4thICAAAE 2013 SEPTEMBER 22-25, Hammamet Tunisia
4th International Conference of the African Association of Agricultural Economists
icaaae.org
aaae-africa.org

Enhancing Smallholder Farmers Income and Food Security through Agricultural Research and Development in West Africa: Impact of the IAR4D in the KKM PLS

By:

Adeolu B. Ayanwale
Luke O. Olarinde
Olufemi A. Oladunni
Kaku S. Nokoe
Adewale A. Adekunle
Oluwole Fatunbi

Invited paper presented at the 4th International Conference of the African Association of Agricultural Economists, September 22-25, 2013, Hammamet, Tunisia

Enhancing Smallholder Farmers Income and Food Security through Agricultural Research and Development in West Africa: Impact of the IAR4D[1] in the KKM PLS.

Ayanwale, Adeolu B.[1*]; Luke O. Olarinde[2]; Olufemi A. Oladunni[3]; Kaku S. Nokoe[4]; Adewale A. Adekunle[5] and Oluwole Fatunbi[5]

[1*] Obafemi Awolowo University, Ile-Ife, Nigeria. Corresponding Author – e mail: aayanwa@yahoo.co.uk.

[2] Ladoke Akintola University, Ogbomoso, Nigeria

[3] Agricultural and Rural Management Institute, Ilorin, Nigeria

[4] Wisconsin University, Ghana

[5] Forum for Agricultural Research in Africa, Accra, Ghana

[1] IAR4D is the acronym for Integrated Research for Development. The concept is explained in the text

Abstract

The Integrated Agricultural Research for Development (IAR4D) is the approach suggested by the Forum for Agricultural Research in Africa (FARA) through the sub Saharan Africa Challenge Programme (SSA CP) to address the acknowledged shortcoming of African Agricultural Research and Development's (ARD) failure to achieve impact on the farmer's field. The IAR4D concept is being implemented in three Pilot Learning Sites (PLS) in eight countries across the continent. This paper focused on t*he Kano, Katsina and Maradi (KKM)* PLS of the West Africa aspect of the programme, and made use of a panel data collected from 1800 households at both the baseline and midline surveys organized using the quasi experimental approach with two sets of counterfactuals, viz: the conventional (traditional ARD), and the clean sites where it was assumed there was no ARD at least two years prior to the commencement of the IAR4D. Using propensity score (PSM) and double-difference methods (DDM) to control for project placement and self selection biases, results show that IAR4D increased participants' income by about 139%, and improved food security by about 229%. The PSM results indicated that participants in the IAR4D will likely be farmers with small household size, and considerable farming experience, with some level of productive assets, who reside near all weather roads, have low level of education and are more likely to reside in the Northern Guinea Savanna agro-ecological zone but less likely from the Sudan Savanna agro-ecological zone. It can be safely concluded from the results that the IAR4D enhances the income and food security status of the participants.

Key words: IAR4D, Propensity Score Method, ARD, Double Difference, SSA CP

1.0 Introduction

The sustainable livelihoods of many African people depend directly on their ability to produce and market agricultural products. Consequently, agricultural growth in sub-Saharan Africa remains fundamental for poverty reduction and food security. However, it has been realized that without urgent revitalization of the sector, the Millennium Development Goals (MDGs) to halve poverty and hunger as well as ensure environmental sustainability by 2015 will be difficult to meet. As a result of this, substantial investments have been made in agricultural research and innovation. However, it has been observed overtime that some of the investments had either failed to make impact or gone beyond the immediate localities of the research environment.

Consequently, extensive consultations amongst stakeholders between 2002 and 2004 led to the formulation of the Sub Saharan Africa Challenge Programme (SSA CP) which had postulated that the principal shortcoming of African agricultural research and development (ARD) has been its failure to achieve impact beyond the localities in which it is conducted and the accumulation of so-called 'improved technologies' on research shelves rather than in farmers' fields. It therefore concluded that for agricultural research to play a more effective role in catalysing development, it should embrace a broader system of agricultural innovation that will facilitate interaction and enhance flow of knowledge among all key actors in agricultural systems and value chains. FARA has branded this systemic and innovation-focused approach to agricultural research as the *Integrated Agricultural Research for Development* (IAR4D).

IAR4D seeks to transform the organisational architecture of R&D actors from a linear configuration (research→ dissemination→ adoption) to a network configuration comprising all actors in agricultural value chains (innovation system). The network configuration facilitates timely interaction and learning and aims at generating innovations (rather than research products per se). The innovation in this concept refers to the activities and processes associated with the generation, product distribution, adaptation and use of new technical and institutional/ organizational knowledge. It adds value to products of research to catalyse the achievement of development impact.

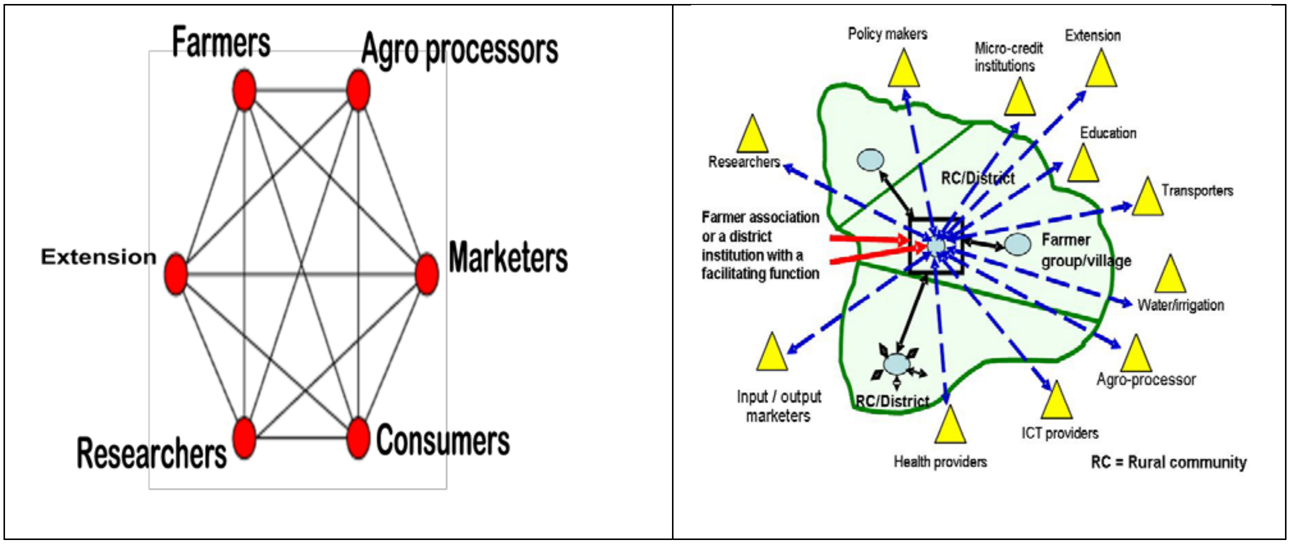

Figure 1: Innovation approaches showing interacting role of various players

2.0 Objectives of the SSA CP

The objectives of SSA CP are to facilitate substantially greater impact from agricultural research for development leading to improved rural livelihoods, increased food security and sustainable natural resource management throughout SSA. The SSA CP was experimented in three Pilot Learning Sites (PLS) across the continent. By applying IAR4D, SSA CP aimed to reverse the underperformance of agricultural research in Africa by developing, testing (proving whether it works) and scaling out/up an approach for conducting agricultural research for development in Africa, which overcomes the shortcomings of conventional approaches. Each PLS defined the domain within which the project's research sites were selected. This paper focuses on t*he Kano, Katsina and Maradi (KKM)* PLS.

Specifically the objective of the paper was to estimate the contribution of the IAR4D to participant's income and food security relative to those of non participants in the counterfactual sites.

3.0 Methodology

3.1 Study Area

The SSA CP is being implemented in three Pilot Learning Sites (PLS) across the continent of Africa. Each PLS has its own unique peculiarities. *The Kano, Katsina and Maradi (KKM)* PLS covers an area of 83,900 sq km area that straddles Nigeria and Niger and covers most of the area under KKM administrative jurisdiction. It is inhabited by approximately 18.3 million people.

The process of IP establishment in KKM was initiated at the first KKM PLS meeting held in Kano in March 2005 (CORAF, 2005a) at which a Pilot Learning Team (PLT) was formed to address priority problems identified with KKM communities. The PLT comprised people from a variety of scientific disciplines (biophysical and social) and from diverse institutions (e.g. national agricultural research institutes, universities, CGIAR Centres and advanced research institutes; extension agencies; NGOs, community-based and farmers' organizations; and the private sector). The PLT led by IITA appointed a team to conduct a validation study for constraints and possible entry points in all three agro-ecological zones of KKM (CORAF, 2005b). This team was drawn from a number of institutions including those involved in research, extension, NGO and the private sector to assess the situation at four levels, community, area, state, and region, with over 90% of the time being spent at local community level. This involved the use of participatory methods and worked in 20 villages selected as being representative of the PLS (Figure2).

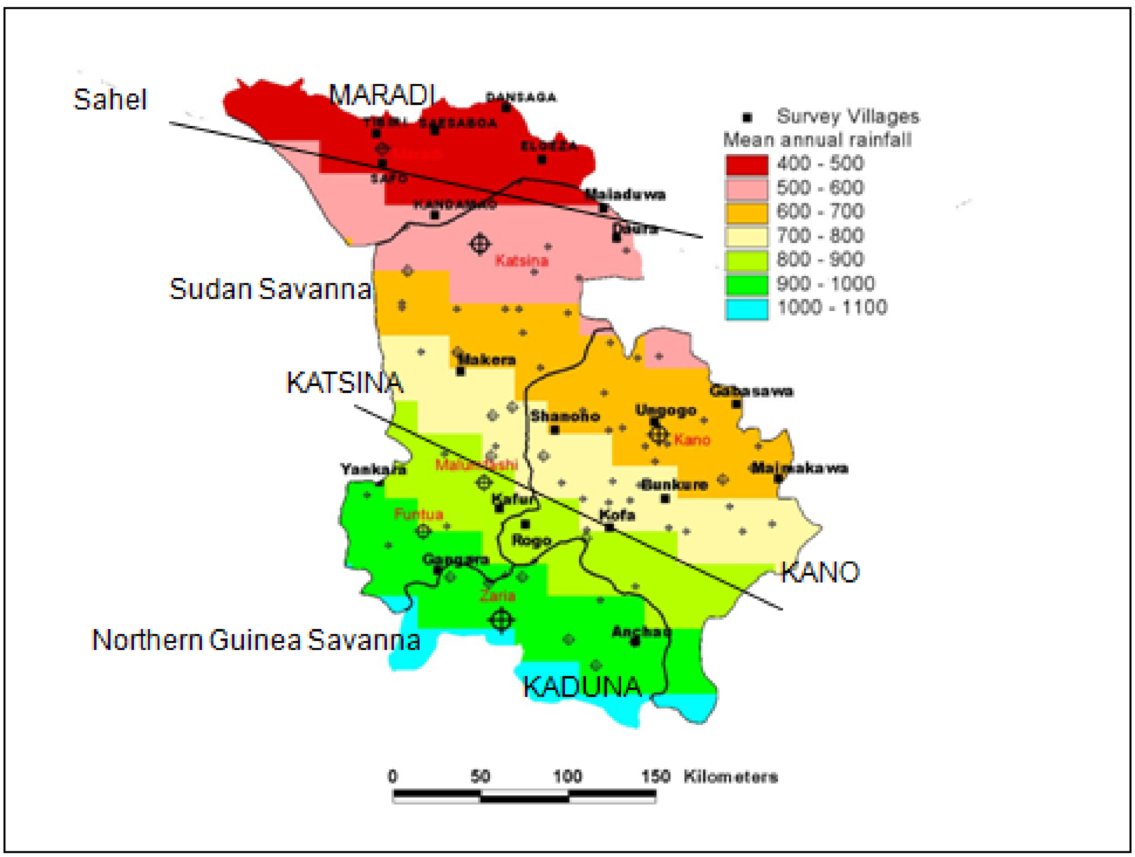

Figure 2: Map of the Kano-Katsina-Maradi PLS (CORAF-IITA, 2005)

This is the aspect (PLS) of the SSA CP being implemented in the Western African sub-region. The project is sited on the Kano-Katsina-Maradi axis of Nigeria and Niger Republic. The project is made up of three Task Forces namely: (i) the Northern Guinea Savanna, which has as theme “multi-stakeholder approach to linking technical options, policy, and market access for improved land productivity in the Northern Guinea Savanna zone”, (ii) the Sudan Savanna Task Force, with theme as “sustainable agricultural intensification and integrated natural resource management in the Sudan Savanna of West Africa and (iii) the Sahel Savanna Task Force having the theme “improving rural livelihoods of rural population through intensification, access to markets, and sustainable management of natural resources in the Sahel agro-ecological zone. For the three Task Forces, the validated research entry points were (i) identification and promotion of appropriate integrated pest management (IPM) and indigenous knowledge systems (IKS) technologies for both crop production and storage (ii) promotion of appropriate labour saving devices e.g. traction and processing equipment (iii) integrated soil fertility management (iv) integrated crops-livestock production (v) promotion of appropriate varieties e.g. early maturing, drought tolerant, pest resistance and (vi) development of irrigation potential using appropriate technologies (FARA, 2006). The objectives of the TFs’ projects were developed and embedded in a framework that was meant to adequately capture the concept of the IAR4D. As has been discussed in the introduction, the implementation of the IAR4D was structured within a system of Innovation Platform and that had informed the selection of project sites based on the peculiarities of the composition of the farming systems of each of the TF.

Table 1: Task forces and innovation platforms in the KKM PLS

	NORTHERN GUINEA SAVANNAH TASK FORCE			
IP	Maize-legume	Rice	Vegetable	Livestock
LGA (district)	Ikara	Dandume	Kudan	Kubau
State	Kaduna	Katsina	Kaduna	Kaduna
Country	**Nigeria**	**Nigeria**	**Nigeria**	**Nigeria**
	SUDAN SAVANNAH TASK FORCE			
IP	Maize-legume-livestock	Sorghum-legume-livestock	Maize-legume-livestock	Sorghum-legume-livestock
LGA (district)	Bunkure	Shanono	Musawa	Safana
State	Kano	Kano	Katsina	Katsina
Country	**Nigeria**	**Nigeria**	**Nigeria**	**Nigeria**
	SAHEL SAVANNAH TASK FORCE			
IP	Groundnut	Cereal-legume	Vegetable	Livestock
LGA (district)	Madarounfa	Guidea Roumdji	Aguie	Zango Daura
State	Maradi	Maradi	Maradi	Katsina
Country	**Niger**	**Niger**	**Niger**	**Nigeria**

3.2 Sample Selection

The data used in this study were taken from a baseline and midline surveys of over 1,800 households across KKM PLS. The survey was conducted by taskforces within the framework of the Sub-Saharan African Challenge Programme supported by the Forum for Agricultural Research in Africa (FARA) and its donors—including the European Union (EU), UK Department for International Development (DFID), and the governments of Italy and Norway.

The sample frame was derived from different districts, selected to represent the three basic areas of taskforces in the KKM PLS. In each district, a sample of households was selected by taking a sample of district wards; a random sample of villages within each ward; and a random sample of households in each selected village. Finally, a household was retained in the sample if it belonged to one of the 180 villages selected within the clean, conventional or IP/action sites. Altogether, 10 households were randomly selected in each village giving a total of 1800 households interviewed in the PLS.

3.3 Baseline surveys for IP and community level characteristics

Baseline surveys, field observations and focus group discussions were conducted to benchmark pre-treatment characteristics of IPs, site characteristics and baseline levels of outcomes predicted under the IAR4D approach: number, variety and time to develop innovations; knowledge and behavioural outcomes (adoption, input supply, input demand, volume of sales), market outcomes (output supply and consumption demand), and productivity outcomes (yields, technical and allocative efficiency, and profit); and impacts (incomes, livelihood assets and equity). Several indicators were used to measure outcomes, which were different with context. The questionnaires were designed for comparison within an IP over time and across IPs. To generate counterfactuals, surveys and field observations were conducted in the comparison sites and villages assigned to conventional and non-IAR4D-non-conventional treatments. Key players in the innovation systems—such as public and private agricultural researchers, extension, farmer leaders, traders, dealers, lenders and key informants—were interviewed to benchmark characteristics of innovation systems and baseline levels of outcomes as for the IP sites.

3.4 Baseline survey for household and village community characteristics

Baseline surveys, observations and focus group discussions were conducted to collect data on household- and village-community-level characteristics, and behavioural, efficiency, environmental and welfare outcomes. Surveys were used to track feedback, information diffusion, awareness and knowledge changes, adoption, and market effects of innovations and spillovers using the Miguel and Kremer (2004) approach and other methodologies.

3.5 Evaluation surveys

Follow-up evaluation surveys and qualitative assessment studies were conducted in the third year (2010) to assess the implementation process; document all the intermediate steps of the research-to-impact pathway and conditioning factors; assess participants' subjective reactions to IAR4D; identify subgroups experiencing greater or lesser impact than the sample as a whole; and measure changes in outcomes at the levels of the IP, household, community and market. Follow-up surveys used the indicators used in the baseline surveys to measure outcomes.

4.0 Data Analysis

Assessing the impact of any intervention requires making an inference about the outcome that would have been observed had the program participants not participated. Following Heckman et al. (1997) and Smith and Todd (2001), let Y_1 be the mean of the outcome conditional on participation, that is, treatment group, and let Y_0 be the outcome conditional on non-participation, that is control group. The impact of participation in the program is the change in the mean outcome caused by participating in the program, which is given by:

$$\Delta Y = Y_1 - Y_0, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

, where Δ is the notation for the impact for a given household (1)

The fundamental problem of evaluating this individual treatment effect arises because, for each household, only one of the potential outcomes either Y_1 or Y_0 and not both can be observed. This leads to a missing-data problem, which is the heart of the evaluation problem (Smith and Todd 2005). The unobservable component in equation (1), be it Y_1 or Y_0, is called the counterfactual outcome. Measuring impact as the difference in mean outcome between all households involved in the project and those not involved, even when controlling for program characteristics, may thus give a biased estimate of program impact. Since there will never be an opportunity to estimate individual treatment effects in (1) directly, one may need to concentrate on population averages for the impacts of a treatment.

Two treatment effects are dominantly used in empirical studies. However, the most commonly used evaluation parameter is the so-called average impact of the treatment on the treated (ATT), which focuses explicitly on the effect on those for whom the programme is actually introduced. In a random program assignment, the expected value of ATT is defined as the difference between expected outcome values with and without treatment for those who actually participated in treatment (Heckman et al. 1998b), which is given by:

$$\Delta Y_{ATT} = ATT\ (\Delta Y|\ X: Z = 1) = E(Y_1 - Y_0|, Z = 1) = E\ (Y_1|\ Z = 1) - E(\ Y_0|\ Z = 1)\ \ ..(2)$$

where, Z is an indicator variable indicating whether a household actually received treatment or not: Z_i being equal to 1 if the household is a beneficiary, and 0 otherwise. X denotes a vector of control variables.

Data on program beneficiaries identify the mean outcome in the treated state E $(Y_1|X, Z=1)$. The mean outcome in the untreated E (Y0|X, Z=1) is not observed and a proper substitute for it has to be chosen in order to estimate ATT.

Various quasi-experimental and nonexperimental methods have been used to address the bias problem Heckman, Ichimura, Smith and Todd (1998). One of the most commonly used quasi-experimental methods is propensity score matching (PSM), which selects project beneficiaries and non beneficiaries who are similar as possible in terms of observable characteristics expected to affect project participation as well as outcomes. The difference in outcomes between the two matched groups can be interpreted as the impact of the project on the beneficiaries Smith and Todd (2001). We used this method to estimate the ATT for impacts of the IAR4D on the key outcomes of the project which in this case are - factor productivity proxied by improved household income and food security.

The PSM method matches project beneficiaries with comparable non-beneficiaries using a propensity score, which is the estimated probability of being included in the project. Only beneficiaries and non-beneficiaries with comparable propensity scores are used to estimate the ATT. Those who do not have comparable propensity scores are dropped from the comparison groups.

Among the advantages of PSM over econometric regression methods is that it compares only comparable observation and does not rely on parametric assumption to identify the impacts of projects. However, PSM is subject to the problem of "selection on unobservables", meaning that the beneficiary and comparison groups may differ in unobservable characteristics, even though they are matched in terms of observable characteristics (Heckman, Ichimura, Smith and Todd 1998). Econometric regression methods devised to address this problem suffer from the problems previously noted. The bias resulting from comparing noncomparable observations can be much larger than the bias resulting from selection on unobservables, although they could not say whether that conclusion holds in general (Heckman, Ichimura, Smith and Todd 1998).

In this paper, we address the problem of selection on unobservables by combining PSM with the use of the double-difference (DD) estimator. The DD estimator compares changes in outcome measures (i.e. change from before to after the project) between project participants and nonparticipants, rather than simply comparing outcome levels at one point in time.

$$DD = (Y_{p1} - Y_{p0}) - (Y_{np1} - Y_{np0}) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(3)$$

where Y_{p1} = outcome (e.g. income) of beneficiaries after the project started; Y_{p0} = outcome of beneficiaries before the project started; Y_{np1} = outcome of nonbeneficiaries after the project started; and Y_{np0} = outcome of nonbeneficiaries before the project started.

The advantage of the double-difference estimator is that it nets out the effects of any additive factors (whether observable or unobservable) that have fixed (time-invariant) impacts on the outcome indicator (such as the abilities of the farmers or the inherent quality of natural resources), or that reflect common trends affecting project participants and nonparticipants equally (such as changes in prices or weather; Ravallion, 2005).

Thus, for example, if project participants and nonparticipants are different in their asset endowments (mostly observable) or in their abilities (mostly unobservable), and if those differences have an additive and fixed effect on outcomes during the period studied, such differences will have no confounding effect on the estimated ATT.

In principle, the DD approach can be used to assess project impacts without using PSM and will produce unbiased estimates of impacts as long as these assumptions hold. However, if the project has differential impacts on people with different levels of wealth or observable characteristics, the simple DD estimator may produce biased estimates if participants and nonparticipant households differ in those characteristics (Ravallion, 2005). By combining PSM with the DD estimator, controls for differences in pre-project observable characteristics can be established. A bias could still result from the heterogeneous or time-variant impacts of the unobservable differences between participants and nonparticipants. For example, communities and households that had participated in ARD may have different responses to IAR4D than those in clean environment because of the cumulative effects of social capital developed under the ARD, favorable or adverse experiences under ARD, or other factors. Such shortcomings are unfortunately inherent in all nonexperimental methods of impact assessment (Duflo *et.al.*, 2006). Although no solution to these potential problems is perfect, we believe the method we have used addressed these issues as well as possible in this case.

The standard errors estimated by the double-difference method may be inconsistent because of serial correlation or other causes of a lack of independence among the errors. In ordinary regression models, serial correlation can result from unobserved fixed effects, but by taking first differences, the double-difference method eliminates that source of serial correlation. However, serial correlation still may be a problem if more than two years of panel data are used (Duflo *et al*., 2004). In this study because we used only two periods, before and after the project, we do not have concern about serial correlation among multiple periods. Another reason for the possible non independence of the errors is clustering of the sample.

The propensity scores were computed using binary logit regression models. We estimated three probit models for three comparisons: (1) IAR4D beneficiaries compared will all nonbeneficiaries; (2) IAR4D beneficiaries with conventional beneficiaries, and (3) IAR4D beneficiaries with nonbeneficiaries in clean communities. The dependent variable in each model is a binary variable indicating whether the household was a beneficiary of the IAR4D project or not.

The explanatory variables used in computing the propensity scores were those expected to jointly determine the probability to participate in the project and the outcome. We focused on the determinants of income and productive assets when selecting the independent variables for computing the propensity score matching.

The independent variables used in the regression are summarized in table 2.

Table 2: Variables Used to compute Propensity Scores and their Expected Signs

Variable	Expected Impact on Participation in IAR4D	Why?	Expected sign on Income and Wealth	Why?
Gender of Respondent (Male=1; Female=0)	-	IAR4D is gender friendly	-	Women are usually poorer than men
Household Size	+	Larger families could be associated with poverty or other vulnerabilities that makes participation in IAR4D worthwhile	-	The larger the family, the poorer
Age of respondent	+/-	IAR4D support both the young and old	+	Older respondents likely to be better off because of accumulation of wealth and experience over the life cycle
Level of Education of respondent(years of formal education)	+	Some project requirements need certain level of education	+	Education increases income opportunities, such as on-farm activities
Area of farmland cultivated (ha)	+/-	IAR4D concept encourages more area of land to be cultivated.	+	More area of land enables households to earn more income and more productive assets
Agro-ecological Zone (taskforces)	+/-	The technologies promoted by IAR4D in each agro-ecology motivate participation	-	Some zones closer to urban centers have more potential of membership than remote ones
Distance to nearest all	+	Closeness to urban center	+	Access to improved road

weather road		encourages participation since products are easily marketed		increases income opportunities and reduces transaction costs
Value of productive asset	+	Same as for land area	+	Same as for land area

Source: Data Analysis 2012

5.0 Results and Discussions

The importance of estimation of propensity scores is twofold: first, to estimate the ATT and, second, to obtain matched treated and non-treated observations. The results of the probit models for the propensity score estimations are reported in Table 3. The results indicate that participants in the IAR4D will likely be farmers with small household sizes, and considerable farming experience, with some level of productive assets, who reside near all weather roads, have low level of education and are more likely to reside in the Northern Guinea Savanna agro-ecological zones but less likely from Sudan Savanna agro-ecological zone. Results further indicate that farmers in the conventional sites are likely to be female with considerable farming experience and productive assets who are mostly from the Sudan savanna agro-ecological zone. However, it is only nearness to all weather roads that was the most important determinant for farmers in the clean sites. These results suggest that the IAR4D was targeted at vulnerable groups with low level of education, smaller household sizes, smaller level of assets and people in remote locations.

These probit model results were used to compute the propensity scores that were used in the PSM estimation of ATT. Several methods are possible for selecting matching observations (Smith and Todd, 2001). We used the kernel matching method (using the normal density kernel), which uses a weighted average of “neighbors” (within a given range in terms of the propensity score) of a particular observation to compute matching observations. Unlike the nearest-neighbor method, using a weighted average improves the efficiency of the estimator (Smith and Todd, 2001). Observations outside the common range of propensity for both groups (i.e. lacking “common support”) were dropped from the analysis. This requirement of common support eliminated about half of the total number of observations, indicating that many of the observations from various strata were not comparable.

Table 3: Probit Regression of IAR4D Participation (Matched Observations)

Explanatory variables	Treated (IAR4D)		Control (Conventional)		Control (Clean)	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Gender (1=male; 0=female)	0.819	0.215	-0.307	0.209*	0.243	0.211
Age of respondent (yrs)	-0.320	0.279	0.383	0.300	-0.073	0.263
Education of respondent (yrs)	-0.209	0.094**	0.134	0.126	0.140	0.087*
Household size	-0.213	0.130*	0.142	0.132	0.074	0.127
Farming experience (yrs)	-0.042	0.136	-0.191	0.135*	0.089	0.122
Assets (productive)	-0.133	0.048***	-0.122	0.048**	0.001	0.045
Roads	-0.234	0.131**	0.134	0.126	0.140	0.087*
Task force dummy (NGS)	0.355	0.180**	-0.149	0.180	-0.120	0.172
Task force dummy (Sahel)						
Task force dummy (Sudan)	-0.586	0.258**	0.371	0.222**	0.023	0.214
Constant	2.606	1.024	-2.868	1.060	-0.914	0.957
Sample size (n)	378		378		378	
R^2	0.072		0.041		0.016	
Prob > χ^2	0.000		0.022		0.543	
Log likelihood	-209.777		-228.741		-248.640	

Source: Data Analysis (2012)

Further testing of the comparability of the selected groups was done using a “balancing test” (Dehejia and Wahba, 2002), which tested for statistical significant differences in the means of the explanatory variables used in the probit models between the matched groups of the IAR4D participants and non-participants. In all cases, that test showed statistically insignificant differences in observable characteristics between the matched groups (but not between the unmatched samples), supporting the contention that the PSM ensures the comparability of the comparison groups (at least in terms of observable characteristics).

We used bootstrapping to compute the standard errors of the estimated ATT, generating robust standard errors because the matching procedure matched control households to treatment households “with replacement” (Abadie and Imbens 2006)

5.1 Impact of IAR4D on household income

The results in Table 4 shows that the 2008 average household income for treated (clean-before intervention), conventional and the clean sites were $1312.71; $1966.52 and $1564.58 respectively. At midline, the average incomes were estimated to be $3096.68; $3791.30 and $5552.62 respectively. The average treatment effect on the treated (ATT) was computed based on two alternative matching methods. The outcome variable is household income per year measured in US Dollars. The z-statistics were based on bootstrapped standard errors with 50 replications which were used to verify whether the observed effect was significant or not.

The results show that the average household income of the treated (IAR4D farmers) sample due to participation in the IP activities based on the PSM (ATT) was $1821.75 in the case of Kernel (p<10%). A comparative analysis shows that the IP farmers are better (with higher household income) than the farmers in the two counterfactuals of conventional and clean sites.

Table 4: Impact of IAR4D on household Income across types of Respondents

	Net real household Income (US$)		**ATT**	**% change due to participation in IAR4D**
	Before IAR4D	**After participation in IAR4D**		
IAR4D (n=544) Conventional (n= 513) Clean (n=514)	1310.29 (2423.39) 1936.26 (2895.13) 1561.09 (2562.39)	3091.37 (4700.28) 3791.30 (5807.36) 5552.62 (34100.41)	1821.75* (1058.56) -3195.81 (11422.99) 1700.35 (1414.58)	139.03 NS
Agro-ecological zones **NGS** IAR4D (n=29) Conv (n=29) Clean (n=29) **Sahel** IAR4D (n=140) Conv (n=140) Clean (n=140) **Sudan** IAR4D (n=169) Conv (n=169) Clean (n=169)	2769.06 (3743.12) 3731.00 (4294.38) 2878.67 (3960.29) 542.71 (1234.74) 1243.19 (1662.10) 1105.42 (859.20) 783.09 (1392.84) 1079.15 (1614.97) 825.45 (1243.22)	3685.39 (4466.91) 5016.94 (6837.08) 11083.87 (64274.75) 3142.17 (6573.93) 3919.71 (6855.91) 3978.97 (6121.41) 2451.04 (2879.31) 2765.40(4087.03) 2781.55 (5346.59)	7433.19* (4544.82) -9305.05 (4757.13) - 1188.07 (1993.09) -1962.01 (1075.84) 819.68 (1542.35) 1821.75* (1263.70) -3286.79 (1619.64)	268.44 232.64

			1823.86 (1868.81)	
Food Security				
IAR4D (n=104)	1040.05 (2158.57)	3041.13 (5878.42)	2337.29** (1239.33)	225.69
Conv (n=107)	1693.30 (2337.18)	3149.39 (5340.33)	-2618.76 (686.97)	
Clean (n=102)	1432.33 (2327.02)	3039.64 (4348.15)	-207.02 (1487.56)	

Note: Numbers in brackets are standard deviations of the corresponding mean.

Source: Data Analysis 2012

ATT = $(Y_{p1}-Y_{p0})-(Y_{np1}-Y_{np0})$. "Before project" is the situation before the IAR4D in 2008, while "After project" is two years after the project started in 2010.

"ATT" and the corresponding "%" refers to the change in measured household income resulting from participation in the Innovation Platform (IP) of the IAR4D. % net change due to participation at the platform = $(ATT/Y_{p0})*100$.

- Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Using the PSM and double difference methods, our results allowed us, with considerable confidence, to attribute the income increases among the beneficiaries to participation in the project. The results in table 4 show the homogenous impact of the IAR4D on the participants' income. The result shows that participation in IAR4D had positive and significant impact on the beneficiaries at the 10 percent level. The quantum of the impact made the beneficiaries about 139 percent better than the baseline condition. However, the counterfactual situations (both conventional and clean) were not statistically significant suggesting that the difference in income between the baseline and midline among these set of respondents were not different from one another.

This result is better appreciated when compared with the achievement of similar projects in the continent. For instance, the World Bank sponsored Fadama II project in Nigeria, which won the Banks' Regional Excellent Award, had an income impact rate of about 60 percent, a feat achieved in six years of operation.

The effect of the IAR4D varied across the major agro-ecological zones of the PLS. the project had significant impact (at $p = 0.10$) at both the NGS and the Sudan Savanna zones, while the impact at the Sahel savanna zone although positive was not statistically significant. Participation in the project at the NGS and Sudan Savanna led to 268% and 233% increase in income respectively. The large net increase in income in the dry NGS and Sudan Savanna could be due to the intense capacity building of the participants at the IP levels which address major production and marketing constraints in the zones.

5.2 Impact of IAR4D on food security

Obviously, one of the major outcomes of the IAR4D is to address the perennial problem of food insecurity among the `rural people in the project area. The project was designed to boost food security among the participants. Results in the table shows that participation in the project boosts the food security among the beneficiaries. There is a positive and statistically significant ($p<0.01$) increase in food security among the beneficiaries even to a substantial tune of about 225% increase. This result shows that participants at the IPs are better able to cope with food security than non participants.

In summary, the IAR4D has caused beneficiaries to realize significant increases in income. However, the impact of IAR4D was different across agro-ecological zones. The impact of the IAR4D on income was not statistically significant in the Sahel savanna and in almost all the counterfactual sites. It should be noted that the full impact of the project cannot be said to have been captured by this study because the project had only operated for two years at most in the PLS, thus our results could not be said to have captured the lagged impacts of the rural infrastructures, productive assets, and other project interventions.

This result is much in line with the Ex Ante report on the KKM PLS (Ayanwale et.al. 2010) in which the projected benefits of IAR4D not only surpassed the costs of investments but that was also superior to both the conventional and clean modes. Furthermore, the expected benefits derivable vary by taskforces (agro-ecological zones) in the sense that the Sahel savanna zone gave the least quantum of benefits of the three. The project had bigger impact on the poorest beneficiaries and could have much greater impact in the future because of the lagged effect of the productive asset acquisition. This study was conducted at an early stage of the project and may not adequately capture its lagged impacts, especially the long term benefits of productive asset acquisition and rural infrastructure development.

Key issues that need to be addressed in scaling up this success story includes amongst others: better targeting of poor and vulnerable groups especially women, finding sustainable methods of promoting development of rural financial services and conscious inclusion of capacity building of IAR4D beneficiaries in efficient management of productive assets.

6.0 Summary and Conclusion

The objectives of the SSA CP are to facilitate substantially greater impact from agricultural research for development leading to improved rural livelihoods, increased food security and sustainable natural resource management throughout SSA. These objectives are being realized in three PLS one of which is the KKM in West Africa.

The anchor of the SSA CP through which these objectives are being realized is the IAR4D which is an extension module. Some of the expected outcomes of the IAR4D are significant improvement in participant's income and food security situation relative to non participants.

Having implemented the IAR4D in the KKM for two years, the objective of this paper was to estimate the contribution of the IAR4D to participant's income and food security relative to those of non participants in the counterfactual sites.

The data used in this report were taken from a baseline and midline surveys of over 1,800 households across KKM PLS. Using the PSM and double difference methods, our results allowed us, with considerable confidence, to attribute the income increases among the beneficiaries to participation in the project. Our results show that participation in IAR4D had positive and significant impact on the beneficiaries at the 10 percent level. The quantum of the impact made the beneficiaries about 139 percent better than the baseline condition.

Furthermore, there is positive and statistically significant ($p<0.01$) increase in food security among the beneficiaries even to a substantial tune of about 225% increase. This result shows that participants at the IPs are better able to cope with food security than non participants.

In conclusion, we can safely assert that the IAR4D has significantly enhanced the participant's income and food security achieving positive impact in the process. Therefore, the concept is a veritable tool to bring about the needed positive transformation of the SSAs agriculture and improve the livelihood of smallholder farming households who constitute the mainframe of the food and agricultural sector of the subregion.

References

Abadie, A. and G. Imbens,2002. Simple and bias-corrected matching estimators. Berkeley: University of California, Department of Economics

Abadie, A. and Imbens, 2006. On the failure of the bootstrap for matching estimators. NBER Working Paper No. T 0325. Cambridge, MA: National Bureau of Economic Research. Available at: http://papers.ssrn.com/sol3/papers/cfm?abstract_id=912426

Ayanwale, A.B., Adebayo A. Akinola and Victoria A. Adeyemo. 2011. Ex Ante Analysis of IAR4D Concept in the Sub Saharan Africa Challenge Programmme (SSA CP) of the Forum for Agricultural Research in Africa (FARA), Report submitted to FARA. November, 2011 177p

Ayanwale, A. B. , Adebayo A. Akinola and Victoria A. Adeyemo 2010. Non Pecuniary Benefits Of The Integrated Agricultural Research For Development In The Kano-Katsina-Maradi (KKM) Pilot Learning Site (PLS) Of The Sub-Saharan Africa-Challenge Program (SSA CP) Draft Report Presented to the Forum for Agricultural Research in Africa (FARA) as part of the Ex-Ante Study of the Sub Saharan African Challenge Programme. May, 2010. 79p

CORAF-IITA 2005a SSA CP KKM PLS *Report of the PLS validation team*. Report for CORAF and IITA

CORAF-IITA 2005b. *Kano/Katsina/MAradi Pilot Learning Site. Team meeting Kano March 22-24. Summary of Main Achievements*. CORAF/WECARD report

Dehejia, R. and S. Wahba 2002. Propensity Score Matching methods for Non-Experimental causal Studies. *Review of Economics and Statistics* 84(1):151-161

Duflo, E., S. Mullainathan, and M.Betrnad. 2004. How much should we trust difference-in-difference estimates. *Quarterly Journal of Economics* 119(1):249-275

Duflo, E., R. Glennerster, and M.Kremer, 2006. Using randomization in Development Economics research: A toolkit. Working Paper No. 138. Cambridge, MA: Harvard University, Center for International Development

FARA (Forum for Agricultural Research in Africa) (2008). Sub Saharan Africa Challenge Programme: Research Plan and Programme for Impact Assessment. Accra, Ghana. 36pp.

Heckman, J., H. Ichimura, J. Smith and P.Todd 1998. Characterising selection bias using experimental data. *Econometrica 66: 1017-1099.*

Heckman, J., H. Ichimura, and P.Todd 1998 Matching as an econometric evaluation estimator. *Review of Economic studies* 65(2):261-294

Miguel, E. and M. Kremer (2004); Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities. *Econometrica* 72(1): pp 159 – 218.

Nkonya, E.M., D. Phillip, T. Mogues, J. Pender, and E. Kato. 2010. From the Ground up: Impact of a pro-poor community driven development project in Nigeria. IFPRI Research Monograph #169, Washington D.C.

Smith, J. and P.Todd 2001. Does matching overcome Lalonde's critique of nonexperimental estimators? *Journal of Econometrics* 125(1-2): 305-353

Ravallion, M. 2005. Evaluating anti-poverty programs. Policy research working paper No. 3625. Washington DC: World Bank

World Bank 2005 downloaded on data.worldbank.org/news/extreme-poverty-rates-continue-to-fall