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RESILIENCE OF IMPROVED MAIZE VARIETIES UNDER SMALLHOLDER AGRICULTURE IN TANZANIA

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Abstract

Cultivation of cereal crops among small holder farmers in Africa is mostly rain-fed and susceptible to climate changes and environmental disasters. This study investigates the resilience (yield stability) of improved maize varieties among smallholder farmers in Tanzania. The study uses the survey data collected by National Bureau of Statistics (NBS) in 2013/2014 whereby a sample of 750 randomly selected smallholder farmers who grown at least one type of improved maize varieties was used for statistical analysis. The mixed effect model has been used to evaluate the resilience of improved maize varieties by calculating the effect size. The total effect size (Cohen's d) is positive (0.241) and significant at 5 percent level, that implies, under the same growing condition, improved maize varieties are more resilient than local varieties. The regression results show that education, quality of extension services, inorganic fertilizer and pesticides/herbicides are significant factors that positively influence resilience of improved maize varieties at 5 percent level. Therefore, the government should create supportive policies that enable smallholder farmer adopt multiple modern agricultural practices so as to harvest higher yield and hence to ensure food security in Tanzania.

Keywords: Effect Size, Improved Maize Varieties, Resilience, Smallholder farmers

1. Introduction

Maize is the major staple food and source of income for more than 300 million people in Sub-Saharan Africa (SSA) occupying about 17 percent of the cultivated land (Macauley, 2015). However, cereal crops cultivation in SSA is susceptible to climate changes and environmental disasters due to being dominated by smallholder farmers who largely use landrace varieties (LMV) and depend mainly on natural environmental conditions (moisture and nutrients). According to Asfaw and Lipper (2012), climate change is projected to decrease yield of cereal crops in SSA due to increase in extreme climatic events including drought, floods and high incidences of diseases, pests and weeds. Currently, about one third of people in SSA live in chronic hunger and famine due to low agricultural productivity and yield loss associated with weather variability (Westengen et al, 2014).

In the climate change literature, stability and resilience are often used interchangeably to describe fluctuations in final crop yields after an extreme weather event. A cropping system is stable/resilient if it is able to retain yield potential and recover functional integrity (produce food and feed) when challenged by environmental stresses (Di Falco and Chavas, 2008).There are several approach to increase climate change resilience in the farming system. Lin (2011) and Gaudin *et al*. (2015) suggest improvement of farming system resilience through increased crop diversification. Crop diversification can improve resilience by increasing the ability to suppress pests/diseases outbreak as well as stabilizing crop production from the effects of greater climate variability and extreme events. However, under smallholder agriculture, diversification could be limited by economies of size due to relatively limited land owned by these farmers. Another approach involves intensification of the agricultural system of agricultural. This approach seeks to get more output with less use of human capital and natural resources by making modifications in crop management practices and mobilizing production and productivity enhancing biological processes that are present and available within the farming system (Uphoff et al. 2006).

Central to farming system, stability or resilience to climate change reduces yield losses during extreme weather events. Such weather events are associated with low yield due to drought, diseases (including the maize streak virus, leaf blight, leaf rust, grey leaf spot and ear rot), and pests (the spotted stalk borer and the larger grain borer). As discussed in Katinila *et al*. (1998), De Groote et al. (2012), and Kassie *et al*. (2014) improved maize varieties (IMV) are characterized by high productivity, drought tolerance, and high resistance to pests and diseases. It is estimated that, on average, an increase of one acre in the area allocated to IMV reduces the probability of chronic and transitory food insecurity by 0.7 and 1.7 percent respectively (Kassie et al, 2014).Therefore, cultivation of IMV reduces food insecurity and poverty among the smallholder farmers.

Statement of the Problem

In Tanzania, the average maize production per hectare is below the SSA average. According to CIMMYT (2014), the average maize yield for 2010-12 was 1,370 kg/ha while the Sub-Saharan Africa (SSA) average maize yield was about 1,800 kg/ha. Maize production in Tanzania is expected to fall by 50 percent in 2020 due to drought while the population is projected to be about 60 million by 2020 (Altieri and Koohafkan, 2008 and NBS, 2012). With the existing population increase, the maize demand for food, feed and bio-energy is expected to double by 2050 (Rosegrant et al. 2008). The food shortage problem is expected to be more widened by seasonal climatic variability (temperature and precipitation) and limited adoption of improved agricultural technologies (Morris,Tripp and Dankyi ,1999 and Rowhani et al. ,2011). Maize yield losses due to drought are estimated to be as high as 50 percent due to low resilience of local varieties (CIMMYT, 2014). Therefore, this study examines resilience of improved maize varieties among smallhoder farmers in Tanzania.

Objectives of the Study

General objective of this study is to examine yield stability of improved maize varieties by analyzing the yield difference between improved and local maize varieties so as to inform breeders on resilience of improved seeds and justify for investment in public research and extension services. Specifically, the study objectives are

i. To evaluate the effect size (yield stability) of improved maize seeds among smallholder farmers.

ii. To determine the degree of yield difference (heterogeneity) due to location-specific effects in order to develop tailored extension messages and public policies targeting specific regions,

iii. To examine the factors influencing of yield stability of improved maize varieties

The study guides maize seed breeders to produce resilient maize seeds with high yield stability for increasing food security. The breeders also can integrate the features of some released improved maize varieties with farmers' and market desired attributes so as to increase adoption rate.

2. Literature Review and Empirical Model

According to Induced Innovation Hypothesis, the decision to adopt new technologies compared to the traditional is primarily based on the motive of farm profit maximization (Hayami and Ruttan, 1971). According to Schultz (1964), traditional agriculture cannot be improved by increasing labor and capital but through application of modern high-pay off inputs. The new high –payoff inputs are classified into three groups; technical knowledge produced by private and public agricultural research centres, technical inputs produced by industrial sector as well as readiness and effectiveness of peasants to adopt new knowledge and inputs. Improved inputs like fertilizer, improved seeds, technology and extension services, soil and water management are aimed at achieving high yield in agricultural sector. The theory of High-pay off inputs emphasize all stakeholders like private firms, nonprofit organisations and the government to support smallholder farmers to adopt modern agricultural inputs so as to get more yield.

Davis and Heemskerk (2012) postulate that extension services have positive impact on farm yield among smallholder farmers. It motivates farmers to accept innovation, improve production and protect environment for sustainable agriculture. However, the extension services alone cannot bring big results, unless accompanied with other agricultural technologies.

Morris et al. (1999) applied the qualitative approach to evaluate the performance of improved maize varieties in Ghana, under the grains development project. They found that improved maize varieties significantly increased yields for farmers switching from local varieties. The yield increase would be even higher if the farmers applied fertilizer on the improved varieties. CIMMYT (2014) outlined the impact of improved maize varieties on household food security in Tanzania. The main results indicated that, growing improved maize varieties increased the chance that a household would be food secure by 18 percent.

Finger *et al*. (2011) conducted meta-analysis of the effects of GM-crops on crop yields, seed costs, pesticide costs, management cost, labor costs as well as gross margins in Spain, Germany, South Africa, and Argentina. The technology included insect resistant Bt crops (made resistant against insect pests by incorporating a gene from the Bacillus thuringiensis (Bt) bacterium) and herbicide tolerant (HT) crops. About 721 publications were reviewed to analyze the impact of Bt cotton and Bt maize on performance measures by using Linear Regression model. The results showed that on average, Bt maize seeds resulted into 46.3 percent higher yields. Likewise, Bt cotton seeds increased yields by 8.5 percent compared to conventional varieties. The magnitude of benefits from GM crops was very heterogeneous between countries and regions, particularly due to differences in pest pressure and pest management practices. The study shows that, environmental condition affect productivity of GM crops. Apart from its contribution, the study involved two unrelated crops, cotton (cash crop) and maize (food crop) with different nutrient and environmental condition requirements.

Corbeels *et al* (2014) used REM to investigate the effect of tillage and residue management on crop yield so as to increase productivity and overcome soil degradation in SSA. The results show that, crop residue application (mulching) significantly and positively influences crop yield. The impact is higher when the farmer integrates mulching with chemical fertilizer application and crop rotation agricultural system. The study show that, adoption of multiple agricultural technologies increases productivity. However, the study does not specify the type of study under consideration.

Klümper and Qaim (2014) conducted Meta-Analysis on the most important GM crops, including herbicide-tolerant (HT) soybean, maize, and cotton, as well as insect-resistant (IR) maize and cotton by reviewing 147 relevant studies from published articles. On average, GM technology adoption observed to reduce chemical pesticide use by 37percent, increased crop yields by 22 percent, and increased farmer profits by 68 percent. Yield gains and pesticide reductions are larger for insect resistant crops than for herbicide-tolerant crops.

Bezu *et al.* (2013) assessed maize adoption and its link impact to household welfare across different wealth and gender groups in Malawi. The data were analyzed by using control function approach and IV regression to control endogeneity of input subsidy and improved maize adoption. It was found that, adoption of improved maize varieties increased household's income, per capita maize consumption and asset holdings. Moreover, improved maize adoption found to have stronger impact on welfare of female-headed households and poorer households. Amare *et al* (2011) used propensity score matching and switching regression regression technique to examine the impact of adoption of improved pigeonpea and maize on welfare of households in Tanzania. The results show that, adoption of improved maize and pegionpea has positive and significant impact on household's income and consumption expenditure.

Wambugu *et al* (2009) studied on-farm seed production system in Western Kenya so as to improve yield and quality of farm saved seeds. The study show that about 85 percent of maize farmers plant local varieties with about 80 percent using own farm-saved seeds. Fertilizer application led to an 88 percent increase in yield, 54 percent increase in number of seeds per cob, and 14 percent increase in 100-seed weight. Fertilizer application also led to an increase in seed vigour and viability. The study focused on local varieties which are not effective nowadays due to climate variability.

Kaliba *et al* (1998) employed the two-stage least squares procedure to study the factors that influence allocation of land for improved maize varieties and inorganic fertilizer in intermediate and lowland zones in Tanzania. The study show that Germplasm characteristics (productivity, drought resistance/tolerance, resistance to storage pests, shelling quality and taste), production potential of the area and extension services (flow of information to farmers and marketing of output) were the most important factors that affect the size of land that a farmer allocate to improved maize and use of inorganic fertilizer.

Kaliba *et al*. (2000) investigated the factors influencing farmer's adoption of improved maize seeds and inorganic fertilizer for maize production in the intermediate and lowland zones of Tanzania. The studies show that, extension services, on-farm field trials, variety characteristics and rainfall significantly influence both the adoption rate of improved maize varieties and the use of inorganic fertilizer.

Despite the release of several IMV, most smallholders in Tanzania plant landrace maize varieties (LMV) that are more resilient to non-normal weather conditions but with low yield. Kathage et al. (2012) estimate that IMV are grown on less than half of the total African maize planted area. Most studies that relate IMV and LMV focus on either factors affecting adoption and impact of adoption on household's welfare. For example, Nkonya *et al* (1997); Kaliba *et al* (2000); Kathage *et al* (2015) and Beyene and Kassie (2015) study on the factors for adoption of improved agricultural inputs while Kassie *et al* (2014), CIMMYT (2014) and Kathage *et al* (2012) studied the impact of adoption on household's welfare. Therefore, this study examines resilience of improved maize varieties so as to convince current adopters to increase adoption rate and potential adopters to adopt the seeds for food security in Tanzania.

3. Methodology

This study is a modified meta-analysis that compares resilience of IMV and LMV by evaluating the standardized mean difference (effect size) of IMV. It is not easy to conduct the traditional meta-analysis because most of on-station and on-farm trials conducted over the past three decades were either not published or not in searchable databases. The result of the study will inform breeders and adopters on yield stability/resilience of IMV in Tanzania and motivate policy makers and other stakeholders to invest in research and extension services in order to stimulate productivity and therefore increase income and ensure food security in Tanzania.

There are two popular statistical models for meta-analysis, the fixed-effect model, and the random-effects model as discussed in Hedges and Olkin (1985), Haddock *et al* (1998), Shadish and Haddock (2009) and Borenstein *et al*. (2009, 2010). Under fixed-effect model, the basic assumption is that the effect sizes differ only because of sampling error and they all share a common mean. The assumption implies that the only reason for the differences among estimates of the effect sizes is due to the fact that each study used a different sample of participants. Whereas each study will estimate a different effect size, meta-analysis under a fixed-effect model we expect to estimate expected value of effect size or a common mean for all studies. The assumption is plausible when our studies are close replications of one another or using the same procedures and measures.

The tenet of a random-effect model is each study is from a different distribution and has its own mean, which is sampled from the underlying population distribution of effect sizes. In addition, the underlying population distribution also has its own variance (the variance component). Simply, the random-effect model approach implies that each effect size has two components of variation, one due to sampling error, and one from the underlying distribution. The studies differ not only because there are different participants, but also because of differences in the way they were conducted (Raudenbush, 2009). The random-effects model approach is more reasonable as most agricultural related meta-analysis look at different types of new technologies that are adopted in different countries or regions. The expectation is that that the effect sizes are not homogenous (are heterogeneous) across countries or regions.

Let T_{i} be the effect size, v_i^2 denotes the sampling variance for our effect size, τ^2 denotes the variance component, and μ is the population mean of the underlying effect size distribution. The fixed-effect and random-effect model could be specified as:

$$\textit{Fixed effet}: \quad T_i = \mu + \varepsilon_i, \quad where\ \varepsilon_i \sim N(0, v_i^2), \qquad 1(a)$$

$$\textit{Random effect}: T_i = \mu + \varepsilon_i + \zeta_i, \quad where \quad \varepsilon_i \sim N(0, v_i^2) \quad and\ N(0, \tau^2). \qquad 1(b)$$

In equation 1(a), each effect size estimates a single population mean that differs by sampling error. In equation 1(b), each effect size differs from the underlying population mean, due to both sampling error and the underlying population variance. Equation 1 (a) implies that under the fixed-effect model there is one true effect size which is shared by all studies. By contrast, under the random-effects model in equation 1(b), the true effect varies from study to study. If there is unexplained variance, random-effects models should be preferred over fixed-

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effect models. If fixed-effect model is used in the presence of significant between-study variance, the resulting confidence intervals are biased and much too small. If random-effect model is used in the presence of unexplained variance, the standard errors are larger, and the estimate of the average effect may be different, depending on the relation between effect sizes and sample sizes in the primary studies (Villar *et al*., 1995; Brockwell and Gordon, 2001).

Lipsey and Wilson (2001) describe a Weighted Least Squares regression procedure for estimating the models in Equation (1) parameters by weighting each effect size by the inverse of the corresponding sampling variance. The method therefore requires a priori knowledge of the between-study variance. When comparing the mean of experimental group with the mean of control group, an appropriate measure for the effect size as suggested by Hedges and Olkin (1985) is the standardized difference between the experimental and the control group. The corrected effect measures and associated sampling variance of the effect estimator T_i is:

$$T_i = \frac{(1-3)}{4(N-9)} \frac{(\bar{Y}_E - \bar{Y}_C)}{S_p}, \qquad 2(a)$$

$$var(T_i) = \frac{(n_E + n_C)}{n_E n_C} \frac{T_i^2}{2(n_E + n_C)}. \qquad 2(b)$$

where N is sample size, S_p is the pooled standard deviation of the two groups, n_E and n_C respectively, number of studies in the experimental and control groups. Note that when N is large (greater than 2), the correction factor *(1-3)/(4(N-9)*, becomes very small. In classical meta-analysis, larger studies include less sampling error, and therefore deserve a larger weight in combining the effect sizes. Hedges and Olkin (1985) prove that the optimal weight is not the sample size, but the precision, which is equal to the inverse of the sampling variance. The fixed-effect model weights each study outcome with the inverse variance of the effect size: $w_j=1/var(T_j)$. The combined effect size is therefore the weighted mean of the effect sizes. The standard error of the combined effect size (SE_d) is the calculated as the square root of the sum of the inverse variance weights and test statistic for homogeneity of study (Cochran Q) are both estimated as:

$$SE_d = \sqrt{1/\sum w_j}\ ;\ and,\ Q = \sum w_j (T_i - \bar{T}). \qquad (3)$$

According to Higgins *et al*. (2003), the appropriate measure of heterogeneity is the I^2 statistic. The I^2 gives the percentage of heterogeneity rather than merely the presence of heterogeneity as given by Q statistic. The I^2 is given as shown below;

$$I^2 = 100\% \times (Q\text{-}df)/Q. \qquad (4)$$

According to Higgin *et al* (2003), the I^2 gives the percentage of total variations due to variation between studies/individuals. The value of I^2 is interpreted as shown in the table 1;

Table 1; The I^2 Value and Heterogeneity

The value of I^2 (percent)	Heterogeneity
0	No heterogeneity
25	Low heterogeneity
50	Moderate heterogeneity
75	High heterogeneity

Source; Higgin *et al* (2003)

However, the I^2 without being multiplied by 100 is generally called the intraclass correlation coefficient.

The test statistics for homogeneity has a chi-square distribution with J-1 degree of freedom. If the chi-square is significant, we reject the null hypothesis of homogeneity and conclude that the studies are heterogeneous meaning that there is significant study level variation. The study level variance for both fixed-effect and random-effect models are estimated by a method of moment estimator given by:

$$\sigma_\varepsilon^2 = \frac{Q-(J-1)}{\sum w_j - \sum w_j^2 / \sum w_j} \quad \text{for fixed-effect model,} \qquad 5(a)$$

$$\sigma_\varepsilon^2 = \frac{Q-(J-1)}{\sum w_j^* - \sum w_j^{*2} / \sum w_j^*} \quad \text{, where } w_j^* = 1/[var(T_j) + \sigma_\varepsilon^2] \text{ for random-effect model.} \qquad 5(b)$$

Note that the random-effect model adds the between study level variance to the known variances when calculating the inverse variance weight. Subsequently, the same methods are used to estimate the combined effect size and its standard error.

In this study we are comparing the yield of IMV with landrace varieties. If famers are indexed by $i=1,2,\ldots I$, and farmers' locations indexed by $j=1,2,..J$, and agro-ecological zone indexed by k$=1,2..,J$, for a larger sample an appropriate measure for the effect size is the standardized difference yield between IMV and landrace, given by:

$$T_{ijk} = \frac{IMV_{ijk} - LRY_{jk}}{LRS_{jk}}, \qquad (6)$$

Where, IMV_{fij} is the mean yield from Improved maize varieties recorded by the farmer, LRY_{ij} is the average yield of landrace varieties in a given location, LRS_{ij} is the pooled standard deviation of improved and landrace maize varieties in a given location and T_{ijk} is the effect size in form of *Cohen's d*. The value of *Cohen's d* is considered as small, medium or large when its value is 0.2, 0.4 and 0.8 respectively (Cohen, 1992).

For each farmer, the effect estimator is affected by farmer characteristics, location characteristics and agro-ecological zone characteristics. The algebraic specification of three-level model is:

$$T_{ijk} = \beta_{oijk} + \beta_1 x_{ijk}, \qquad 7(a)$$

Where, $\beta_{ojk} = \beta_0 + v_k + \mu_{jk} + \varepsilon_{ijk}$. 7(b)

In Equation 6(a) index i represents level 1 (farmer) and the covariate of the farmer are x_{ijk}, index j represent level 2 (locations), and index k represent level 3 (agro-ecological zones). Also, v_{ok} is the random-effect at the agro-ecological level, an allowed-to-vary from the grand mean; μ_{0jk} is the random-effect at the locations level, a departure from the agro-ecological zones effect; and, ε_{ijk} is the random-effect at the farmers' level, a departure from the locations effect within agro-ecological zones. Variance between agro-ecological zones (var(v_{0k})) is σ_v^2, variance between locations (clusters) within agro-ecological zones (var(u_{0jk})) is σ_u^2, variance between farmers within locations within agro-ecological zone (var(e_{ijk})) is σ_ε^2, and variance between locations is $\sigma_v^2+\sigma_\mu^2$. If the cluster has little effect, the value of the respective variance approaches to zero. If the cluster has little effect, the value of the respective variance approaches to zero.

It is also possible to estimate intra-location correlation (ρ_1) -within same agro-ecological zone and same location and intra-agro-ecological correlation (ρ_2)-within same agro-ecological zone but different locations as follows:

$$\rho_1 = \frac{\sigma_v^2 + \sigma_\mu^2}{\sigma_v^2 + \sigma_\mu^2 + \sigma_\varepsilon^2} \quad . \qquad 8(a)$$

$$and \quad \rho_2 = \frac{\sigma_v^2}{\sigma_v^2 + \sigma_\mu^2 + \sigma_\varepsilon^2} \qquad 8(b)$$

The following model describe the impact of farmer's characteristics and other inputs on effect size of IMV

$$ES_i = f(ageh, eduh, hsize, maritalh, genderh, extse, qherpest, qinorg) \qquad (8)$$

Where,

ES$_i$ is the effect size of improved maize seeds. It is the standardized mean different of IMV, It is positive when the IMV yield is higher than the mean of the `LMV in the respective cluster.

Ageh is the age of the household head. It indicates the experience of the household head in agricultural activities.

Eduh is the education level of the household head. Education make the household easily access agronomic information and adopt modern agricultural practices.

Hsize is the number of family members at the given household. The number of household at the household indicates the potential labor for increasing productivity.

Maritalh is the marital status of the household head. It takes the value of 3 if the household married, 2 if the household divorced/separated and 1 if never married.

Genderh is the gender of the household head. It takes the value of 1 if male and 2 if female.

Extse is the quality of extension service the household receive. It is the product of the extension service rating and the frequency of visit.

Qpeherb is the pesticides/herbicides application status. It take the value of 1 if the household applied pesticides/herbicides, otherwise it is 0.

Qinorg is the inorganic fertilizer application status. It takes the value of 1 if the household applied inorganic fertilizer. Otherwise, it is 0.

Model specification

$$ES_i = \beta_o + \beta_1 ageh + \beta_2 eduh + \beta_3 hsize + \beta_4 maritalh + \beta_5 genderh + \beta_6 extse + \beta_7 qpeherb + \beta_8 qinor + w_i \qquad (9)$$

Where,

β_o is the intercept.

$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, and\ \beta_7$ are coefficient parameters

From the theoretical review, the following are expected sign of the coefficients.

Table 2: Expected Signs of coefficients

Variable	ageh	eduh	hsize	maritalh	genderh	extse	qpeherb	qinorg
Expected sign	-/+	+	-	+	-/+	+	+	+

This study uses cross sectional secondary data collected by national bureau of statistics (NBS) from 750 households who grew at least one type of improved maize variety in 2013/2014. Other sources are Ministry of Agriculture, Livestock and Fisheries (MALF) and the Food and Agriculture Organization Corporate Statistical Database (FAOSTAT).

The effect size is estimated by OLS of the multilevel mixed effect model. The model was used since it allow for inclusion of predictors and flexibility for both fixed and random effects. The analysis was done using R software 3.3.1, Stata 9.1 and StatsDirect.

4. RESULTS AND DISCUSSION

Table 3: Descriptive Statistics

	effectsize	ageh	eduh	hsize
observation	750	750	750	750
Mean	0.2241211	44.676	11.34667	6.829333
Std. Deviation	1.711633	15.99559	7.000273	4.021663
Minimum	-8.301617	14	1	1
Maximum	5.947296	88	18	21
Skewness	-0.5431232	0.4263981	-0.6458777	0.916766
kurtosis	6.10481	2.587922	1.557737	3.574668

The table 3 shows that the study has used 750 observations. The average age of the household is 44.7 years of which 0.4 percent of them were below 18 years, 87.2 percent were aged between 18 to 64 and 12.4 percent were aged 65 years and above, this implies high number of workforce among smallholder farmers. Out of 750 households, 76 percent were male headed and 24 percent were female headed indicating that most of Tanzanian societies are patrilineal. About 85.2 percent of households are married while 14.8 percent were not married.

Household size is about 7 people per household on average of which 10.27 percent consist of 1 to 2 family members, 72.4 percent with 3 to 10 and 17.33percent consist of more than 10 people indicating high fertility rate, existence of polygamies and extended families and hence high dependence ratio.

GSJ: Volume 7, Issue 11, November 2019
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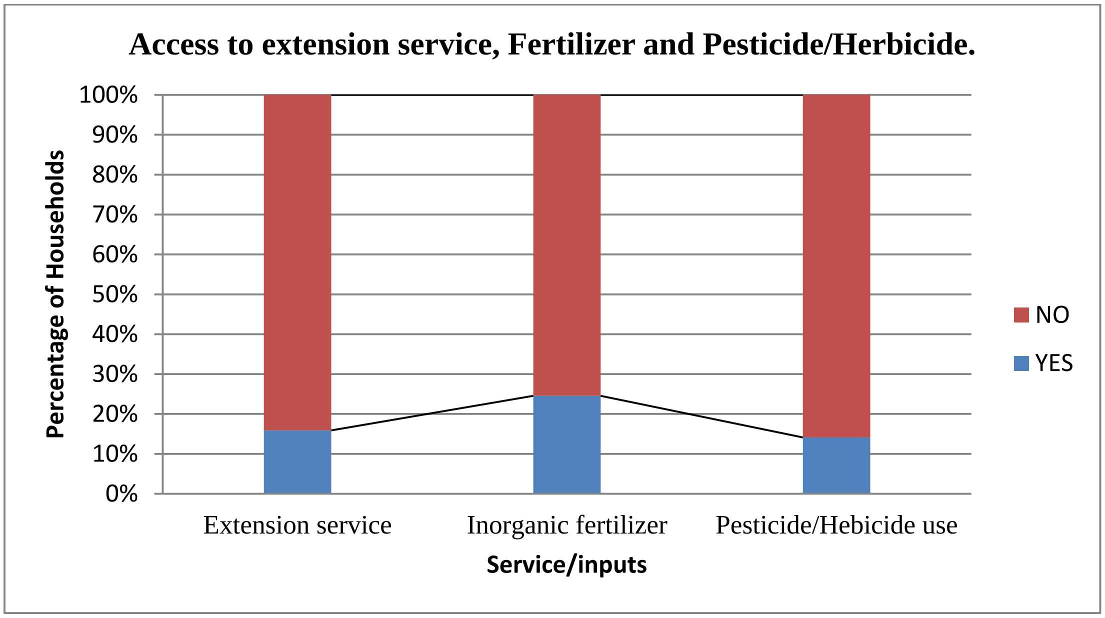
Figure: 1 Access to Extension Services, Fertilizer and Pesticide/Herbicide.



As indicated on the figure 1, about 84.13 percent had no access to extension services, only 15.87 percent of household accessed for extension serviced. About 85.73 percent of the households did not use pesticides and herbicides and about 75.47 percent of households do not use inorganic fertilizer in their farming. This show high association between extension services accessibility and adoption of other improved agricultural practices (Davis and Heemskerk, 2012).

Multicollinearity of explanatory variables was tested by using both correlation analysis (Table 4) and Variance Inflation Factor (VIF) and Tolerance (Table 5). From the result presented in Table 4, correlation of bivariate predictors are less than 0.8 and the tolerance is approximately 1 and the mean VIF is 1.14 which indicates no severe multicollinearity problem. Therefore, since there is no severe multicollinearity, nothing was done to correct it as suggested by Gujarat (2003).

GSJ: Volume 7, Issue 11, November 2019
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Table 4: Correlation Matrix of Independent Variables of the Model.

Variable	ageh	eduh	hsize	maritalh	genderh	extse	qpeherb	qinorg
ageh	1.0000							
eduh	-0.2289	1.0000						
hsize	0.2533	-0.0390	1.0000					
maritalh	-0.1489	0.0910	0.2089	1.0000				
genderh	-0.0890	-0.1533	-0.1222	-0.3278	1.0000			
extse	-0.0545	0.0103	0.0975	0.0998	0.0165	1.0000		
qpeherb	-0.0242	0.0899	0.1520	0.0225	0.0118	0.0311	1.0000	
qinorg	-0.0412	0.1454	0.0921	0.0223	-0.0157	0.1763	0.1838	1.0000

Table 5: VIF and Tolerance

Variable	VIF	1/VIF (Tolerance)
maritalh	1.24	0.806117
ageh	1.21	0.824168
hsize	1.19	0.838854
genderh	1.18	0.844911
eduh	1.12	0.894737
qinorg	1.09	0.916697
qpeherb	1.06	0.939264
extse	1.05	0.949476
Mean VIF	**1.14**	

The effect size has been calculated as the Cohen's d statistic in StatsDirect as shown in the table below;

Table 6: The Cohen's d

Pooled Cohen's d	z	P(p>z) at 95%
0.241	**6.341**	**0.0001**

From the table 6, the effect size is significant (at 5% significant level) and positive indicating that the improved maize varieties perform better than the local varieties given that other things remain constant.

The heterogeneity of the households has been evaluated by using both Cochran Q and I^2 statistic as shown in the table 7.

Table 7: The Cochran Q and I^2 Statistics.

Cochran Q	I square	P(I^2>p)
2292.96	67.3%	0.0001

From the table above, the Cochran Q value is significant at 5 percent level. The heterogeneity is 67.3 percent indicating inconsistence among individuals of different locations (clusters). This indicates that improved maize seeds yield impact differs across agro-ecological zones.

Table 8: Results from Mixed Effect Model with Maximum Likelihood (ML)

effectsize	Coef.	Std. Err.	P>z
ageh	.0040703	.0040694	0.317
eduh	.0339197	.0089242	0.000
hsize	-.0048658	.016043	0.762
maritalh	.1626689	.161657	0.314
genderh	.1177283	.1504273	0.434
extse	.0726847	.0192832	0.000
qpeherb	.5566562	.1742267	0.001
qinorg	.6934847	.1433427	0.000
_cons	-1.255028	.6251522	0.045

From the table 8, the Chi square shows that the estimates are simultaneously different from zero since Prob > chi2 =0.0000. Each factor has explained below;

Age of household (ageh); The result show that the age coefficient is positive as expected but statistically insignificant at 5 percent level. This shows that older smallholder farmers have more experience on agricultural practices than the younger ones. One year increase in age result into increase in effect size by 0.0040703.

Education level of the household head (eduh); The result show that the household's head education coefficient is positive as expected and statistically significant at 1 percent level. One level increase in education of the household increases the effect size by 0.0339197. It is an important factor that influences the effect size.

Household size (hsize); The results show that the household size coefficient is negative but statistically insignificant. As the household increase by one person, the effect size decreases by 0.0048658. This is contrary to what expected and implies that the increase of household size was largely contributed by dependents (children) who weakened the economic strength of the family to invest in improved agricultural technologies.

Marital status of the household head (maritalh); the results show that marital status (married) coefficient is positive as expected but insignificant. The married households increase the effect size by 0.1626689. That implies that married household put more effort on their farms due to well-organized and shared decisions for prosperity of their family.

Gender of the household head (female); the results show that the gender coefficient is positive but statistically insignificant at 5 percent. As the household is female headed, the effect size increases by 0.1177283. That shows that female work effectively in their plots of their family than males.

Quality of extension services (extse); the results show that extension service is positively related and significantly influence the effect size at 5 percent level. One stage improvement in the quality of extension services increases the effect size by 0.0726847.

Application of inorganic fertilizers (qinorg); the results show that the coefficient of the variable is positive and statistically significant at 5 percent level. Lastly, application of pesticides and herbicides (qpeherb) is positively related and significantly influence the effect size at 1 percent level.

By using meta-analysis approach, the mixed effect model has been used to evaluate the effect size. The effect size is taken as standardized mean yield difference between improved and local maize varieties. The pooled effect size is small (0.241) but positive. That imply that, under the same growing condition, improved maize varieties perform better (higher yield stability) than local varieties.

The regression results show that education, quality of extension services, inorganic fertilizer and pesticides/herbicides are factors that positively and significantly influence effect size of improved maize varieties at 5 percent level. Therefore, yield stability of improved maize seeds can be increased if the farmers use several agricultural technologies in production.

5. Conclusion

Application of chemical fertilizers and pesticides/herbicides play a significant contribution on the seed resilience. Moreover, relevant and quality education to increases the ability of the farmer to access different extension service information as well as the readiness to adopt IMV. That means, adoption of improved maize varieties alone is not sufficient strategy for higher yield. Rather, the government should create supportive policies that enable smallholder farmers to adopt multiple modern agricultural practices so as to resist negative impacts of environmental shocks.

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