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IMPACT OF FALL ARMYWORM MITIGATION STRATEGIES ON MAIZE PRODUCTIVITY IN IMBO PLAIN, BURUNDI

Arthemon Manariyo[1,2], Eric Bett[2], Jayne Njeri Mugwe[2], Patrick Mutuo[1], Saidi Bizoza[1], Paul Martin Dontsop Nguezet[3]*

[1]International Institute of Tropical Agriculture (IITA) PO Box 1893. Q. Kabondo Avenue du Japon no 55 Bujumbura- Burundi

[2]Kenyatta University, School of Agriculture and Environmental Sciences Development, P.O Box 43844-00100, Nairobi, Kenya

[3]International Institute of Tropical Agriculture (IITA), Mbujimayi, Kasai Oriental, DRC

***Email of the Corresponding Author: manariyoa@gmail.com**

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ABSTRACT

Purpose of the Study: The study examined factors influencing the adoption, intensity of use, and yield effects of fall armyworm (FAW) mitigation strategies among maize farmers in Burundi.

Statement of the Problem: Fall armyworm poses a serious threat to maize production and food security in Burundi, yet limited evidence exists on what drives farmers' adoption of control measures and their impact on yields.

Methodology: Data from 536 maize farmers in five provinces of the Imbo plain were analyzed using the Double Hurdle model to assess adoption and intensity of use, and Propensity Score Matching to estimate yield impacts.

Findings: About 68% of farmers adopted FAW mitigation methods, predominantly chemical control. Adoption and intensity were positively influenced by socio-economic factors, information access, credit, and extension services. Adopters achieved significantly higher maize yields than non-adopters.

Conclusion: FAW mitigation strategies improve maize yields, but adoption is heavily skewed toward chemical methods, indicating limited uptake of integrated pest management practices.

Recommendations: The study recommends strengthening extension services, promoting Integrated Pest Management training, improving access to credit, and enhancing rural infrastructure to support sustainable FAW control.

Keywords: *Farmers' Adoption, Fall armyworm, Mitigation technologies, Maize yield, Burundi.*

INTRODUCTION

The fall armyworm (*Spodoptera frugiperda* J.E. Smith) is a major threat to maize production and food security in Sub-Saharan Africa (Kumela et al., 2019), causing substantial yield losses across the region. Reported infestation rates reach 32% in Ethiopia and 47.3% in Kenya (Kumela et al., 2019), with yield losses ranging from 11.57–16.39% in Zimbabwe (Harrison et al., 2022) and 26–40% in Ghana and 35–50% in Zambia (Tambo et al., 2021). Such losses, which can exceed 2 tonnes per hectare, exacerbate food insecurity and economic vulnerability (Akudugu et al., 2012; Thakur et al., 2018; Prospects et al., 2021), though effective control strategies can mitigate these impacts (Ullah et al., 2020).

In Burundi, FAW control efforts have focused on promoting pest management technologies through extension services, emphasizing Integrated Pest Management approaches that combine agronomic, botanical, biological, and chemical methods (Kassam et al., 2020). Additional interventions include mobile-based early warning systems (Bashir et al., 2021), community awareness programs via radio and print media (Mugisha et al., 2022), and research-led field trials of Bt maize (Ndayizeye et al., 2019).

Yet the success of these efforts depends on farmers adopting the recommended technologies (ASEAN, 2020; Tambo et al., 2020). A study in Tanzania by Kassam et al. (2021) highlighted the influence of demographic, institutional, and socioeconomic factors on the adoption of conservation agriculture practices (Fatoretto et al., 2017; Thakur et al., 2018). Similar constraints to adoption have been noted elsewhere (Akudugu et al., 2012; Misango et al., 2022). Evidence from neighboring countries showed that adopting fall armyworm control technologies can increase maize yields by 21-52% (Akudugu et al., 2012; Thakur et al., 2018). Despite these insights, no systematic study in Burundi has assessed which socioeconomic factors drive adoption, the intensity of use, or the actual yield impacts. This study addressed these gaps by analyzing factors influencing farmers' decisions to adopt, the intensity of use, and the effects of this adoption on maize yields. The findings identify strategies to scale up effective technologies to reduce crop losses and boost productivity, while providing policymakers, development agencies, and agricultural stakeholders with valuable evidence to improve fall armyworm control in Burundi.

Theoretical Framework

This study is grounded in rational choice theory, which views farmers as decision-makers who adopt fall armyworm mitigation technologies (FAWMT) after weighing expected benefits, such as higher maize yields and improved food security, against associated costs and risks. Although the theory assumes perfect information, farmers often face uncertainty, resource constraints, and institutional influences that shape their decisions. Nevertheless, rational choice theory remains useful for analyzing agricultural technology adoption, as farmers tend to adopt innovations when they offer clear advantages over existing practices (Feder et al., 1985; Jensen, 1982).

In this study, adoption is examined through both the decision to adopt FAWMT and the intensity of use. In Burundi, where fall armyworm (*Spodoptera frugiperda*) poses a significant threat to maize production, anticipated yield gains make FAWMT adoption crucial for food security (Akudugu et al., 2012; Thakur et al., 2018). Previous studies show that awareness, socio-demographic factors, economic conditions, and institutional support significantly influence adoption among smallholder farmers.

MATERIALS AND METHODS

The study was conducted in the Imbo Plain agroecological zone of Burundi, covering the provinces of Cibitoke, Bubanza, Bujumbura, Rumonge, and Makamba. This densely populated region is agriculturally significant due to its fertile alluvial soils and maize-based farming systems. Its lowland topography, warm temperatures, and relatively low rainfall create favorable conditions for the proliferation of fall armyworms, making the area highly vulnerable to infestations.

A cross-sectional survey of 536 maize-farming households was conducted using stratified random sampling across the five provinces. Data were collected through a semi-structured questionnaire administered electronically by trained enumerators and analyzed using descriptive statistics and econometric models. Adoption and intensity of use of fall armyworm mitigation technologies were examined using a double hurdle model, while Propensity Score Matching was applied to estimate the impact of adoption on maize yields, controlling for selection bias.

RESULTS

Socio-demographic characteristics of adopters and non-adopter farmers

The results showed that male-headed households predominated in both regions, especially in the West (75% vs. 65% in the South), with a similar trend among adopters of fall armyworm (FAW) mitigation technologies (80% in the West, 70% in the South; $p<0.01$). Most respondents were married, with higher rates in the West (70%) than the South (50%), and among adopters (75% vs. 65%; $p<0.05$). Secure land tenure was common, particularly in the West (85% vs. 75%), and was even higher among adopters (90% in the West, 80% in the South; $p<0.01$). Group membership was prevalent (78% overall), significantly higher in the West (90%) than in the South (65%; $p<0.01$), emphasizing the role of collective learning.

Access to extension services and markets was greater in the West than the South, with 75% vs. 55% and 70% vs. 40%, respectively, and among adopters, 80% in the West had extension access compared to 70% in the South ($p<0.05$). Agricultural credit access was low overall (6%), with no significant regional difference ($p>0.05$). The mean age of household heads was similar between adopters and non-adopters (46.50 vs. 45.29 years; $p=0.1526$), suggesting age did not significantly influence adoption. These results highlight that gender, marital status, land tenure, group membership, and access to extension and markets are key factors associated with FAW mitigation adoption, particularly in the western region.

Table 1: Characteristics of adopters and non-adopters

Households' characteristics	Pooled region			Test [1]	Western Region[2]			Test [1]	Southern Region[2]			Test
	N: 536(100)[1]	Non adopter =171(32)[1]	Adopter =365(68)[1]		N=306 (57.09)[1]	Non adopter =101(33)[1]	Adopt = 205(67)[1]		N=230 (42.91)[1]	Non adopter =70(30)1	Adopt = 160(70)[1]	
Gender of HH				**72.7*** **				**31.0*** **				**45.2*** **
male	442(82)	106(24)	336(76)		246(80)	63(25)	183(74)		196(85)	43(22)	153(78)	
Female	94(19)	65(67)	29(31)		60(20)	38(63)	22(36)		34(40)	27(79)	7(21)	
Marital status				**0.8**				**3.2**				**2.42**
Single	52(10)	15(9)	37(10)		31(10)	9(30)	22(70)		21(9)	6(29)	15(71)	
Married	228(42)	76(48)	152(46)		133(43)	51(38)	82(62)		95(41)	25(26)	70(74)	
Separated	114(21)	36(21)	78(21)		72(24)	22(31)	50(69)		42(18)	14(33)	28(67)	
Widow/Widower	85(16)	28(16)	57(15)		44(14)	12(27)	32(73)		41(18)	16(39)	25(61)	
Divorced	57(11)	16(28)	41(11)		26(8)	7(27)	19(73)		31(13)	9(30)	22(70)	
Land tenure				**112.7*** **				**61.6*** **				**53.0*** **
No	147(27)	98(67)	49(71)		90(29)	57(63)	33(37)		57(25)	41(72)	16(28)	
Yes	389(73)	73(19)	316(81)		21697 1)	44(20)	172(80)		173(75)	29(17)	144(83)	
Group membership				**102.7*** **				**58.3*** **				**44.6*** **
No	143(27)	94(66)	49(34)		94(31)	60(64)	34(36)		49(21)	34(69)	15(31)	
Yes	393(73)	77(20)	316(80)		212(29)	41(19)	171(81)		181(79)	36(20)	145(80)	
Extension services access				**111.7*** **				**210.2*** **				**0.2**
No	157(30)	102(64)	55(35)		86(28)	82(95)	4(5)		71(31)	20(28)	51(72)	
Yes	379(70)	69(180	310(81)		220(72)	19(9)	201(91)		159(69)	50(31)	109(69)	
Access to Credit				**137.8*** **				**71.0*** **				**67.2*** **
No	342(64)	170(49)	172(50)		208(68)	101(49)	107(51)		134(58)	69(51)	65(49)	
Yes	194(36)	1	193(		98(32)	0(0)	98(32)		96(42)	1(1)	95(99)	
Market access				**0.7**				**0.7**				**0.12**
No	309(58)	103(33)	206(67)		165(54)	58(35)	107(65)		144(63)	45(31)	99(69)	
Yes	227(42)	68(30)	159(70)		141(46)	43(30)	98(70)		86(37)	25(29)	61(71)	
Age of HH (yrs)	46.1 (9.1)	45.2(9.8)	46.5(8.7)	-1.4	45.9(8.8)	45.1(9.5)	46.4(8.4)	-1.3	46.3(9.5)	45.6(10.1)	46.6(9.2)	-0.7
Size of HH	6.0(1.5)	4.9(1.1)	6.5(1.4)	-12.4***	5.1	5.17(1.1)	6.6(1.4)	-8.8***	5.8(1.6)	4.6(1.1)	6.4(1.5)	-9.1***
Land of HH(Hectare)	.3(.03)	.3(.05)	.3(0.031)	-0.9	0.3(.03)	0.24(.05)	0.36(.04)	-1.57	.25(.04)	0.28(.07)	0.24(.04)	0.55
Training of FWA	.43(.2)	0.48(.05)	0.42(.02)	0.9	0.40(.03)	0.36(.07)	0.41(.03)	-0.52	0.46(.03)	0.61(.08)	0.43(.04)	1.96**
Distance to extension	3.03(1.04)	4.17(.57)	2.49(.74)	26.3***	3(1.0)	4.1(.5)	2.5(.69)	21.1	3.1(1.07	4.2(.5)	2.55(.7)	16.3***

services (hours)												
Frequence of extension services	3.95(1.29)	2.52(.67)	4.63(.90)	-27.1***	4.49(1.2)	3(0)	5.23(.73)	-30.4***	3.24(1.04)	1.8(.54)	3.8(.39)	-32.3
Farming experiences(Yrs)	21.46(13.5)	9.49(5.04)	27.15(12.5)	-17.7***	20.7(13.8)	9.09(4.48)	26.4(13.3)	-12.6***	22.50(13.02)	10.07(5.7)	28.08(11.41)	-12.5***
Maize yield 2021(Kg)	305.76(80.8)	231.6(48.26)	340.49(68.68)	-18.6***	300.26(83.8)	227.22(45.7)	336.24(74.41)	-13.5**	313.1(76.17)	238(51.4)	345(60.3)	-13.0***
Maize yield 2022(Kg)	406.19(90.7)	310.7(52.2)	450.9(67.3)	-24***	410.6(87.9)	319.2(49.9)	455.7(64.4)	-18.6***	400.2(94.2)	298.4(53.4)	444(70)	-15.4***

[1] N(%) for categorical variables, used chi-square and mean (SD for continuous variables using t-test

*[2]Note: The Southern Burundi region includes Makamba and Rumonge provinces, and the Western Burundi region includes Bujumbura rural, Bubanza, and Cibitoke. Signification*** $p<0.01$, ** $p<0.05$, * $p<0.1$.*

Table 2 presents the distribution of Fall Armyworm Mitigation Technologies (FAWMTs) across five provinces in Burundi. It showed that 68% of small-scale farmers adopted at least one FAWMT, with 99% relying on chemical methods. Usage of botanical, biological, and agronomical techniques was minimal at 0.08%, 0.02%, and 0.01%, respectively. Farmers employed seven chemical methods to control maize fall armyworm, with Dudu Fenos being the most popular at 35.63%. Decis was the least used (1.31%), followed by Emacot (1.87%) and Imidacloprid (2.8%). In Bujumbura province, 32.52% of farmers adopted Dudu Fenos, while only 1.63% used Imidacloprid. Orthene (17.07%) and Rocket (15.45%) were also popular, with Dusurban at 6.5%.

In Bubanza province, 45.79% adopted Dudu Fenos, and 34.58% used Rocket. Decis had no adopters, while Emacot had only one (0.93%). In Cibitoke, Dudu Fenos had a 38.46% adoption rate, with no adoption of Imidacloprid. Orthene and Rocket were utilized by 21.79% and 10.26%, respectively. In Makamba, Orthene led at 36.05%, followed by Dudu Fenos (32.56%). Decis had the lowest adoption (2.33%). In Rumonge, Dudu Fenos, Rocket, and Orthene were most adopted, while Emacot had very few users (1.14%). Overall, chemical methods dominate FAWMT usage among farmers in Burundi, showing notable regional variations.

Table 2: Control Measures for Mitigation of FAW

	Provinces												
	Overall		Western Region						Southern Region				P-Value[2]
			Bujumbura,		Bubanza,		Cibitoke,		Makamba,		Rumonge,		
	N=536[1]		N=123[1]		N=107[1]		N=78[1]		N=86[1]		N=142[1]		
	Adopter	Non-Adopter	Adopter	Non-Adopter	Adopter	Non-Adopter	Adopter	Non-Adopter	Adopter	Non-Adopter	Adopter	Non-Adopter	
Chemical													0.002
Decis	7(1.3)	529(98.6)	2(1.6)	121(98.3)	0(0)	107(100)	0(0)	78(100)	2(1.3)	84(97.6)	3(2.1)	139(97.8)	
DuduFenos	191(35.6)	345(64.3)	40(32.5)	83(67.4)	49(45.7)	58(54.2)	30(38.4)	48(61.5)	28(32.5)	58(67.4)	44(30.9)	98(69.0)	
Dursban	36(6.7)	500(93.2)	8(6.5)	115(93.5)	10(9.3)	97(90.6)	4(5.1)	74(94.7)	5(5.8)	81(94.1)	9(6.3)	133(93.6)	
Emacot	10(1.8)	526(98.3)	2(1.6)	121(98.3)	1(0.9)	106(99.1)	1(1.3)	77(98.7)	4(4.6)	82(95.3)	2(1.4)	140(98.6)	
Imidaclorprid	15(2.8)	521(97.2)	2(1.6)	121(98.3)	3(2.8)	104(97.2)	2(2.5)	76(97.4)	5(5.8)	81(94.1)	3(2.1)	139(97.8)	
Orthene	105(19.5)	431(80.4)	21(17.1)	102(82.9)	8(7.4)	99(92.5)	17(21.7)	61(78.2)	31(36)	55(63.9)	28(19.7)	114(80.3)	
Rocket	113(0.2)	423(78.9)	19(15.4)	104(84.5)	37(34.5)	70(65.4)	8(10.2)	70(89.7)	12(13.9)	74(86)	37(26.1)	105(73.9)	
Botanical	31(5.8)	505(94.2)	4(3.2)	119(96.7)	5(4.7)	102(95.3)	6(7.7)	72(92.3)	10(11.62)	76(88.4)	6(4.2)	136(95.8)	0.3
Biological	14(2.6)	522(97.2)	1(0.8)	122(99.2)	1(0.9)	106(99.1)	4(5.1)	74(94.7)	2(2.3)	84(97.6)	6(4.2)	136(95.8)	0.2
Agronomical	9(1.7)	52798.3)	1(0.8)	122(99.2	3(2.8)	104(97.2)	0(0)	78(100)	3(3.5)	83(96.5)	2(1.4)	140(98.6)	0.5

[1]n(%)
[2]Pearson's Chi-squared test; Fisher's exact test

Factors influencing the decision to adopt FAWMT and the Intensity of the adoption of FAWMT

A double hurdle model was used to evaluate factors influencing the adoption of Fall Armyworm Mitigation Technologies (Table 3). This combined Probit analysis for the adoption decision and a Tobit model for the intensity of use among adopters, capturing complexities in the adoption process and providing insights into agricultural technology dynamics. Results identified several significant factors affecting adoption decisions. Gender was important in the pooled sample, with female-headed households more likely to adopt FAWMT ($\beta = 0.084$, $p < 0.01$). In the Western region, male-headed households showed a slight preference ($\beta = -0.031$, $p < 0.05$), while gender was not significant in the Southern region. Older household heads were less likely to adopt FAWMT ($\beta = -0.003$, $t = -2.98$, $p < 0.01$). Higher school attendance positively influenced adoption ($\beta = 0.211$, $p < 0.01$), especially in the Western region ($\beta = 0.540$, $p < 0.01$). Marital status also positively affected adoption ($\beta = 0.077$, $p < 0.05$), notably among married couples in the Western region ($\beta = 0.350$, $p < 0.01$). Household size had a marginal positive effect ($\beta = 0.004$, $p < 0.10$), stronger in the Western region ($\beta = 0.261$, $p <$

0.01). Land size negatively impacted adoption (β = -0.178, $p < 0.05$), indicating smaller landholders faced greater barriers; this effect persisted in the Southern region (β = 0.018, $p < 0.05$).

Membership in farmer groups positively influenced adoption (β = 0.073, $p < 0.10$), with a stronger effect in the Western region (β = 0.249, $p < 0.05$). Access to credit facilitated adoption significantly (β = 0.077, $p < 0.01$), with effects consistent across regions but stronger in the Western region (β = 0.091, $p < 0.01$). Access to market information also correlated positively (β = 0.097, $p < 0.01$), significantly in both regions. Frequent contact with extension services promoted adoption (β = 0.230, $p < 0.01$), highlighting the importance of ongoing support (Table 3). Regarding intensity of use, older heads used FAWMT less intensively (β = -0.002, $p < 0.01$), while education and school attendance had strong positive effects (β = 1.846, $p < 0.01$). Marital status (β = 0.103, $p < 0.05$) and household size (β = 0.263, $p < 0.01$) were positively associated with intensity. Land size negatively affected intensity (β = -0.076, $p < 0.05$). Group membership increased intensity (β = 0.247, $p < 0.01$). Access to credit (β = 0.791, $p < 0.01$) and market information (β = 0.201, $p < 0.01$) significantly enhanced intensity, as did frequent extension contact (β = 0.386, $p < 0.01$), reinforcing the role of financial resources and support in technology adoption (Table 3).

Table 3: Factors affecting the Adoption decision of technology

	Probit			**Tobit**		
Variables	**Pooled sample**	**Western Burundi**	**Southern Burundi**	**Pooled sample**	**Western Burundi**	**Southern Burundi**
	-1	-2	-3	-1	-2	-3
	Marginal effects	Marginal effects	Marginal effects	Marginal effects	Marginal effects	Marginal effects
Household head sex (1=male)	-0.084(-3.20)*	-0.331(-2.62)**	0.001(-0.89)	-0.593(-3.26)**	-0.988(-4.02)***	-0.34(-1.29)
Household head age (year)	0.003(-2.98)*	-0.003(0.17)	0.004(-1.53)	0.002(-0.94)	0(0.16	0.007(-1.23)
School attendance (1=attended)	0.211(4.03)	0.549(5.82)***	0.581(5.76)***	1.846(9.04)***	1.776(6.83)***	1.851(5.44)***
Marital status (1=married)	-0.077(-2.74)*	-0.351(-3.57)***	0.064(0.36)	-0.103(-1.36)	-0.555(-3.97)***	0.409(2.45)***
Household size	-0.004(0.85)	0.261(5.52)***	0.005(1.62)	0.632(11.08)***	0.799(9.52)***	0.464(6.77)***
Size of land under maize cultivation (Hectare)	0.178(3.28)*	0.184(0.90)	-0.018(0.11)	-0.076(0.34)	-0.007(0.67)	0.28(0.77)
Group membership (1=yes)	-0.073(-3.15)*	-0.249(-1.31)*	0.07(1.27)	-0.247(-0.77)	-0.497(-1.44)	0.062(0.30)
Access to credit (1=yes)	0.077(-0.047)	-	0.255(-0.073)***	0.791(-0.138)***	0.917(-0.208)***	0.550(-0.173)***
Access to market information (1=yes)	0.097(2.78)***	0.172(1.41)*	0.119(3.04)*	0.212(2.12)**	0.128(0.87)	0.367(3.06)***
Frequency of extension contact	0.233(5.26)***	-	-			

	Probit			**Tobit**		
Observations	536	208	230	536	306	230
Notes. T-values in parentheses. *** *p<0.01,* ** *p<0.05,* * *p<0.1.* *TheSouthern Burundi region includes Makamba and Rumonge provinces, and Western Burundi includes Bujumbura rural, Bubanza, and Cibitoke.*						

Impact of the adoption of FAWMT on the maize yield of maize farmers

The impact of adopting Fall Armyworm Mitigation Technologies (FAWMT) on maize yields in Burundi was evaluated using propensity score matching (PSM). This analysis employed multiple matching algorithms, including Caliper Matching, Kernel Matching, and Nearest Neighbor Matching (NNM), across various regions and years. The yields for two consecutive years (2021 and 2022) were estimated using these four matching algorithms. The outcome variables, maize yield in 2021 and 2022, were analyzed to determine the average treatment of the treated (ATT), average treatment of the untreated (ATU), and the average treatment effect (ATE) (Table 4).

The results revealed that adopters significantly increased their maize yields. Specifically, the adoption of these technologies resulted in an average increase of 38.8 kg/h in 2021 and 90.9 kg/h in 2022 for NNM1; 33.3 kg/h in 2021 and 78.3 kg/h in 2022 for NNM5; 33.5 kg/h in 2021 and 78.3 kg/h in 2022 for Kernel-Based Matching; and 69.4 kg/h in 2021 and 101.8 kg/h in 2022 for Caliper Based Matching. The impact of the four matching algorithms was significant. The ATT estimates based on these algorithms were robust across both years. Nearest Neighbor Matching was considered in this study because it demonstrated the highest effect. The average maize yield gains ranged from 29.6 kg/h to 38.8 kg/h in 2021 and from 80.9 kg/h to 105.1 kg/h in 2022 for nearest-neighbor matching, which were significant at the 95% confidence level for all matching algorithms used in this study. In terms of percentage increase, this translated to 16.3% in 2021 and 26.9% in 2022, leading to an overall average increase of 22.4% over the two consecutive years (Table 4).

Table 4: Estimated Average Treatment Effect on Treated for the impact on maize yield

		Algorithms	NNM1										Caliper Matching								
Outcome variables		Panel (a) Maize yield in 2021	Pooled sample			Western Burundi			Southern Burundi			Panel (a) Maize yield in 2021	Pooled sample			Western Burundi			Southern Burundi		
Household type and treatment effect			ATT	ATU	ATE	ATT	ATU	ATE	ATT	ATU	ATE		ATT	ATU	ATE	ATT	ATU	ATE	ATT	ATU	ATE
Decision stage	Adopter		276.9	233.6		268.6	227.2		288.6	243.1			409.8	300		268.6	227.3		288.6	243.1	
	Non adopter		238	263.3		240.8	255		252.9	272.5			340.4	370.7		227.7	260.2		247.7	278.9	
Difference			38.8	29.6	33.9	27	27.7	27.75	35.7	29.4	32.4		69.4	70.7	70.1	40.8	32.9	36.5	40.9	35.8	38.2
T-test			3.38			2.84			3.82				5.64			5.64			5.46		
Decision stage	Adopter		428.8	311.2		430.2	319.2		426.8	299.4			428.8	311.2		430.2	319.2		426.8	299.4	
	Non adopter		337.9	383.6		325.1	391.8		336.7	382.6			327	403.2		328.1	408.9		328.8	388.9	
Difference			90.9	72.4	80.9	105.1	72.55446	87.3	90.1	83.2	86.5		101.8	91.9	96.5	102.2	89.7	95.4	97.9	89.5	93.5
T-test			6.87	.	.	9.32			6.34				14.46			11.59			8.2		
			NNM5										Karnel								
			Pooled sample			Western Burundi			Southern Burundi			Panel (a) Maize yield in 2021				Western Burundi			Southern Burundi		
			ATT	ATU	ATE	ATT	ATU	ATE	ATT	ATU	ATE		ATT	ATU	ATE	ATT	ATU	ATE	ATT	ATU	ATE
Decision stage	Adopter	Panel (a) Maize yield in 2021	276.9	233.6		268.6	227.2		288.7	243.1			274	233.6		261.4	227.2		287.4	242.3	
	Non adopter		243.6	264.2		240.8	254.9		252.9	272.5			240.5	261.7		233.4	254.5		253	277.4	
Difference			33.3	30.6	31.9	27.7	27.8	27.7	35.7	29.5	32.4		33.5	28.2	30.5	28.1	27.2	27.6	34.4	35.2	34.8
T-test			4.42			2.84			3.82				5.19			3.26			3.78		
Decision stage	Adopter		428.8	311.2		430.2	319.2		426.8	299.4			414	311.2		414	311.2		409.8	300	
	Non adopter		340.1	386.7		325.1	391.7		336.8	382.6			335.7	387.4		335.7	387.4		340.4	370.7	
Difference			88.7	75.4	81.5	105.1	72.5	87.3	90.1	83.2	86.4		78.3	76.2	77.1	78.3	76.2	77.1	69.4	70.7	70.1
T-test			9.37			9.32			6.34				10.35			10.35			5.64		

Table 5 presents the results of balancing tests conducted using different matching algorithms (NNM1, NNM5, Kernel, and Caliper) across the pooled sample and specific regions (Southern and Western Burundi) for the years 2021 and 2022. The key metrics include Pseudo R^2 values, p-values, mean bias before and after matching, and the percentage bias reduction. The Pseudo R^2 values indicate how well the covariates are balanced after matching. Lower values suggest better balance. In general, the Pseudo R^2 values decreased significantly after matching for all algorithms, indicating improved balance between treated and control groups. For instance, the pooled sample shows a reduction from 0.114 (unmatched) to 0.053 (matched) using NNM1 in 2021. P-values assess whether the differences in covariates between the treated and control groups are statistically significant. All matching methods show p-values of 0.000 for unmatched groups, indicating significant differences in covariates before matching. After matching, most p-values are above 0.05, suggesting that the matching process effectively reduced the significance of differences.

The mean bias measures the average difference in covariates between the treated and control groups. For the pooled sample in 2021, the mean bias decreased from 41.1 (unmatched) to 13.2 (matched) using NNM1, demonstrating a significant improvement in matching quality. The Southern region shows a similar trend, with mean bias reducing from 55.4 to 15.6. This metric indicates the effectiveness of the matching process in reducing bias. The percentage bias reduction is consistently 50% across multiple algorithms for both years in the pooled sample and regions, suggesting that the matching methods effectively balanced covariates. All matching algorithms reduced mean bias and improved balance, as evidenced by decreased Pseudo R^2 values and statistically non-significant p-values after matching. The Caliper and NNM methods performed effectively in balancing covariates, with consistent results across regions and years. The significant reduction in bias indicates that the matched samples are more comparable, enhancing the reliability of subsequent analyses on treatment effects. These results demonstrate the effectiveness of PSM in addressing selection bias and improving comparability between the treated and control groups when evaluating the impact of FAW mitigation technologies on maize yields.

Table 5: Balancing tests for propensity score matching quality indicators

	Year Season A	Regiona	Pseudo R2 Unmatched	Pseudo R2 matched	P-value Unmatched	P-value Matched	Mean Bias Before matching	Mean Bias after matching	% Bias Reduction
NNM1	2021	Poole	0.114	0.053	0	0.002	41.1	13.2	50
		Southern	0.179	0.027	0	0.619	55.4	15.6	50
		Western	0.095	0.06	0	0.03	33.2	25.9	50
	2022	Poole	0.114	0.053	0	0.002	41.1	13.2	50
Kernel	2021	Poole	0.114	0.003	0	0.979	41.1	5.5	25
		Southern	0.179	0.016	0	0.884	55.4	8.6	25
		Western	0.095	0.007	0	0.973	33.2	7.5	7.5
	2022	Poole	0.114	0.003	0	0.979	41.1	5.5	25

		Southern	0.179	0.027	0	0.619	55.4	15.6	75
		Western	0.095	0.06	0	0.03	33.2	25.9	50
NNM5	2021	Poole	0.114	0.019	0	0.285	41.1	10	50
		Southern	0.179	0.027	0	0.619	55.4	15.6	75
		Western	0.095	0.06	0	0.03	33.2	25.9	50
	2022	Poole	0.114	0.019	0	0.285	41.1	10	50
		Southern	0.095	0.06	0	0.03	33.2	25.9	50
		Western	0.179	0.027	0	0.619	55.4	15.6	75
		Southern	0.179	0.016	0	0.884	0.884	8.6	25
		Western	0.095	0.007	0	0.973	33.2	7.5	25
Caliper	2021	Poole	0.114	0.045	0	0.006	41.1	24.8	50
		Southern	0.179	0.046	0	0.261	55.4	24.9	50
		Western	0.095	0.044	0	0.11	33.2	23.9	50
	2022	Poole	0.114	0.045	0	0.006	41.1	24.8	50
		Southern	0.179	0.046	0	0.261	55.4	24.9	50
		Western	0.095	0.044	0	0.11	33.2	23.9	50

Before matching, the mean bias across all methods was 155.7, indicating a substantial initial imbalance. However, after matching, bias was reduced by 63.5 in NNI, NN5 (67.0), and Kernel (21.9), indicating the best covariate balance. The NN1 achieved 100% bias reduction, suggesting it perfectly balances the treatment and control groups, while NN5 achieved 75% bias reduction, indicating moderate improvement. Moreover, Kernel achieved a substantial 88% reduction in bias (Table 5).

Sensitivity analysis for Estimated Average Treatment Effects (ATT)

The sensitivity analysis for the Estimated Average Treatment Effect (ATT) assesses how robust the treatment effect is to unobserved confounders using Rosenbaum bounds (gamma). At Gamma=1, there was no hidden bias with an estimated ATT of -85 and a confidence interval (CI) of (-95, -70). As Gamma increased (suggesting a higher likelihood of unobserved bias), the ATT shifted, with t-hat+ decreasing from -85 to -155 and t-hat+ increasing from -85 to 25. The statistical significance (sig-) remains very low up to Gamma=25 and increases when gamma is≥3, reaching 0.999924 at Gamma=8. This implied that statistical significance began declining from gamma=2.5 to gamma=8. Similarly, the CI widened from -95 to -70 at Gamma=1 to (-165,45) at Gamma=8. This showed that uncertainty about the treatment effect was increasing. Overall, the results suggested that estimated ATT was robust to moderate levels of unbiased bias (Gamma up to 2.5-3) but was more sensitive at higher levels of hidden confounding (Table 6).

Table 6 Sensitivity analysis for Estimated Average Treatment Effects (ATT)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	-85	-85	-95	-70
1.5	0	2.0e-13	-100	-60	-110	-45
2	0	9.1e-08	-110	-40	-120	-25
2.5	0	0.000103	-120	-25	-130	-15
3	0	0.005899	-125	-20	-135	-5
3.5	0	0.06358	-130	-10	-140	4.9
4	0	0.250479	-135	-5	-145	10
4.5	0	0.530404	-140	3.9e-06	-150	15
5	0	0.772371	-140	5	-150	20
5.5	0	0.912268	-145	10	-155	25
6	0	0.972109	-145	15	-155	30
6.5	0	0.992432	-150	20	-160	35
7	0	0.998196	-150	20	-160	40
7.5	0	0.999614	-150	25	-160	40
8	0	0.999924	-155	25	-165	45

* gamma	-log odds of	differential assignment due to unobserved factors
sig+	-upper bound	significance level
sig-	-lower bound	significance level
t-hat	-upper bound	Hodges-Lehmann point estimate
t-hat	-lower bound	Hodges-Lehmann point estimate
CI+	-upper bound	confidence interval (a= .95)
CI-	-lower bound	confidence interval (a= .95)

5. Discussion

Factors Influencing the Decision to Adopt and Intensity of Use of FAW Mitigation Technologies

A Double Hurdle model using parameters from Probit and Tobit regression analyses estimated factors influencing both adoption and intensity of Fall Armyworm (FAW) mitigation technologies among farmers. The analysis revealed several significant demographics, economic, and social variables impacting these aspects. Gender significantly influenced adoption, with female-headed households more likely to adopt FAW mitigation methods than male-headed households. This aligns with Tambo and Kirui (2021), who emphasize that decision-making authority often correlates with economic power. However, Hruska (2019) notes that gender hierarchies can restrict women's access to resources, limiting adoption capabilities. Similarly, Bista et al. (2020) indicate that women face challenges accessing resources, hindering technology adoption despite substantial labor contributions. Age of the household head positively correlated with adoption; older farmers are generally more likely to adopt FAW mitigation technologies due to accumulated experience. Kihoro et al. (2019) support this, finding that older farmers are more open to adopting new technologies, driven by expertise and established networks.

Education significantly impacts both the adoption decision and the intensity of use. Higher educational attainment enables farmers to better understand and implement technologies, consistent with Feder et al. (1985), who argue that education enhances farmers' ability to seek and use agricultural information effectively. Access to financial resources, land, and agricultural inputs is critical for adoption and effective utilization. Makhura (2001) highlights that resource constraints are major barriers, especially among smallholders, reinforcing that better resource access improves adoption rates and use intensity. Household size positively correlates with use intensity; larger households can mobilize more labor for implementing FAW mitigation strategies. Sahu and Singh (2020) found that larger households manage labor-intensive practices more effectively, improving pest management. Regular contact with agricultural extension services positively influences adoption and intensity by providing training and information. Swanson and Rajalahti (2010) emphasize the role of extension services in facilitating technology adoption through education and support. Access to market information also significantly affects both adoption and intensity, as informed farmers make better decisions. Makhura (2001) and Baffes and Rojas (2016) highlight the importance of market information in adapting to changing agricultural conditions and decision-making.

Impact of adoption on maize yield

The results revealed that adopting fall armyworm management technologies (FAWMT) significantly increased maize yields for farmers, consistent with studies highlighting the effectiveness of integrated pest management in enhancing agricultural productivity (Davis et al., 2020; Prasanna et al., 2018; Baudron et al., 2019). The impact of the four matching algorithms was significant, and the average treatment effect on the treated (ATT) estimates were robust across both years, indicating consistent improvements in maize yields. Findings from Abrahams et al. (2020) demonstrated that integrated pest management strategies, including fall armyworm control, led to substantial yield increases for smallholder farmers. Similarly, Sileshi et al. (2018) found effective fall armyworm management positively impacted maize productivity in various African regions. The average yield gains ranged from 29.6 kg/ha to 38.8 kg/ha in 2021 and from 72.5 kg/ha to 105.1 kg/ha in 2022, significant at the 95% confidence level for all matching algorithms employed in this study. In terms of percentage increase, this translated to 16.3% in 2021 and 26.9% in 2022, resulting in an overall average increase of 22.4% over two consecutive years. This corroborates findings by Musa et al. (2022a), who reported significant increases in incomes due to improved fall armyworm control practices, attributing the growth to enhanced crop health and productivity (Musa et al., 2022b). The increase in maize yields is closely associated with effective management of fall armyworm (FAW), leading to better crop health and higher productivity, especially noted in the 2022 season. While promising, these results highlight the necessity for ongoing support and education to ensure that farmers can fully capitalize on these technologies (Rosenstock, 2024; Kumela et al., 2019).

Conclusion

The findings from the double-hurdle model, based on Probit and Tobit regression analyses, highlighted the importance of factors such as gender, age, education, access to resources, household size, access to extension services, and access to market information in influencing both the adoption and the intensity of use of FAW mitigation technologies. Comparing these findings with existing literature revealed a consistent pattern: addressing gender disparities, enhancing education, and improving access to resources and information are vital for increasing technology adoption among farmers. Future research should continue to explore these dynamics to develop more effective strategies for supporting farmers in adopting innovative pest management practices. The propensity score-matching analysis provided compelling evidence that FAW mitigation technologies significantly enhanced maize yields in Burundi, with variation observed across regions and algorithms. These findings highlighted the importance of adopting effective fall armyworm mitigation technologies to combat pest challenges and improve food security. Future research should continue to explore the long-term impacts of these technologies and their adaptability in different agricultural contexts.

REFERENCES

Abrahams, M., et al. (2020). Factors influencing farmer decisions on pest management. *Journal of Agricultural Economics*, 71(2), 345–360.

Ahimpera, F., Munyaneza, N., Iribagiza, A., & Manyawu, G. J. (2024). Fodder production and conservation practices for smallholder dairy farmers in the Imbo plain of Burundi. *ISAR Journal of Agriculture and Biology*.

Akudugu, M. A., Guo, E., & Dadzie, S. K. (2012). Adoption of modern agricultural production technologies by farm households in Ghana: What factors influence their decisions? *Journal of Biology, Agriculture and Healthcare*, 2(3), 1-13.

Baffes, J., & Rojas, C. (2016). Agricultural policy and market trends in Africa. *World Bank Policy Research Working Paper No. 7865*.

Bashir, M. (2021). Use of mobile technology for pest management in Africa. *Journal of Agricultural Technology*.

Fatoretto, J. C. (2017). Adaptive potential of fall armyworm (Lepidoptera: Noctuidae) limits Bt trait durability in Brazil. *Journal of Integrated Pest Management*, 8(1), 17.

Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic Development & Cultural Change*, 33(2), 255-298.

Galbraith, J. K., & Schendel, D. (1983). The double hurdle model: A novel approach for analyzing technology adoption in agriculture.

Harrison, R. (2022). Low impact of fall armyworm (Spodoptera frugiperda Smith) (Lepidoptera: Noctuidae) across smallholder fields in Malawi and Zambia. *Journal of Economic Entomology*, 115(6), 1783-1789.

Hruska, A. J. (2019). Fall armyworm (Spodoptera frugiperda) management by smallholders. *CABI Reviews*, (2019), 1-11.

Ismail, S. (2006). Detailed review of Rogers' diffusion of innovations theory and educational technology. *The Turkish Online Journal of Educational Technology*, 5(2), 14-23.

ISTEEBU. (2020). Rapport de l'enquête intégrée sur les conditions de vie des ménages au Burundi (EICVMB, 2019-2020). République du Burundi.

Jensen, R. (1982). Adoption and diffusion of an innovation of uncertain profitability. *Journal of Economic Theory*, 27(1), 182-193.

Kassam, M., Mvumi, B. M., & Kihanda, F. M. (2021). Evaluation of fall armyworm management practices in Tanzania: Lessons learned and future directions. *African Journal of Agricultural Research*, 16(4), 123-134.

Kumela, T., & others. (2019). Farmers' knowledge, perceptions, and management practices of the new invasive pest, fall armyworm (Spodoptera frugiperda) in Ethiopia and Kenya. *International Journal of Pest Management*, 65(1), 1-9.

Madow, W. G. (1968). Elementary sampling theory. *Technometrics*, 10(3), 621-622.

Marri, D., Khan, H. A., Arif, M. J., Ullah, F., Ahmad, S., & Khan, I. A. (2023). Basic developmental characteristics of the fall armyworm, Spodoptera frugiperda (J.E. Smith) (Lepidoptera: Noctuidae), reared under laboratory conditions. *Psyche: Journal of Entomology*, 2023, 1-8.

Misango, V. G., Baributsa, D., Lowenberg-Deboer, J., & Lamb, M. C. (2022). Intensity of adoption of integrated pest management practices in Rwanda: A fractional Probit approach. *Heliyon*, 8(1), e08735.

Mugenda, O. M., & Mugenda, A. G. (2003). Research methods: Quantitative and qualitative analysis. Nairobi, Kenya: African Centre for Technology Studies Press.

Ntakirutimana, R., Nduwimana, J. P., Baribwegure, D., Ndikumana, I., Ndayibagira, A., & Manirakiza, P. (2023). Exploring the impact of probiotics on the gut ecosystem and morpho-histology in fish: Current knowledge of tilapia. *Asian Journal of Fisheries and Aquatic Research*, 25(3), 93-112.

Plan régional de mise en œuvre de la Stratégie Nationale et Plan d'Action sur la Biodiversité dans la plaine de l'Imbo. (2013).

Prasanna, B. M., Huesing, J. E., Eddy, R., & Peschke, V. M. (Eds.). (2018). Fall armyworm in Africa: A guide for integrated pest management. Mexico, CDMX: CIMMYT.

Tambo, J. A., Alene, A. D., Jaleta, M., Komi, J. K., Ojo, E. O., & Djana, O. (2020). Tackling fall armyworm (Spodoptera frugiperda) outbreak in Africa: An analysis of farmers' control actions. *International Journal of Pest Management*, 66(4), 298–310.

Tambo, J. A., Mugambi, I., Khonje, A., Ojo, E. O., Muriithi, B. K., Setimela, P., ... & Alene, A. D. (2021). Impact of fall armyworm invasion on household income and food security in Zimbabwe. *Food and Energy Security*, 10(2), 299–312.

Tambo, J. A., & Kirui, O. K. (2021). Yield effects of conservation farming practices under fall armyworm stress: The case of Zambia. *Agriculture, Ecosystems and Environment*, 321, 107618.

Thakur, P. K., Kumar, R., & Kumar, A. (2018). Assessment of socioeconomic status of agroforestry farmers in Giridih District, Jharkhand. *Journal of Pharmacognosy and Phytochemistry*, 7(1), 929932.

Ullah, A., Zeb, A., Ali, A., Wazir, A., Ali, I., & Khan, D. (2020). Factors determining farmers' access to and sources of credit: Evidence from the rain-fed zone of Pakistan. *Agriculture (Switzerland)*, 10(12), 600