected by FAW			HH FAW Adaptation		
	NFAH	**FAH**	**Difference**	**NFMH**	**FMH**	**Difference**
HH size (Number)	5.002	5.103	−0.1	4.877	5.158	−0.281***
Output value per Ha (MWK)	130000	100000	25000	120000	120000	4116
Labour (Personal days)	62.94	63.99	−1.053	60.87	65.28	−4.417***
Farm size (Ha)	2.592	1.688	0.904	3.165	1.704	1.461
Inorganic Fertilizer (kg)	70.82	67.85	2.97	73.73	66.95	6.782
Organic Fertilizer (Yes = 1)	23.50%	35.00%	0.115	20.90%	30.40%	−0.095**
FAW (Yes = 1)	0.00%	100.00%	−100.00	11.80%	28.20%	−0.164***
FAW Adaptation (Yes = 1)	46.60%	72.00%	−0.253***	0.00%	100.00%	−100.00

Note: * p < 0.10, ** p < 0.05, *** p < 0.01.

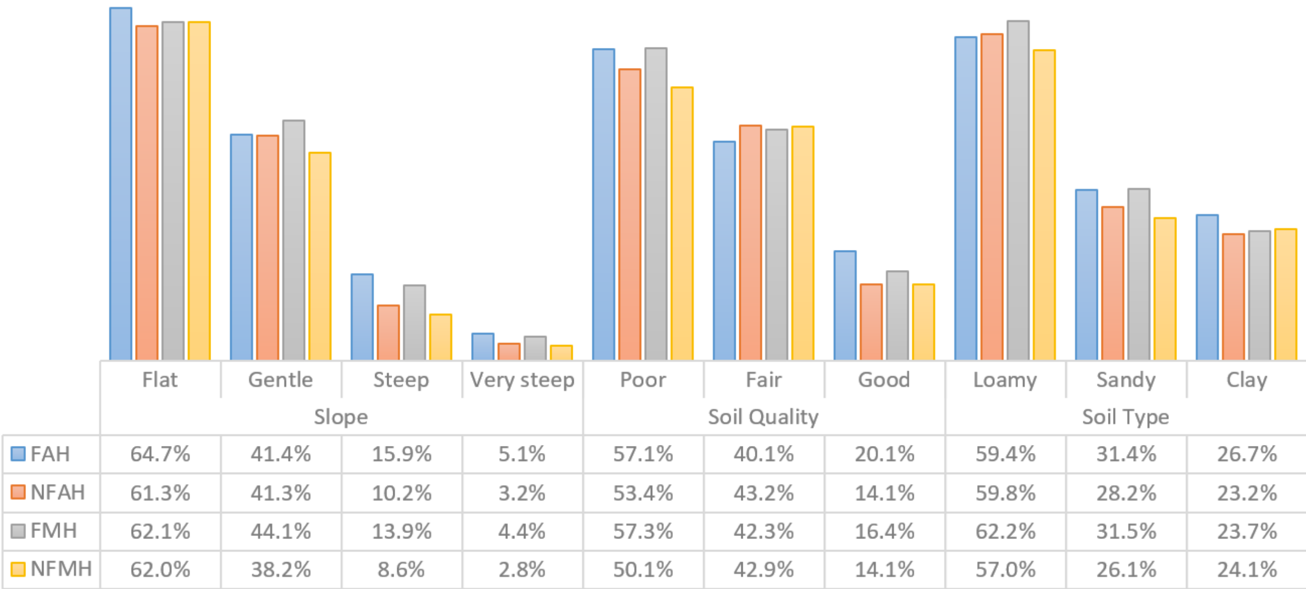

Figure 2. Summary statistics for farm-level characteristics between FAH and NFAH as well as FMH and NFMH.

Furthermore, farm-level characteristics, namely slope, soil quality, and soil type are presented in **Figure 2**. On average, the study finds households having 0.5 hectares. Regarding slope, six in ten households, whether affected by FAW or not, had flat slopes, followed by gentle and steep sloped farms. In terms of soil quality, the study notes that more than half of the households in FAH and NFAH have loamy soils. Most households (60%) have farms with loamy soils, followed by sandy and clay soils.

In general, there is a substantial difference between FAH and NFAH adaptation towards FAW, where 45% of NFAH and 72% of FAH had undertaken various related practices to manage FAW on the farm. On the one hand, **Table 1** shows FAH having less output per hectare than NFAH. On the other hand, when adopting the ACS practices, FAH derive more yield than those households not adopting any of the ACS practices. These results were in line with previous studies [12].

We noted that FAW affected 51% of households in 2020, which was seven times higher than the number of households (7%) that experienced FAW in 2010. Households adopted various ACS practices, explicitly, sustainable landscape management practices (SLM), intercropping (ICROP), mulching (MULCH), timely planting (TPLANT), improved varieties (IVAR), dusting (DUST), agroforestry (AGROF), crop residual (CRESD), and pesticides (PCIDE) as displayed in **Figure 3**. The study observed a significant difference in the adoption of ACS practices between FAH and NFAH, at the one percent level of significance, where more FAH adopted the ACS practices. However, a small number of households used pesticides to control the FAW. Although literature cautioned against pesticide use [49], the lower percentage point might be due to its related prohibitive costs for resource-constrained households.

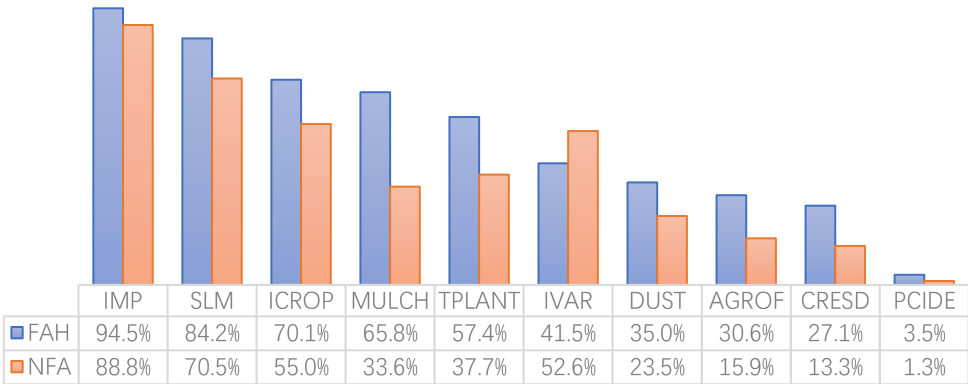

Figure 3. Percentage distribution of households affected by FAW and ACS adapting to control its effect on farm productivity in Malawi: 2010–2020.

3.2. What is the Effect of FAW and ACS Practices on Household Farm Productivity

This study further estimated the Endogenous Switching Regression (ESR) model, with the results presented in **Table 2**, which highlight the impact of FAW and Agronomic and Cultural Strategies (ACS) practices on household farm productivity. The ESR model was statistically significant at the 1% level, with a p-value less than 0.01. As expected, FAW had a significant negative effect on farm productivity in households affected by FAW, reducing productivity by 13%. Qualitative data indicated that FAW damaged both vegetative and reproductive parts of the crops, consistent with findings from previous studies [3,8,26]. Moreover, a positive correlation was found between FAW experience and the adoption of ACS practices, with this relationship being significant at the 1% level, which is in line with the findings of [15,50].

Column (1) is the pooled classical linear regression model based on Ordinary Least Square, and Column (2) employs the pooled endogenous switching regression full maximum likelihood estimation (movestay) method, Column (3) adopts the maximum likelihood estimation procedure of pooled endogenous treatment effect regression model, while Column (4) follows a two-step pooled endogenous treatment effect regression model approach.

Households that adopted ACS practices had a 28% higher probability of improving farm productivity compared to those that did not. The study findings indicated that farm size, fertilizer use, and improved crop varieties positively impacted household farm productivity. Specifically, farm size increased farm productivity by 37% for households that adopted ACS practices (FMH) and by 50% for non-adopters (NFMH). The use of inorganic fertilizers boosted farm productivity by 15% for FMH and 11% for NFMH. Improved crop varieties significantly enhanced farm productivity by 11% for FMH households only. These results align with the findings of previous studies [51], which highlighted that improved varieties serve as effective biological controls against FAW attack.

Table 2. Estimated effect of the FAW and ACS practices on farm productivity (Yield value per Ha in MWK) in Malawi.

	Farm Productivity			**ACS Adoption**	
	POOLED	**FMH**	**NFMH**	**Probit**	**ESR**
Lnland	−0.371***	−0.369***	−0.512***	0.0817*	0.0825*
	(14.37)	(12.39)	(3.73)	(1.97)	(1.98)
lnlabor	0.175***	0.159***	0.0545	0.0384	0.0294
	(4.06)	(3.53)	(0.31)	−0.51	−0.39
lnfert	0.145***	0.152***	0.109***	−0.00991	−0.0083
	(12.99)	(13.17)	(3.96)	(−0.58)	(−0.48)
lnseed	0.108***	0.111***	0.0344	0.0997***	0.105***
	(5.89)	(4.40)	(0.33)	−4.69	−4.46
Loamy soil	0.159**	0.0765	0.177	0.315***	0.313***
	(3.19)	(1.63)	(0.45)	−3.98	−3.98
Sandy soil	0.0392	−0.0276	0.194	0.174*	0.177*
	(0.76)	(−0.54)	(0.78)	−1.97	−2.05

Table 2. *Cont.*

	Farm Productivity			ACS Adoption	
	POOLED	**FMH**	**NFMH**	**Probit**	**ESR**
Fair soil	−0.120**	−0.0925*	−0.228*	−0.0191	−0.0306
	(−2.79)	(−2.19)	(−2.01)	(−0.26)	(−0.44)
Good soil	−0.156**	−0.157**	−0.390	0.127	0.13
	(−2.65)	(−2.81)	(−1.88)	−1.2	−1.21
Gentle slope	0.151***	0.0881*	0.0187	0.298***	0.301***
	(3.31)	(2.09)	(0.05)	−4.05	−4.1
Steep slope	0.186**	0.111	−0.239	0.543***	0.570***
	(2.76)	(1.84)	(−0.46)	−4.07	−4.38
Weeding	0.0159	0.0749*	1.340		
	(0.36)	(2.28)	(1.43)		
FAW	−0.0936	−0.128**	−0.233		
	(−1.80)	(−2.64)	(−0.54)		
Adopt ACS	0.280*				
	(2.00)				
Female				−0.088	−0.0861
				(−1.10)	(−0.78)
Age in years				0.0124	0.014
				−1.44	−1.74
Age square				−0.00152	−0.00163*
				(−1.73)	(−1.98)
Education_Years				−0.0807	−0.0901
				(−0.81)	(−0.78)
Own cellphone (Yes)				0.0567	0.0782
				−1.13	−1.2
Access credit/Input subsidies (Yes)				0.269**	0.25
				−2.67	−1.58
Access extension (Yes)				0.143*	0.138*
				−2.01	−2.09

Note: t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.3. What Factors Influence the Adoption of the ACS Practices, 2010–2020

Factors influencing the adoption of Agronomic and Cultural Strategies (ACS) practices in the study area are discussed and summarized in **Table 2**. The results indicate that FAW-induced crop damage significantly increased the likelihood of adopting ACS practices. Additionally, farm size was found to increase the probability of adopting ACS practices by 8%. The use of improved crop varieties was associated with an 11% higher probability of ACS adoption, highlighting the vulnerability of these varieties to FAW attack. Qualitative data further emphasized the need for introducing FAW-resistant crop varieties, supporting the findings of previous studies [52].

The study also found that access to extension services significantly enhanced the adoption of ACS practices, increasing the likelihood by 14%. Extension services played a critical role in educating farmers about the disadvantages and effectiveness of ACS practices in the context of FAW, helping households understand and apply ACS information more efficiently. Furthermore, access to credit was found to significantly increase the probability of ACS adoption by 27%. The qualitative data revealed that credit enabled households to purchase pesticides for managing FAW on their farms. Although not statistically significant, female-headed households were less likely to adopt ACS practices compared to male-headed households, likely due to resource constraints. The qualitative data suggested the need for complementary ACS packages and extension services specifically targeted at female smallholder farmers. Households with loamy soils were also more likely to adopt ACS practices compared to those with clay soils. These findings are consistent with previous studies [3,13,20].

3.4. What is the Impact of ACS Practices on Household Food Security

In rural areas, where crop production is the primary source of livelihood, we examined the impact of ACS practices on household food security using the maximum likelihood estimated endogenous treatment effect regression model, with results presented in **Table 3**. Overall, the adoption of ACS practices was found to improve household food security by 17%. This finding aligns with the results from [28], which also demonstrated the positive effect of such practices on food security in similar contexts.

The study further found that each ACS practice had a significant impact on household food security. Notably, the use of sustainable landscape management (SLM) techniques was associated with a remarkable 130% improvement in food security. Qualitative data revealed that households utilizing vegetative SLMs could deter FAW with their strong odor. Among the various ACS practices, agroforestry species contributed a 19% increase in food security, followed by dusting (22%), mulching (16%), synthetic pesticides (9%), intercropping (8%), and timely planting (7%). Households emphasized the importance of timely planting to avoid FAW damage, noting that FAW had minimal impact on mature crops. The study also found that combining different ACS practices effectively mitigated FAW's impact on food security. However, there is an optimal combination of ACS practices that maximizes farm food security [3,20,26].

Table 3. The impact of various ACS practices on household food security.

	FMH	NFMH	ATET		
ACS (combined effect)	23.54	20.12	3.42	17.00%	***
Agroforestry	26.35	22.17	4.18	18.85%	***
Dusting/Organic/Lime	26.70	21.81	4.89	22.42%	***
SLM techniques	26.51	11.52	14.99	130.12%	***
Intercropping	23.79	21.96	1.83	8.33%	***
Mulching	26.13	22.45	3.68	16.39%	***
Improved varieties	23.00	23.29	−0.29	−1.25%	
Timely Planting	24.03	22.37	1.66	7.42%	***
Pesticides	26.23	24.08	2.15	8.93%	***

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4. Conclusions and Policy Recommendations

This study investigates the impact of Fall Armyworms (FAW) and Agronomic and Cultural Strategies (ACS) practices on household farm productivity in Malawi. Using panel survey data from the National Statistics Office (NSO) collected between 2010 and 2020, we address potential endogeneity issues by applying an endogenous switching regression model to estimate the causal effects of FAW and ACS practices on farm productivity and food security. Our findings reveal a significant increase in FAW attack, with 51% of households affected in 2020, up from less than 10% in 2010. In response, 83% of affected households adopted a range of ACS practices, including dusting, intercropping, timely planting, landscape management, synthetic pesticides, and mulching. The results show that these ACS practices have a substantial positive effect on household food security. According to the endogenous switching regression and treatment effect model, FAW has a significant negative impact on farm productivity, reducing household productivity by 10–13% at the 1% level of significance. In contrast, households that adopted ACS practices saw a 28% increase in farm productivity. The analysis further identifies several household characteristics that influence ACS adoption, such as farm size, the use of improved crop varieties, soil type (loamy soils), topography, and access to extension services and credit. Specifically, access to extension services increased the likelihood of FAW adaptation by 14%, while access to credit or input subsidies enhanced the probability of adopting ACS practices by 26%. Additionally, the study finds that the use of improved crop varieties plays a key role in ACS adoption, particularly because of their varying susceptibility to FAW.

These findings have important implications for smallholder farmers in Sub-Saharan Africa (SSA), where Fall Armyworm (FAW) outbreaks have severely impacted farm productivity. In the absence of effective policies to manage FAW, continued outbreaks will likely push more households into poverty and worsen food insecurity. While ACS practices offer a promising solution, rural households face challenges such as inadequate access to extension services, which can result in improper pesticide use, posing health and environmental risks. Additionally, the high cost of synthetic pesticides remains a significant barrier to effective FAW management. Therefore, this study recommends integrating ACS practices into governmentsubsidized input programs. For instance, the government should prioritize the promotion of FAW-resistant crop varieties that have been recently released to be part of the subsidy programme. Agricultural extension messages should target training farmers about FAW, ACS practices, and the urgency of adopting crop varieties that are resistant or tolerant to FAW attack. Finally, future research should explore the role of machine learning in detecting and managing FAW outbreaks in rural farming households.

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Institutional Review Board Statement

This was not applicable as study did not involve any human or animal samples.

Informed Consent Statement

This was not applicable as the study used secondary data from the NSO database: https://microdata.worldbank.org/index.php/catalog/3819/get-microdata.

Data Availability Statement

This study used data from the National Statistical Office that is the Integrated Household Surveys, which can be obtained from the NSO microdata through https://microdata.worldbank.org/index.php/catalog/3819/get-microdata.

Conflicts of Interest

The authors declare no conflict of interest.

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