# Impact of extension training on farmers' knowledge of integrated striga (<u>Striga spp.</u>) Management in Bauchi State, Nigeria

<sup>1</sup>Abbas Shehu,\* <sup>2</sup>Nuru Muhammad Inuwa, <sup>3</sup>Mustapha Yakubu Madaki. <sup>4</sup>Muhammad Ibrahim Kadafur, <sup>1</sup>Nasiru Murtala, <sup>5</sup>Yusuf Lawal Idrisa, <sup>6</sup>Ashafa Salisu Sambo 

<sup>1</sup>Abubakar Tafawa Balewa University, Bauchi, Nigeria 

<sup>2</sup>Bauchi State College of Agriculture, Nigeria 

<sup>3</sup>Faculty of Tropical Agrisciences, Czech University of Life Sciences 

<sup>4</sup>Socio-economic Department, International Institute of Tropical Agriculture, Ibadan, Nigeria

<sup>1</sup>Abubakar Tafawa Balewa University, Bauchi, Nigeria.

<sup>5</sup>Department of Agricultural Extension Services, University of Maiduguri, Nigeria.

<sup>6</sup>Department of Agricultural Extension and Management, Nuhu Bamalli Polytechnic)

Corresponding author: ashehu@atbu.edu.ng

#### Abstract

Striga is a parasitic weed that affects cereal crops, especially maize, sorghum and rice in many parts of Africa that can cause up to 100 percent crop losses. The International Institute for Tropical Agriculture (IITA) promoted Integrated Striga Management for Africa (ISMA) in Nigeria and Kenya to stop the menace of the weed. This study therefore evaluated the impact of the ISM training provision on ISM knowledge among farmers. Multistage (3 stages) sampling procedure was used to sample respondents for the study. Data were collected through an interview schedule administered by trained enumerators. Data analysis was done using cross tabulation, logistic regression, propensity score matching and Inverse Probability Weighted Regression Adjusted (IPWRA). Result reveals that majority (65%) of the trained farmers had good knowledge of the ISM technology. Formal education and number of training positively affected participation in ISM project. The farmers that were formally trained by ISM project had 2.74-2.91 out of 5 knowledge score higher than the untrained farmers. It could then be concluded that provision of training hold great potential to improve farmers' knowledge on how to identify, monitor and manage their production problem as in the case of striga pest, which, in turn, can facilitate the adoption of complementary integrated management practices. Hence, it is recommended that training should be intensified in order to diffuse more knowledge of ISM to farmers by the promoters of the project.

**Keyword**: Extension training, integrated striga management, Propensity score matching

### IMPACT DE LA FORMATION EN EXTENSION SUR LA CONNAISSANCE DES AGRICULTEURS SUR LA GESTION INTEGREE DE STRIGA (Striga SPP.) DANS L'ÉTAT DE BAUCHI, NIGERIA

#### Résumé

Le striga est une mauvaise herbe parasite qui affecte les cultures de céréales, en particulier le maïs, le sorgho et le riz dans de nombreuses régions de l'Afrique qui peuvent causer jusqu'à 100% de pertes de cultures. L'Institut international de l'agriculture tropicale (IITA) a promu la gestion intégrée de Striga pour l'Afrique (GISA) au Nigéria et au Kenya pour arrêter la menace des mauvaises herbes. Cette étude a donc évalué l'impact de la

disposition de formation des GIS sur les connaissances des GIS chez les agriculteurs. La procédure d'échantillonnage à plusieurs étapes (3 étapes) a été utilisée pour échantillonner les répondants pour l'étude. Les données ont été collectées par le biais d'un calendrier d'entrevue administré par des énumérateurs formés, L'analyse des données a été effectuée à l'aide de la tabulation croisée, de la régression logistique, de la correspondance des scores de propension et de la régression pondérée par la probabilité inverse ajustée (IPWRA). Le résultat révèle que la majorité (65%) des agriculteurs formés avaient une bonne connaissance de la technologie GIS. L'éducation formelle et le nombre de formation ont affecté positivement la participation au projet ISM. Les agriculteurs qui ont été officiellement formés par GIS Project avaient 2,74-2,91 sur 5 score de connaissances plus élevé que les agriculteurs non formés. On pourrait ensuite conclure que la prestation de formation a un grand potentiel pour améliorer les connaissances des agriculteurs sur la façon d'identifier, de surveiller et de gérer leur problème de production comme dans le cas de Striga Pest, qui, à son tour, peut faciliter l'adoption de pratiques de gestion intégrée complémentaires . Par conséquent, il est recommandé que la formation soit intensifiée afin de diffuser davantage de connaissances de GIS aux agriculteurs par les promoteurs du projet.

Mots-clés: formation d'extension, gestion intégrée du striga, correspondance de score de propension

إدارة سرغ المتكاملة في ولاية بوتشى نيجيريا

مختصرة نبدة Striga هي عشب طفيلي يؤثر على محاصيل الحبوب، وخاصة الذرة والذرة الرفيعة والأرز في أجزاء كثيرة من إفريقيا ويمكن أن يتسبب في خسائر تصل إلى 100 في المائة في المحاصيل. قام المعهد الدولي للزراعة الاستوائية (IITA) بتشجيع الإدارة المتكاملة للبستريج الأفريقيا (ISMA) في نيجيريا وكيني الوقف خطر الأعشاب الضارة. لذلك قيمت هذه الدراسة تأثير توفير التدريب على ISM على معرفة ISM بين المزار عين. تم استخدام إجراء أخذ العين اتمت عدد المراحل (3 مراحل) لعينة المستجيب ينل لدراسة . تم جمع البيانات من خلال جدول المقابلة الذي يديره العدادين المدربين تم إجراءت حليلا لبيانات باستخدام الجدولة المتقاطعة، والانحدار اللوجستي، ومطابقة درجة الميل، وتعديل الانحدار المرجح العكسى .(IPWRA) تظهر النتيجة أن الغالبية (65%) من المزار عين المدربين لديهم معرفة جيدة بتكنولوجيا . ISM أثر التعليم الرسمي وعدد التدريب بشكل إيجابي على المشاركة في مشروع . ISM حصل المزارعون الذين تم تدريبهم رسميًا من خلال مشروع ISM على ISM على 5 درجات معرفة أعلى من المزارعين غير المدربين ويمكن بعد ذلك استنتاج أن توفير التدريب ينطوي على إمكان اتكبيرة لتحسين معرفة المزار عين حول كيفية تحديد ومراقبة وإدارة مشكلة إنتاجهم كما في حالة ستريَّجا آفة، والتيب دورها يمكن أن تسهل اعتماد ممارسات الإدارة المتكاملة التكميلية . ومن ثم، يوصلي بتكثيف التدريب من أجل نشر المزيد من المعرفة حول ISMللمز ار عين من قبل مروجي المشروع.

الكلمة الرئيسية: تدريب إضافي، إدارة striga متكاملة، مطابقة نقاط الميل

#### Introduction

Pests and diseases are the second most important threat to nature due to their severe impact on populations' livelihoods; on the health of people, animal and plants; and on the economy. They are affecting those most vulnerable; the poorest farmers and can ultimately threaten food security on a global scale (FAO, 2017). Striga is a parasitic weed that affects cereal crops, especially maize and sorghum, in many parts of Africa. It can also affect other

grass-like plants, such as finger millet, rice, sugar cane, Sudan grass and Napier grass. Two types of Striga are found in Africa: Striga hermonthica grows up to 1 meter tall, with pinkish flowers, while Striga asiatica is shorter, growing to just 30 cm height, with reddish flowers (FAO, 2011). Striga constitutes one of the severe pests that are affecting millions of lives globally, which can cause substantial losses in crops productivity (IITAa, 2012). Striga seeds can lie in the soil for a long time up to 15 years germinating only when a cereal crop is planted. Striga can only grow by attaching itself to the roots of a grass-like plant, most commonly maize and sorghum. It absorbs water and nutrients from maize or sorghum, making the plants smaller and weaker. It can reduce the yield of maize by more than half and even cause complete crop failure (FAO, 2011). Striga attacks and greatly reduces the production of staple foods and commercial crops such as maize, sorghum, millet, rice, sugarcane, and cowpea. The weed attaches itself to the roots of plants and removes water and nutrients and can cause losses of up to 100% in farmers' crops. Furthermore, a single flower of the weed can produce up to 50,000 seeds that can lie dormant in the soil for up to 20 years. Current yield of Maize (1200 to 1500 kg/ha) and Cowpea (300 to 500 kg/ha) on farmers field in sub-Saharan Africa were relatively very low. The main constraint achieving sustainable productivity was due to the menace of parasitic weeds such as Striga and Alectra species (Mignouna, Abdoulaye, Kamara & Oluoch, 2013; IITA, 2014).

The productivity in farmers' field were generally low in Bauchi state due to high pressure of pest and diseases that were associated with poor management practices and lack of adequate use of input. Most farmers reported the Striga as the most constraints to maize and cowpea production (Mignouna, et. al., 2013).

Baseline studies conducted showed limited adoption of ISM technologies in Bauchi and Kano states; only about 25% of the farmers in these states were aware of Integrated Striga Management (ISM) technologies, while only about 20% of these had adopted the technologies. Lack adequate of information and knowledge about ISM technologies among farmers is one of the reasons identified non-adoption for (Mignouna, et. al., 2013). This showed that farmers were aware of the adverse effect of Striga on their productivity. Therefore, the need arises for higher yielding crop varieties and quality information on judicious inputs use for better knowledge gain.

This make IITA in collaboration with some African government to provide training for farmers on ISM with the purpose to adapt and intensively promote proven Integrated Striga control strategies that would improve the livelihood of over 25 million small scale farmers through generation of USD 5.7 million worth grain annually and about 112,000 target farmers have been reached (IITA, 2014)

The ISM projects chose the integrated striga control approach that encompasses: maize legume rotation and other crop management strigapractices; resistant/tolerant Maize and Cowpeas; herbicide resistant Maize and Seed coating with herbicides; Push-pull technology for small holder crop-livestock production; and Bio-control. ISM project started in 2011 and ends in 2015 which taught some 3,500 farmers on group dynamics. participatory approaches, modern crop management and Striga control practices in Northern Nigeria.

Furthermore, project also the disseminated Striga management technologies to about 38,000 Nigerian farmers through farmer-to-farmer knowledge transfer. on-farm demonstrations, field days, television and radio (IITA, 2012).

Agricultural extension is typically based on the delivery of education and the provision of advisory services (Cathal and Kevin, 2016). Growth in the human capital of the agricultural sector is a key aspect of the "ISM" agenda set out to curtail the menace of Striga. Information sieving was reported from the extension agents to lead farmers overtime (Niu and Ragasa, 2018). Several studies were conducted on the ISM in Bauchi State, for instance, Mudege, Mdege, Abidin & Bhatasara (2017); whom the conducted a baseline survey, Hassan, Ortmann & Baiyegunhi (2018); they studied Impact of ISM technology on maize productivity of farmers; and Baiyegunhi, Hassan, Danso-Abbeam & Ortmann (2019) whom they studied Diffusion Adoption **ISM** and of technology in Rural Northern Nigeria, but there is sparse information on the impact ISM of on farmers' knowledge. Therefore, the study evaluated the impact of ISM training on farmer's knowledge of striga management in Bauchi state, Nigeria. Specifically, the study describe the farmers' Socio-economic characteristics; ISM knowledge of both trained and untrained farmers; and Impact of ISM's training on farmers knowledge of ISM

### Materials and Method Study Area

The study area for this study is the five local government areas (LGAs) of Bauchi State, namely: Alkaleri, Bauchi, Ganjuwa, Dass and Toro which were used as the project zone. The zone has the population of 1,715,404 representing 36% of State's entire population (NPC, 2006). According to National Bureau of Statistics (NBS, 2014) with recent increase in the rate of population growth (3.2% per annum), the study area has a total estimated population of 2,264,333.28 and land mass of 23,247 square kilometers (BSADP, 2010). It's situated within latitudes 9° 3' and 12° 3' north and 8° 50' and 11° 0' east.

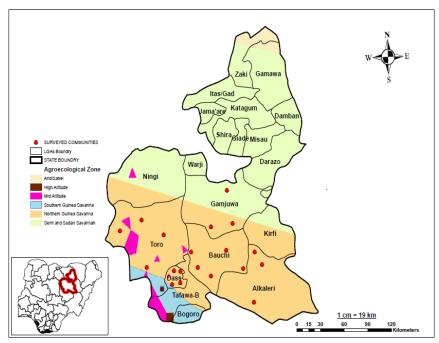


Figure 1: Map of the project area showing the study area (Bauchi state)

### Sampling Strategy

The sampling approach was adapted from baseline survey of the ISM project, multistage sampling procedure was used and random sampling procedure was used in drawing households from the maize and cowpea growing areas of Bauchi State. The first stage involved the selection of five Local Government Areas (LGA) in the state based on the biophysical survey preceding of the baseline survey conducted by IITA.

The sampling frame including households in the surveyed villages were developed by extension agents collaboration with community heads in each community as a source list and this stage involved a random selection of farm households through a random number generator available in Microsoft Excel Lastly 8 households randomly selected from each surveyed community. Thus a total of 192 households (without segregating project participants and non-participants) were retained for the study.

### Data collection and analysis

Data were collected through an interview administered by trained schedule means enumerators through a of questionnaire which was designed to assess the impact of training on knowledge of ISM in Bauchi State, Nigeria. The types of questions in the data collection instrument were farmers' socio-economic, institutional, farm characteristics, ISM problem components adoption and associated with ISM technologies.

### **Empirical Strategy**

The knowledge of farmers about ISM was measured by given a five test questions in regards to component of ISM technology to the respondents. Each questions carry's 1 mark, making it a total of five marks. The knowledge level of farmers was categorized into; No knowledge (for those

with a score of 0), Fair knowledge (for those with a scores of 1-2), Good knowledge (for those with a scores of 3-4) and Very good knowledge (if respondents scores 5).

The study employ propensity score matching (PSM) and Inverse Probability Weighted Adjusted Regression (IPWRA) mis-specification bias. The basic idea behind PSM is to match each treated household with a similar untreated household and then measure the average difference in the outcome variable between the treated and untreated households. Following Imbens and Wooldridge (2009), the average treatment effect on the treated (ATT) is defined as: ATT=E{Y(1)-Y(0) T-1}

where Y(1) and Y(0) are outcome indicators (in our case, knowledge score of treated and untreated households, respectively). T is a treatment indicator. However, we can only observe

 $ATT=E\{Y(1)\}/T=1$  in the data set and  $ATT=E\{Y(0)\}/T=1$  is missing. In essence, the study cannot observe the knowledge score of treated households had they not been treated, once they are treated. Simple comparison of ISM knowledge of farmers with and without treatment status introduces bias in estimated impacts due to self-selection bias. The magnitude of selfselection bias is formally presented as: E[Y(1)-Y(0)/T-1]=ATT=E(Y(0)/T=1-Y(0)/T=0

By creating comparable counterfactual households for treated households, PSM reduces the bias due to observables. Once households are matched with observables, PSM assumes that there are no systematic differences in unobservable characteristics between treated and untreated households. Given this assumption of conditional independence and the overlap conditions, ATT is computed as follows:

ATT = E(Y(0) T=1, P(x)-E[Y(0)/T-0/P(x)]However, ATT from PSM can still produce biased results in the presence of mis-specification in the propensity score model (Robins et al., 2007; Wooldridge, 2007, 2010). A potential remedy for such misspecification bias is to use IPWRA. According to Wooldridge (2010), IPWRA estimates will be consistent in the presence mis-specification treatment/outcome model, but not both. As a result, the IPWRA estimator has the double-robust property that consistent results as it allows the outcome and the treatment model to account for mis-specification. Following Imbens and Wooldridge (2009), ATT in the IPWRA model is estimated in two steps. Suppose that the outcome model is represented by a linear regression function of the form Y = $\propto_i + \varphi_i X_i + \varepsilon_i$  for  $i = [0 \ 1]$  and the propensity scores are given by  $p(x; \gamma)$  and the propensity scores are given by  $p(x; \hat{\gamma})$ In the second step, we then employ linear regression to estimate  $(\propto_0, \varphi_0)$  and  $(\propto_1, \varphi_1)$ using inverse probability weighted least squares as

$$\min_{\alpha_0, \ \varphi_0} \sum_{i}^{N} (Y_i - \alpha_0 - \varphi_0 x_i) / p(x, \hat{\gamma}) \text{ if } T_i$$

$$= 0$$

$$\min_{\alpha_0, \ \varphi_0} \sum_{i}^{N} (Y_i - \alpha_1 - \varphi_1 x_i) / p(x, \hat{\gamma}) \text{ if } T_i$$

The ATT is then computed as the difference

$$ATT = \frac{1}{N_w} \sum_{i}^{N_w} [(\widehat{\alpha}_1 - \widehat{\alpha}_0) - (\widehat{\varphi}_1 - \widehat{\varphi}_0) X_i]$$

where,  $(\widehat{\alpha}_1 - \widehat{\varphi}_1)$  are estimated inverse probability weighted parameters for treated households while  $(\widehat{\alpha}_0 - \widehat{\varphi}_0)$  are estimated inverse probability weighted parameters for untreated households.

Finally, Nw stands for the total number of treated households.

### **Result and Discussion**

# Descriptive result/ Description of the study sample

Table 1 presents the descriptive results of the key variables of interest. The trained untrained farmers were significantly different statistically in terms of sex, marital status, years of formal education and group membership. The average age of trained and untrained farmers was about 46 years and 43 years, difference respectively. The statistically significant  $(P \le 0.05)$ . The average household size of trained and untrained farmers was about 13 people and 10 people, respectively. The difference was statistically significant  $(P \le 0.05)$ . Moreover, the average farming experience of trained and untrained farmers was about 23 years and 17 years, respectively. The difference was statistically significant  $(P \le 0.05)$ . Furthermore, the trained farners had more formal education than the untrained farmers (P≤0.05). More so, the average farm size of trained and untrained was 4.5 ha and farmers 3.5 ha. respectively. The difference was statistically significant  $(P \le 0.1)$ . The average training of trained and untrained farmers was about 2 and 1, respectively. The difference was statistically significant (P≤0.01). The average knowledge level of trained and untrained farmers was about 1.96 and 0.69, respectively. The difference was statistically significant  $(P \le 0.01)$ . Lastly, the average knowledge score of trained and untrained farmers about 3.69 and 0.69 respectively. The difference was statistically significant  $(P \le 0.01)$ .

Table 1: Descriptive Statistics by treatment

		Not			
		Treated	treated	Mean	
Variable	Description	(n=141)	(n=36)	Difference	t-value
Age	In years	45.87	42.5	3.37	1.88**
Sex	1= male, 2=female	1.1	1.08	0.02	0.32
Marital status	Married= 1, 2= single	1.14	1.08	0.06	0.67
Household Size	Number of family members	12.81	10.14	2.67	2.05**
Farming					
Experience	in years)	22.57	16.92	5.65	2.21**
Formal	formal education $=1,, 0=$				
Education	no)	0.79	0.61	0.18	2.24**
Years of Formal					
Education	in years	8.91	8	0.91	0.84
Group					
Membership	1 = yes, 0 = no	1.2	1.25	-0.05	-0.56
Farm Size	in hectare	4.5	3.5	1	1.65*
Number of ISM					
Training	in number	1.85	1.06	0.79	3.01***
	No knowledge=1, Fair				
	knowledge=2, Good				
Knowledge	knowledge=3 and Very good				
Level	Knowledge=4	1.96	0.69	1.27	11.97***
Knowledge	<del>-</del>				
Score	0-5 score	3.61	0.69	2.92	17.26***

## ISM Knowledge Level of Trained and Untrained Farmers

Cross tabulation of knowledge score of farmers by training they had received from ISMA is presented in Table 2. . The model was reliable as proved by the Likelihood Ratio 42.023 (df= 5, P≤0.001). Pearson chi square value of 49.804 (df= 5, P<0.001) depicts dependence of having ISM knowledge over receiving **ISMA** knowledge. The result reveals that there was a significant difference between trained and untrained farmers in a category of those scored zero in the ISM knowledge test, untrained farmers differs significantly with the trained farmers.

Also, in a category of those that scored 1 in the ISM knowledge test, untrained farmers were significantly different from the trained ones. This shows that untrained ones were more in numbers than the trained ones in the category of those that scored 1.

In a category of those that scored 2 in the ISM knowledge test, trained farmers significantly differed from the untrained ones, trained ones out-numbered the untrained ones. Furthermore, in a category of hose that scored 3, trained farmers likewise out-numbered the untrained ones significantly. This shows that trained

farmers were had relatively better knowledge than the untrained ones.

In category of those that score 4, similarly the trained farmers outnumbered the untrained ones significantly. This implies that untrained farmers had relatively poor knowledge of ISM technology in the study area.

In a category of those that scored 5, furthermore the trained farmers outnumbered the untrained ones significantly. This shows that untrained farmers had relatively low knowledge of ISM technology in the study area. This shows that all in all, provision of training improves trained farmers knowledge and there was farmer-farmer extension but in a slower condition as the negatively skewed knowledge was observed from the untrained farmers. This depicts that ISMA had a staying power. This is in line with Carrión Yaguana, Alwang, Norton & Barrera (2016) who found that farmer-tofarmer extension of Integrated Pest Management (IPM) exist within potato farmers in Carchi, Ecuador. Similarly, Jørs, Konradsen, Huici, Morant, Volk & Lander (2016) found out that farmer-tofarmer extension exists between trained and untrained farmers but trained IPM farmers performed better that the untrained farmers in Bolivia.

Table 2: Distribution of farmers based on ISM knowledge n=192

Variable			TRAIN	Tota 1	
Knowledge score			Untrained by ISMA	Trained by ISMA	1
	0	Observed	9 <sup>a</sup>	6 <sup>b</sup>	15
		Expected	2	13	15
		Count			
	1	Count	9 <sup>a</sup>	18 <sup>b</sup>	27
		Expected	3.5	23.5	27
	2	Count	03	2.43	26
	2	Observed	$2^{\mathrm{a}}$	24ª	26
		Expected Count	3.4	22.6	26
	3	Observed	$0^{a}$	26 <sup>b</sup>	26
	3	Expected			
		Count	3.4	22.6	26
	4	Observed	$2^{\mathrm{a}}$	64 <sup>b</sup>	66
		Expected	8.6	57.4	66
		Count	8.0	37.4	00
	5	Observed	$3^{a}$	$29^{a}$	32
		Expected	4.2	27.8	32
		Count		27.0	
Total		Observed	25	167	192
		Expected	25	167	192
		Count	23	107	1).
Pearson Chi-Square					
(5)	49.804				
Likelihood Ratio (5)	42.023	3***			
	0.39				
Eta	5				

Note: Each subscript letter denotes a subset of TRAINING categories whose column proportions do not differ significantly from each other at the 0.05 level.

# Factors that Predisposed Training Participants to ISM

Table 3 represents the p-score matching estimation of participation in ISM technology training. The result shows that LR  $\text{Chi}^2$  was 20.19 (P $\leq$ 0.05), this implies that the explanatory variables included in the model jointly explained the participating in the training as proved by the Log likelihood of -74.93. Only formal education and number of training were found to be positively significant (P $\leq$ 0.1 and P $\leq$ 0.05 respectively).

Formal education was found to be positively significant (P≤ 0.1). This implies that as farmer had formal education, the likelihood of participating in the training of ISM technology increases by 6% if other variables were held constant. This is probably due to the fact that, educated farmers had exposure to analyse the benefits of a technology to spare their time to learn it. This connotes the findings of Zossou, Arouna, Diagne & Agboh-Noameshie (2020) who found that formal of education was affecting

knowledge acquisition among rice farmers in West Africa; and Mustafa, Latif, Bashir, Shamsudin & Daud (2019) who found education as the driver of awareness of climate change in Pakistan.

Number of training was found to be positively significant ( $P \le 0.05$ ), this depicts that if training increases by one, the likelihood of farmer to participating in the subsequent training will increases by 0.23 if other variables were held constant. This

is probably due to the fact that repetitions make learning permanent. That was why farmers chose a technology that teaches them to have indepth understanding of the content of the technology. This is in line with the findings of Zossou, Arouna, Diagne & Agboh-Noameshie (2020) who found that number of training was affecting knowledge acquisition of rice farmers in West Africa.

Table 3: P-score Matching Estimation n=192

		Std.			[95%	
Variable	Coef.	Err.	Z	P> z	Conf.	Interval]
Age	0.01	0.02	0.64	0.52	-0.02	0.05
Sex	0.28	0.43	0.66	0.51	-0.55	1.12
Household Size	0.02	0.02	0.80	0.43	-0.03	0.07
Farming Experience	0.01	0.01	0.98	0.33	-0.01	0.03
Formal Education	0.60	0.33	1.8*	0.07	-0.05	1.25
Years of Formal						
Education	-0.01	0.03	-0.23	0.82	-0.06	0.05
Farm Size	0.00	0.04	0.11	0.91	-0.08	0.09
Group Membership	-0.26	0.29	-0.92	0.36	-0.82	0.30
Number of Training	0.23	0.09	2.52**	0.01	0.05	0.41
Constant	-0.89	0.97	-0.92	0.36	-2.78	1.00
Log likelihood	-74.93					
LR Chi <sup>2</sup>	20.19**					
Pseudo R <sup>2</sup>	0.12					

# Impact of ISM's Training on Farmers' Knowledge

Table 4 reveals that using different matching algorithm, the results were consistent and robust to alternative matching method. The same sign, significant level and comparable ATT. The nearest neighbor, radius and stratification matching method show that the knowledge score of untrained farmers would have been 2.74-2.86 out of 5 (about 60%) respectively if they had participated in ISM training. This might be due to the fact that those that were formally trained received a firsthand knowledge. This concurs with the

findings of Tambo et. al. (2019) who found that training campaign significantly had impact on knowledge of fall army worms of farmers that translates about 20% knowledge improvement among fall army campaign participants. it is also in tandem with Gautam. Schreinemachers, Uddin & Srinivasan (2017) who found that trained farmers had better knowledge about insect pests and the proper use of pesticides in Bangladesh as well as Niu & Ragasa (2018) who averred that more intensive modes of extension delivery during teaching sessions improve learning results in the lab-to-farm knowledge chain in Malawian agricultural extension programs. Singh, Peshin & Saini (2010) found extension training provision to have resulted in continued-adoption of beekeeping and mushroom cultivation

enterprises by 20 % and 51 % trained farmers, respectively in Krishi Vigyan Kendras (Farm Science Centres) in Indian Punjab.

Table 4: Impact of ISM's Training on Farmers' Knowledge

n = 162

Matching Algorithm	Number of Treatment	Number of Control	ATT	Std. Err.	Т
Nearest Neighbour	129	27	2.86	0.149	19.23***
Radius	129	33	2.74	0.128	21.47***
Stratification	129	33	2.80	0.116	24.20***

# Impact of ISM Training on Untrained Farmers' Knowledge

The result in Table 5 revealed that farmers that attended ISM training were having better knowledge of ISM technology than the untrained farmers by ISM with about 3 out of 5 scores. This showed that our PSM result was devoid of selection bias as it is consistent both in sign, significant level and amount.

 Table 5:
 IPW Regression Adjustment

n = 192

Knowledge	Coef.	Robust S.E	Z
ATE			_
Training			
(1  vs  0)	2.91	0.18	17.41***
Pomean			
Training			
0	0.66	0.14	4.63***

#### **Conclusion and Recommendation**

All in all, the study showed that ISM training campaigns hold great potential to improve farmers' knowledge (by 3 scores on a scale of 5) on how to identify, monitor and manage the striga pest, which, in turn, can facilitate the adoption and appropriate use of complementary integrated management practices. The results also imply that ISM had a staying power in Nigeria.

It is therefore recommended that training should be intensified in order to have more

spread of knowledge of ISM to farmers by the promoters of the project.

#### References

Akhvlediani, T., & Cieślik, A. (2019).

Human capital, technological progress and technology diffusion across Europe: education matters. *Empirica*, 1-19.10.1007/s10663-019-09468-z

Baiyegunhi, L. J. S., Hassan, M. B., Danso-Abbeam, G., & Ortmann, G. F. (2019). Diffusion and adoption of Integrated Striga

- Management (ISM) technologies among smallholder maize farmers in rural northern Nigeria. *Technology in Society*, 56, 109-115. https://doi.org/10.1016/j.techsoc.2 018.09.009
- Carrión Yaguana, V., Alwang, J., Norton, G., & Barrera, V. (2016). Does IPM have staying power? Revisiting a potato- producing area years after formal training ended. *Journal of agricultural economics*, 67(2), 308-323. 10.1111/1477-9552.12140
- Cathal, O'. D and Kevin, H. (2016). The impact of formal agricultural education on farm level innovation and management practices. 10.1007/s10961-016-9529-9
- FAO (2017). Urgent need to step up efforts to fight fast-spreading pests and diseases. http://www.fao.org/news/story/en/item/1070276/icode/
- FAO (2011). How to control striga and stemborer in maize. http://www.fao.org/3/CA2539EN/ca2539en.pdf
- Gautam, S., Schreinemachers, P., Uddin, M. N., & Srinivasan, R. (2017). Impact of training vegetable farmers in Bangladesh in integrated pest management (IPM). Crop Protection, 102, 161-169.

10.1016/j.cropro.2017.08.022

Hassan, M. B., Ortmann, G. F., & Baiyegunhi, L. J. S. (2018). Impact of integrated striga management (ISM) technology on maize productivity in Northern Nigeria: A treatment effect approach. African Journal of

- Science, Technology, Innovation and Development, 10(3), 335-344.
- IITA (2014). Research for Development Project Chalks: Significant Progress. Available at: https://www.iita.org/news-item/research-development-project-chalks-significant-progress-save-maize-striga-weed/
- IITA (2012). Saving Africas maize and cowpea from the violet vampire. https://www.iita.org/news-item/saving-africas-maize-cowpea-violet-vampire/
- Jørs, E., Konradsen, F., Huici, O., Morant, R. C., Volk, J., & Lander, F. (2016). Impact of training Bolivian farmers on integrated pest management and diffusion of knowledge to neighboring farmers. *Journal of Agromedicine*, 21(2), 200-208. 10.1080/1059924X.2016.114342
- Mignouna, B. D., T. Abdoulaye, A. Kamara, and M. Oluoch (2013). Baseline Study of Smallholder Farmers in Striga Infested Maize and Cowpea-Growing Areas of Northern Nigeria. Ibadan, Nigeria: International Institute of Tropical Agriculture, 60 pp.
- Mustafa, G., Latif, I. A., Bashir, M. K., Shamsudin, M. N., & Daud, W. M. N. W. (2019). Determinants of farmers' awareness of climate change. Applied Environmental Education & Communication, 18(3), 219-233. 10.1080/1533015X.2018.145435
- Niu, C., & Ragasa, C. (2018). Selective attention and information loss in the lab-to-farm knowledge chain:

  The case of Malawian agricultural

- extension programs. *Agricultural* systems, 165, 147-163.
- Perez-Trujillo, M., & Lacalle-Calderon, M. (2020). The impact of knowledge diffusion on economic growth across countries. *World Development*, 132, 104995. 10.1016/j.worlddev.2020.104995
- Shikuku, K. M. (2019). Information links. knowledge exchange adoption exposure, and agricultural technologies in northern Uganda. World Development, 115, 94-106. 10.1016/j.worlddev.2018.11.012
- Singh, K., Peshin, R., & Saini, S. K. (2010). Evaluation of the agricultural vocational training programmes conducted by the
- Zossou, E., Arouna, A., Diagne, A., & Agboh-Noameshie, R. A. (2020). Learning agriculture in rural areas: the drivers of knowledge acquisition and farming practices by rice farmers in West Africa. *The Journal of Agricultural Education and Extension*, 26(3), 291-306.10.1080/1389224X.2019.170 2066

- Krishi Vigyan Kendras (Farm Science Centres) in Indian Punjab. *Journal of Agriculture and Rural Development in the Tropics and Subtropics (JARTS)*, 111(2), 65-77. http://nbn-resolving.de/urn:nbn:de:hebis:34-
- resolving.de/urn:nbn:de:hebis:34-2010091334536
- Tambo, J.A., Aliamo, C., Davis, T., Mugambi, I., Romney D, Onyango DO, et al. (2019) The impact of ICT-enabled extension campaign on farmers' knowledge and management of fall armyworm in Uganda. PLoS ONE 14(8): e0220844. 10.1371/journal.pone.0220844