Journal of Economics and Sustainable Development www.iiste.org
ISSN 2222-1700 (Paper) ISSN 2222-2855 (Online)
Vol.8, No.4, 2017

Impact of Small-Scale Irrigation on Poverty in Rural Malawi

Zephania B. Nyirenda[1*] Abdi-Khalil Edriss[2] Lawrence D. Mapemba[2]
1.International Food Policy Research Institute
2.Lilongwe University of Agriculture and Natural Resources, Department of Agricultural and Applied Economics, Box 219, Lilongwe, Malawi

Abstract
The aftermath of the Structural Adjustment Policies (SAPs) and droughts in the 1990s which culminated into the 2002 food crisis renewed government and donor interest to reinvest in irrigation agriculture in Malawi. As a result, a number of investments were instituted to spur irrigation agriculture between 2006 and 2014. However, there is little evidence from Malawi on the national scale on whether irrigated farming translates into poverty reduction. This study, therefore, sought to establish the impact of small-scale irrigation on poverty reduction in rural Malawi by examining poverty, crop productivity, crop income, and food security configurations of irrigation impacts. Using the Third Integrated Household Survey Data (IHS3) and Propensity Score Matching, the study found positive and statistically significant impacts of irrigated agriculture on crop productivity, food security and poverty reduction and a statistically insignificant impact on crop income. However, the reduction in poverty is not huge even though it is statistically significant. There is, therefore, need for the government to establish large scale irrigation schemes along the lake and big rivers where water is abundantly available. This should be coupled with the creation of infrastructure in transport and communication to aid distribution and marketing of the crops to be produced.
Keywords: Irrigation, poverty, crop productivity, crop income, food security, propensity score matching.

1. Introduction

Poverty eradication is the key purport of all growth and development policies and strategies for all developing economies in the world. For most of these economies, especially those whose main resource endowment is land, agriculture is the most viable option out of poverty. Malawi is well endowed with land resources and agriculture is the most important economic activity. Since independence, the agricultural sector has accounted for between 30% and 39% of the gross domestic product (GDP), employing about 64% of the country's workforce, accounting for over 80% of foreign exchange earnings, and contributing significantly to national and household food security (NSO, 2014, GoM 2014).

The major thrust in growing an agro-based economy rests in improving productivity of the sector. The most effective engine for growth of the agricultural sector is irrigation which addresses problems of land availability and erratic rainfall patterns by enabling dry season cultivation; thus, permitting more than one harvest in a year (Kassie, Shiferaw and Murich, 2011). As a consequence, the government of Malawi embarked on serious irrigation development in 1960s. By the 1970s, it had constructed major irrigation schemes including Likangala and Domasi irrigation schemes. In the 1980s, it supported the development of self-help irrigation schemes (GoM, 2002). These investments precipitated into high agricultural production to the extent that, as Chilowa (1998), Orr et al. (2001), and Harrigan (2001) pointed out, Malawi was on the boarders to experiencing its own Green revolution.

However, with the advent of Structural Adjustment Policies (SAPs) in the 1980s, the country started seeing the collapse of the agricultural sector including irrigation farming. As a result, Malawi became a net importer of agricultural commodities. Since then, Malawi has been experiencing food deficits for most of the years except in 2006 and 2008 when it managed to produce surplus food with the Farm Input Subsidy Programme. In addition, there were droughts in the 1990s, and in the 2001/2002 season there was a food deficit which culminated into a major food insecurity crisis in 2002. This forced the government and the donor community to renew their interest in irrigation agriculture.

With respect to the identified challenges, a number of irrigation initiatives have been implemented in Malawi between 2006 and 2014. The fundamental question is: "have these irrigation initiatives and resources helped in moving rural farming households out of poverty?

Other researchers have argued that irrigation has helped in reducing poverty in Malawi including Mangisoni (2008) and Nkhata (2014). However, poverty in Malawi is still rampant and agricultural productivity has predominantly remained low (GoM, 2011). These paradoxes prompted the need for empirical evidence on the role of irrigation on poverty reduction at national level.

A review of literature on the impact of irrigation in Malawi leads to four important points worth considering. First, all the studies on irrigation in Malawi have been based on irrigation schemes except for a few studies that had a relatively bigger geographical coverage. It should be noted that not all irrigation in the country is scheme based and that it becomes limiting to inform policy on data that is not representative (see Chinsinga

2003; Ferguson and Mulwafu, 2005; Kambewa 2005; Mangisoni, 2008; Oxfam, 2011; International Federation of Red Cross and Red Crescent (IFRC), 2012; and Nkhata; 2014 for scheme-based irrigation studies and FAO, 1996 for bigger geographical coverage irrigation studies). Second, these studies, except Mangisoni (2008) and Nkhata (2014) either proxied poverty with food security situation of households or asset ranking and/or farmers' own assessments of what they consider as symbols of wealth, i.e., ownership of an iron roofed house, and being able to pay school fees and medical expenses for family members. However, studies from other countries have demonstrated the importance of using standard poverty metrics in analyzing poverty impacts of irrigation for comparison of impacts (Gebrehaweria and Regassa undated; Hagos et al., undated; Meliko 2010). Third, these studies did not follow the standard impact analysis of having a treatment and a control group for assessing impacts. Mangisoni (2008) and Nkhata (2014) are the only studies that followed a quasi-experimental approach of having a treatment and a control group but the data that was used was not representative of the country. Lastly, none of these studies have employed a double difference method, probably because of lack of panel data in Malawi when they were conducted.

It is from this background that the current study was undertaken, taking advantage of nationally representative data, with standard poverty metrics and standard impact analysis of having a treatment and control group. This provides a solid ground for evidence based policy simulation.

This study contributes to the overall strategy for the country (Second Malawi Growth and Development Strategy (MGDS II) and the Agriculture Sector Wide Approach (ASWAp)-section 5.3.5) on improving agricultural productivity through evidence based policy research. The ASWAp particularly notes the absence of regular household surveys to document changes occurring at household and individual levels in the agricultural sector. This study directly fills that gap and will inform policy makers on the impacts that irrigation agriculture has had on the livelihoods of rural Malawians. It will further help in identifying gaps that need to be filled to enhance performance and hence, yield more positive results.

The objective of the study was to analyze the impact of small-scale irrigation on poverty, crop productivity, crop income, and food security situation of participating farmers. The rest of this paper is organized as follows: The next section presents the methodology used in the study, then results, discussion, conclusion and policy implications will follow.

2. Methodology

2.1 Conceptual Framework

Taping from Hussain and Hanjra, (2004); five key dimensions relating to the contribution of irrigation to uplifting welfare can be traced. These include crop productivity, income and consumption, employment, food security, and other social impacts. These variables are interrelated and interact as shown in Figure 1. Irrigation technology allows multiple cultivation of crops and increases the total yield per annum. These high yields help to raise returns to farmers' land and labor endowments. Besides increasing yields, irrigation creates opportunities for increasing crop area which allows for crop diversification and intensification while at the same time, creating opportunities for cultivation of high value crops like rice. High production results into reduced levels of consumption shortfalls and increased volume that is off-loaded to the market thereby increasing farm income and reducing food prices for net-consumers (Lipton et al., 2002).

In terms of food security, irrigation reduces the risk of production failure, production seasonality and consumption shortfall. Furthermore, it creates opportunities for buffering future food supply shocks. The effects described above can collectively be termed "direct effects" of irrigation agriculture. However, there are also "indirect effects" which tend to be unidirectional and long term in nature. These include reduced rural-urban migration as a result of rural employment thus created, and increased resources for other sectors of the economy like education and health. Notwithstanding these positive impacts, irrigation is known to have spillover and unintended negative effects. These result from the chemicals applied in crop cultivation which affect water resources downstream. Other effects include river bank cultivation which results in soil erosion, leaching of soil nutrients, and salinization. Irrigation technology can also be costly in terms of scheme establishment and diseases that are associated with irrigation schemes like Malaria and Schistosomiasis (Lipton et al., 2002; Hussain and Hanjra, 2004).

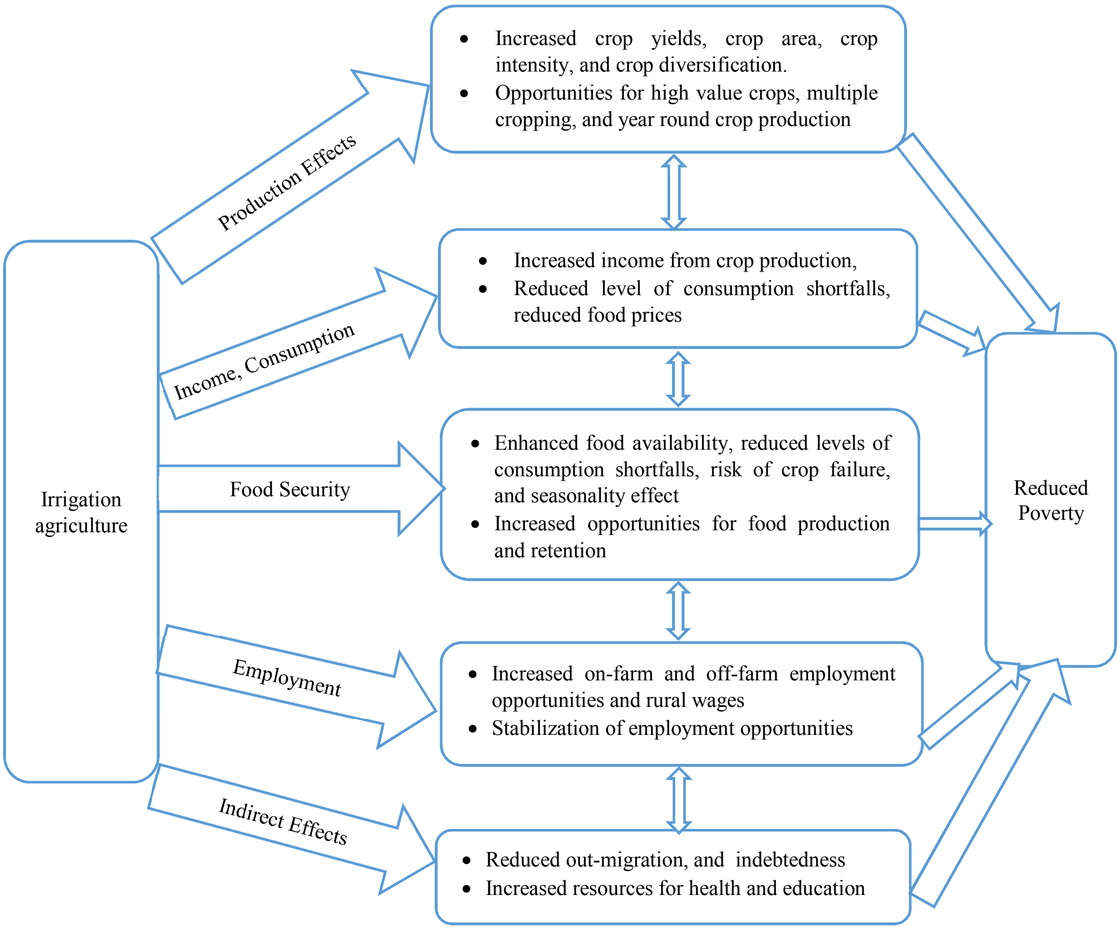

Figure 1: Irrigation-Poverty Nexus
Source: Adapted from Hussain and Hanjra, (2004)

Figure 1 shows that there is multiplicity of linkages and simultaneity which pose methodological challenges in estimation to effectively separate the impacts of irrigation. As such, matching is the most appropriate tool to overcome endogeneity and attribute impacts to an intervention (Ravallion, 2005).

2.2 Data Source

The Third Integrated Household Survey (IHS3) data from National Statistical Office (NSO) was used in the study. IHS3 was a very large study which collected information from a representative sample of 12,271 households between March 2010 and March 2011. It was statistically designed to be representative of national, district, urban and rural levels; hence the data provides reliable estimates at these levels. The data shows that about 81% of Malawi's total population are farming households. Of these, 90% resided in the rural areas and the remainder resided in urban areas. Over 12% of the faming population practiced irrigation farming during the study period. For the sake of this study, focus was on smallholder farmers (those who hold at most 2 hectares of crop land) who practice irrigation.

Table 1: Analytical Samples Used in the Study

	Malawi	**Urban**	**Rural**
Full Survey	12, 271	2, 233	10,038
Farming households	9,959	746	9, 004
Farmers practicing irrigation	1, 219	39	1, 180
Proportion of irrigation farmers	12.2	5.2	12.8
Irrigation farmers planting maize	887	29	858

2.3 Variable definition and measurement

Table 2 below provides description and measurement of variables used in the study.

Table 2: Variable description and measurement

Variable	Description/measurement
Dependent Variables:	
Headcount Ratio	1 = if household per capita income is below national poverty line; 0 = otherwise
Poverty Gap	Gap between income and poverty line
Poverty Severity	Poverty gap squared
Ultra-poverty	1=if household per capita income is below the ultra-poverty line; 0= otherwise
Maize Crop Productivity	Yield (Kg/ha)
Maize crop income	Gross margin (Revenue-Variable costs)
Food security situation	1=if food secure; 2= otherwise
Explanatory Variables	
Inputs	
Total cultivated land	Hectares
Fertilizer Applied to Maize	Amount of fertilizer applied (Kg)
Maize Seed	Amount of seeds used (Kg)
Labour for Maize	Amount of labour used on the farm (in man days)
Institutional Variable	
Access to extension advisory services	1=if advisory services were accessible and 0=otherwise
Demographic and Social Economic Variables	
Household head age	In years
Household head education	1=if household head attained primary education; 0=otherwise
Household gender	1=Male, 0=Female
Household size	Number of household members
Real Expenditure per capita	Malawi Kwacha per capita
Endogenous variable	
Treatment	1=if household participates in irrigation and 0=otherwise

2.4 Analytical Framework

Non-experimental evaluation techniques are an approach to impact evaluation in which there are no natural experiments to control for observable characteristics. Ravallion (2005) postulated that selection bias, spill-over effect and data measurement errors are the major confounding factors in non-experimental evaluation techniques. Before impact assessment can be successful, these problems have to be addressed.

Selection bias originates from sample selection and/self-selection (endogeneity). Sample selection bias involves non-random selection of certain individuals based on available observable data such as access to land for irrigation. This results in inconsistent estimation results. Self-selection results from correlation between exogenous variables and other observable/unobservable variables. Heckman, (1974, 1979) addressed this problem by employing a two-step estimation procedure in which the probability of participating in a program was first estimated and then a model to determine the impact of the program on the outcome of interest was estimated taking into account the probability of participation.

The second problem is that of spill-over effect. The assumption in non-experimental evaluation techniques is that an intervention (irrigation in this case) only affects those households which participated (Average Treatment on the Treated -ATT) in the intervention. However, the conceptual framework presented in this study shows that there are also indirect effects in terms of wage employment and reduction in food prices that comes with irrigation. This makes it difficult to compare outcomes between participant and non-participant households. Other researchers have addressed this problem by employing a double difference technique to observe changes between participants and non-participant across time. This approach handles selection bias and spill-over effects (Khandker, Bakht, and Koolwal 2009; Ravallion and Chen, 2005). In other cases, the Instrumental Variables regression (IV) method has been used by researchers to address the problem of selection bias (Heckman and Robb, 1985; Imbens and Angrist 1994, Ravallion and Wodon 2000; and Dontsop Nguezet et al., 2011). This technique is most appropriate when a predictor variable that is correlated with the treatment variable but not with the outcome variable in a discrete choice model can be identified. The major limitation of this approach rests in finding an appropriate instrument (Blundell and Costa Dias, 2000; and Heckman et al., 1997).

2.4.1 Propensity Score Matching

According to Ravallion (2005), participation in poverty reducing programs is a non-random event; hence, matching is the most appropriate evaluation tool. To apply this tool, it is necessary to identify households with similar pretreatment characteristics and then create a statistical comparison group based on the probability of participating in irrigation agriculture. Rosenbaum and Rubin (1983) defined the propensity score as the conditional probability of receiving treatment given some pretreatment characteristics. The probability of participating in irrigation given pretreatment characteristics can be mathematically expressed as:

$$p(x) \equiv \text{pr}(d = 1|x) = E(d|x) \quad (1)$$

Where d= [0, 1] indicates exposure to treatment and x is a vector of pretreatment characteristics.

This model is estimated as a probit to take advantage of the binary nature of the dependent variable. The estimated probabilities called propensity scores are used to match participants with non-participants in an outcome model and the mean difference in outcomes of participants and non-participants known as the Average Treatment Effect (ATE) of irrigation is generated. This entails that if a household is randomly selected from a community, the (ATE) represents the effect of the intervention.

However, before matching can be successful, Rosenbaum and Rubin (1983), pointed out that the assumptions of conditional independence and common support have to be satisfied to makes matching on $p(x)$ as equally well as matching on x. Letting y_1 represent the outcome for participants and y_0 represent the outcome for non-participants, the conditional independence assumption can mathematically be expressed as:

$$(y_1, y_0\ ) \perp d_i|x_i \quad (2)$$

This implies that uptake of the program solely depends on observable characteristics (Khandker, Koolwal, and Samad, 2010). To estimate the treatment on the treated (TOT) or otherwise called Average Treatment on the Treated (ATT) unlike ATE, a weaker assumption is specified as follows:

$$y_0 \perp d_i|x_i \quad (3)$$

The ATT would be estimated as the mean effect of irrigation on a subpopulation of irrigators, and define mathematically as:

$$E(y_1 - y_0)|d = 1 \quad (4)$$

Khandker, Koolwal and Samad, (2010) pointed out that the conditional independence assumption is not directly testable but depends on the features of the intervention itself in terms of the design. If unobservable characteristics influence participation, this assumption is violated and PSM fails to be an estimation technique; hence other methods are employed i.e. Instrumental Variable and Double Difference methods.

The second assumption in PSM is that of common support which is basically used to determine the degree of overlap i.e. $0 < p(d_i = 1|x_i) < 1$. It states that treatment observations have comparable observations nearby in the propensity score distribution (Heckman, Lalonde and Smith, 1999).

If the two above assumptions hold, PSM estimates for ATT can be estimated as the mean difference in outcomes over common support, based on propensity scores:

$$ATT = E_{p(x)|d=1}\{E[y_1|d = 1,\ p(x)] - [y_0|d = 0,\ p(x)]\} \quad (5)$$

Since cross-sectional data was used, ATT can explicitly be specified as;

$$ATT_{PSM} = \frac{1}{N_d}\left[\sum_{i \in d} y_{i1} - \sum \omega(i,j) y_{i0}\right] \quad (6)$$

Where N_d is the number of participants i and $\omega(i,j)$ is the weight for aggregating outcomes for matched non-participants j. It should be noted that agricultural data in IHS3 contains cases of farmers who did irrigation during the rainy season (rainy season module) and cases of farmers who did irrigation during the dry season (dry season-dimba[1] module). The majority of these cases were found in the dry season module. As such, a variable called "Treatment" was generated with a value of 1 for all farmers participating in irrigation in either season, or 0 otherwise.

Poverty was estimated as poverty incidence, ultra-poverty, poverty gap, and/or poverty severity. Estimates of poverty used the national poverty line and ultra-poverty lines provided by NSO. IHS3 used 2010 national poverty line of MK37, 002.00 per person per annum for poverty figures and MK22, 956.00 per person per annum for ultra-poverty figures. This was equivalent to USD 1.25 at the purchasing power parity rate.

Having estimated impacts on poverty; crop productivity, crop income, and food security impacts were also analyzed to support poverty analysis results since these variables directly influence poverty outcomes of households.

Food security impact of irrigation was analyzed taking food security as a binary outcome variable with the value of 1 if a household is food secure and 0 otherwise. The Food Security Continuum was used to measure household food security situation. As MacRae et al. (1990), McCullum et al. (2005), and Kalina (2001) pointed out, the continuum has six levels for categorizing food security situation. The first is "adequate intake with

[1]A dimba is a piece of land use for winter/dry season cultivation in areas boarding streams and rivers for their residual moisture (Peters, 1996 and Kambewa, 2005).

sustainable future supply of food"; the second, "adequate intake but worry about future food supply"; the third, "sub-adequate intake –hidden hunger"; the fourth, "chronic hunger"; the fifth, "acute hunger"; and the sixth, "starvation/famine". It further describes food secure households as those that do not worry about what they will eat tomorrow and in the future. Those households that are food secure were given a value of 1 and those that are food insecure were given a value of 0.

Propensity Score Matching has a number of advantages. Firstly, when comparing outcomes for individuals who are not comparable, it addresses the problem of selection bias. This results in perfect estimation of the effect of treatment on the outcome variable. Ravallion (2005) added that the model allows for estimation of mean impacts without arbitrary assumptions about functional forms and error term distribution. Secondly, matching approximates randomization by balancing observable characteristics and determining the appropriate control group given that pretreatment characteristics are in place (Becker and Ichino, 2002). Thirdly, Ravallion (2005) noted that while regression models use full sample techniques, PSM does estimation on matched samples only (i.e. those under region of common support). Therefore, PSM produces robust results than those based on unmatched samples. Nonetheless, the approach has limitations in that it relies on an untestable hypothesis that unobservable characteristics do not affect treatment participation. Khandker, Koolwal and Samad (2010), Hickman, Firsin, & Monnard (undated) pointed out that PSM on its own is a useful technique when there is belief that only observable characteristics affect participation in an intervention. However, if there are unobservable factors influencing participation, estimates may be biased. It also requires a large set of untreated individuals for common support to be met. Furthermore, Imben and Woodrigde (2007); and Khandker, Koolwal and Samad (2010) pointed out that PSM fails to deal with the problem of selection on unobservable factors. This problem can be handled by employing a double difference (DD) technique.

2.4.2 Difference-in Differences

Difference-in-differences analysis was also employed to compare outcomes for each of the outcome equations of poverty, crop productivity, crop income, and food security. The double difference technique is best applied when there is panel data (Khandker, Koolwal and Samad, 2010). However, in the absence of panel data, cross-section data can be used by comparing targeted and non-targeted areas.

This study followed the approach laid down by Khandker, Koolwal and Samad (2010) in the estimation of double difference. A dummy variable called "target" was created for farmers eligible to participate in small-scale irrigation programs in the country. The criterion was that farmers must be holding at most 2ha of land to participate in the programs. Then, another dummy variable called "reside" was created with all households living in rural areas taking the value of 1 and 0 otherwise. Then a variable called "program target" was generated, which was a multiple of "target" and "reside". This variable was included in the outcome equations to determine if the program target variable had an influence on the outcomes of interest. From this, observable and unobservable characteristics affecting program participation can be accounted for assuming that unobservable characteristics are constant across the two areas. To do this, a fixed effects regression model was employed to remove unobservable selection bias and improve robustness of the results as given in the equation below.

$$Y_i = \beta_0 + \beta_i X_i + \varepsilon_i \tag{7}$$

Where Y_i is the dependent variable, X_i is a vector of explanatory variables, β_0 is the constant term, β_i is a vector of parameter estimates, and ε_i is the stochastic noise.

3. Results

3.1 Household Demographic and Social Economic Characteristics

This section presents household demographic and social economic characteristics. This is done to provide a basis for explaining some of the findings of this study. Table 3 provides descriptive statistics of all important variables used in the study.

Table 3: Descriptive statistics

Variable	**All**	**Irrigating Households**	**Non-irrigating households**	
	Mean or proportion			**p-value**
Household size	4.7 (0.02)	5.1 (0.06)	4.6 (0.02)	1.0000
Household head age	43.1 (0.2)	41.6 (0.4)	43.4 (0.2)	0.0003
Household head gender	0.75 (0.4)	0.82 (0.4)	0.74 (0.4)	0.0000
Prop of household heads with primary education.	10.0 (0.003)	11.7 (0.009)	9.8 (0.003)	0.0158
Total cultivated land size (ha)	0.4 (0.003)	0.5 (0.02)	0.4 (0.003)	0.0000
Real expenditure per capita (MK)	47,170.18 (405.86)	47,964.50 (1078.77)	47057.32 (437.46)	0.7696
Poverty Incidence	50.8 (0.5)	45.9 (1.5)	51.5 (0.5)	0.0020
Ultra-poverty	23.1 (0.4)	18.7 (1.1)	23.7 (0.5)	0.0001
Poverty gap	18.1 (0.2)	15.1 (0.6)	18.6 (0.3)	0.0000
Poverty severity	8.6 (1.1)	6.9 (0.4)	8.9 (0.2)	0.0000
Crop productivity	1,444.4 (28.5)	1,823.25 (147.5)	1,421.8 (28.8)	0.0006
Maize Crop income (MK)	17,736.58 (1823.87)	17,188.11 (600.65)	17814.05 (656.59)	0.6346
Food security situation	1.65 (0.005)	1.71 (0.013)	1.64 (0.005)	0.0000
Access to extension advisory services	0.04 (0.002)	0.03 (0.009)	0.04 (0.003)	0.8570
Observations	9437	1175	8262	

Note: Standard errors in parentheses.

The study showed that there were statistically significant differences between participant and non-participant households in terms of household head age, household gender, proportion of household heads with primary education, and total land cultivated. The mean age of irrigating households was found to be significantly lower than that of non-irrigating households. Small-scale irrigation tends to be more labor intensive hence older households heads have less propensity to engage in irrigation than younger household heads. The study also found a higher proportion of male headed households participating in irrigation relative to female headed households. Additionally, most irrigating farmers had attained primary education as compared with non-irrigating farmers. In terms of cultivated land sizes, irrigating farmers were found to have statistically significant bigger land sizes of 0.5 hectares as compared to non-irrigating farmers whose land sizes were estimated at 0.4 hectares. There were also statistically significant differences between irrigating and non-irrigating farmers in terms of poverty incidence, ultra-poverty, poverty gap, and poverty severity. However, the rates of poverty were observably high even though there were statistically significantly different. Finally, there were statistically significant differences between participant and non-participant farmers in terms of crop productivity, and food security situation with irrigating farmers' maize crop productivities and food security situations estimated at 1.8 tons per hectare and 71% respectively as compared to 1.4 tons per hectare and 64% for non-irrigating farmers respectively.

3.2 Impact of Irrigation on Poverty

The model for estimating poverty impacts of irrigation was employed. In the first stage, a Probit model was used to determine factors that influence participation of smallholder farmers in irrigation. In this study, factors that may have a strong influence over the participation decision were included in the model. Table 4 shows Probit model estimates of determinants of participation in irrigation.

Table 4: Determinants of Participation in Irrigation

Probit regression			**Number of obs**		=	**9218**
			LR chi2(17)		=	474.28
			Prob > chi2		=	0.0000
Log likelihood = -3258.7246			Pseudo R2		=	0.0678
Treatment	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Adulteq	-0.06478	0.053442	-1.21	0.225	-0.169527	0.0399611
Hhsize	0.077965	0.044249	1.76	0.078	-0.008761	0.1646901
head_age	-0.00439	0.001303	-3.37	0.001	-0.006948	-0.0018401
Head_age^2	-0.000018	0.000069	-0.27	0.788	-0.00015	0.000116
head_gender	0.145847	0.044699	3.26	0.001	0.058239	0.2334557
head_edlevel						
Primary	0.057234	0.057834	0.99	0.322	-0.056118	0.1705859
Secondary	-0.10034	0.059327	-1.69	0.091	-0.216621	0.0159358
Tertiary	-0.3957	0.219076	-1.81	0.071	-0.825078	0.0336842
Access_to_Ext	0.035701	0.040108	0.89	0.373	-0.04291	0.114312
Total_land_planted	1.026788	0.056256	18.25	0.000	0.916529	1.137048
soil_type						
Btwn sandy & clay	0.036402	0.047076	0.77	0.439	-0.055866	0.128669
Clay	0.051429	0.058044	0.89	0.376	-0.062335	0.1651927
Other	0.249711	0.09533	2.62	0.009	0.062867	0.4365539
soil_quality						
Fair	-0.0921	0.037384	-2.46	0.014	-0.165367	-0.018826
Poor	-0.07315	0.059122	-1.24	0.216	-0.189022	0.0427311
wet_land	0.054217	0.050611	1.07	0.284	-0.04498	0.1534131
TotalLabor	0.000193	2.57E-05	7.51	0.000	0.000143	0.0002438
Rexpaggcap	1.07E-06	4.91E-07	2.17	0.030	1.04E-07	2.03E-06
_cons	-1.59315	0.131806	-12.09	0.000	-1.851481	-1.33481

The study revealed that variables that positively and significantly influence the decision to participate in irrigation agriculture among smallholder farmers include size of their households, the gender of the household head, and total land available for cultivation, other soil types apart from sandy clay and clay soils, total amount of labor available for cultivation, and per capita expenditure (proxy for income). The study also found that attainment of primary education, access to extension advisory services, soils of between sandy and clay, and clay soils, and whether farms are in a wetland have positive but statistically insignificant influence on the decision to undertake irrigation agriculture. This study found that household heads who have primary education are more likely to engage in irrigation agriculture. However, as the level of education goes up, the household heads tend to move away from small scale irrigation. Additionally, the study found as household heads grow older, they become less likely to participate in irrigation agriculture. This can be explained by the fact that small-scale irrigation is more labor intensive. The study also found that fair and poor soils are a disincentive for farmers to engage in irrigation agriculture. This implies that farmers need good soils for them to engage in irrigation.

Having estimated the determinant of participation in irrigation, various matching algorithms were employed to find the method that would best match treated and control groups for estimation of ATT and ATE. These included, Nearest Neighbor Matching (NNM), Kernel Based Matching (KBM), Mahalanobis Matching and Local Linear Regression Matching (LLRM). In each matching algorithm, variables were tested for balancing. A balancing test determines the success of matching for exogenous variables. It tests the hypothesis that the mean value of each variable is the same for treated and control groups and this is done before and after matching. For each variable, balancing takes place when the difference between the treated and control group is not statically significant. This results in failure to reject the null hypothesis. Additionally, the algorithm produce overall balancing test. For the sake of brevity, results of overall model balancing tests have been presented in table 5.

Table 5: Balancing tests for various matching algorithms

	Sample	Ps R2	LR chi2	p>chi2	MeanBias	%Bias	%Reduct	%Variation
NNM	Unmatched	0.073	510.9	0.000	11.6	73.2*	1.46	57
	Matched	0.009	27.39	0.053	4.9	21.7	0.87	43
KBM	Unmatched	0.068	474.28	0.000	11.5	70.8*	1.43	57
	Matched	0.005	16.23	0.508	2.5	16.8	0.73	29
Mahal	Unmatched	0.073	510.9	0.000	11.6	73.2*	1.46	57
	Matched	0.022	71.9	0.000	4.7	35.0*	1.26	57
LLR	Unmatched	0.077	537.15	0.000	11.4	75.0*	1.48	57
	Matched	0.008	25.34	0.087	4.5	21	0.93	43

*if B>25%, R outside [0.5; 2]

The best matching algorithm was selected based on the quality of match produced. Of these, kernel based matching method provided the best match as it can be seen from table 5 above that the mean values were not statistically significantly different between matched treated and control groups at 90% confidence level. In addition, the matching technique provided the least percentage of bias after matching as compared to other matching techniques.

Before invoking PSM, it was imperative to test for common support. This was done before and after matching. The study tested for overlap of propensity scores between treated and control groups before and after matching. Figures 2 and 3 below show the results.

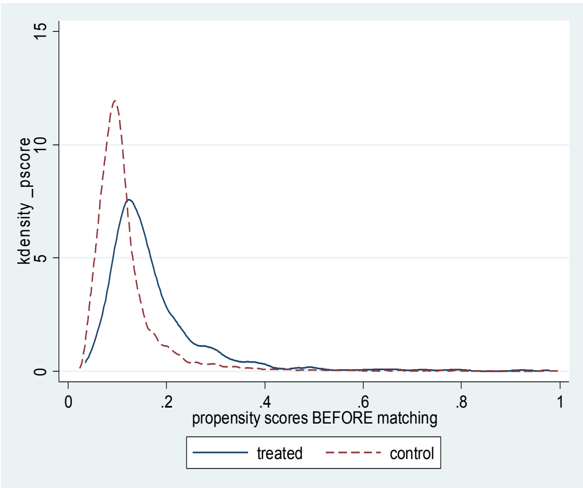

Figure 2: PSM kdensity before matching

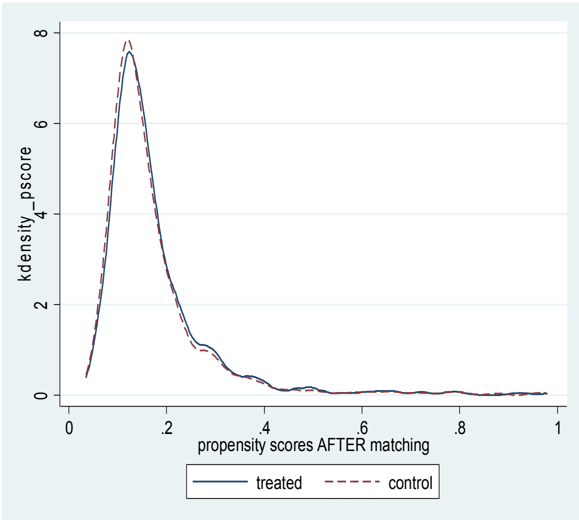

Figure3: PSM kdensity after matching

Figure 2 and Figure 3 above show that there was sufficient overlap between treated and control groups after matching. The study went further to check for observation in the region of common support. Where observations were failing outside common support region, they were dropped and the model re-estimated. Of all the matching techniques, LLRM produced observations that were off common support even after drop observations a number of times. NNM, KM and Mahalanobis matching produced observations within the common support region.

Table 6: Common support

Treatment	**NNM**	**KBM**	**Mahalanobis**	**LLRM**		
Assignment	On support	On support	On support	Off support	On support	Total
Untreated	8,045	8,054	8,045	5	8,002	8,007
Treated	1,162	1,164	1,162	1	1,160	1,161
Total	9,207	9,218	9,207	6	9,162	9,168

Since matching was successful, Propensity Score Matching was employed to estimate the impact of irrigation on poverty. The means values for treated and control groups for each of poverty incidence, ultra-poverty, poverty gap, and poverty severity were tested for significant differences. This was testing the hypothesis that irrigating farmers were poorer than non-irrigating farmers. Table 7 shows the ATT and ATE of irrigation on poverty.

Table 7: ATT and ATE Estimates for Poverty Measures

		NN			**Kernel**		
Variable	Sample	Treated	Controls	Difference	Treated	Controls	Difference
Poor	ATT	45.95525	52.4957	-6.54045**	45.87629	52.33294	-6.45665**
	ATE			-6.08233			-6.39292
ultra_poor	ATT	18.76076	25.7315	-6.97074***	18.72852	24.72817	-5.99965***
	ATE			-6.44075			-6.22885
gap_poor	ATT	15.16504	19.62765	-4.46261***	15.13898	19.24137	-4.10239***
	ATE			-3.69323			-3.98171
gap2_poor	ATT	6.912348	9.683192	-2.77084***	6.900472	9.369485	-2.46901***
	ATE			-2.18886			-2.37069
		Mahal			**LLR**		
Variable	**Sample**	**Treated**	**Controls**	**Difference**	**Treated**	**Controls**	**Difference**
Poor	ATT	45.95525	50.34423	-4.38898**	45.81536	51.92032	-6.10496**
	ATE			-5.21342			-5.32048
ultra_poor	ATT	18.76076	21.42857	-2.66781***	18.72304	24.74261	-6.01957
	ATE			-5.88683			-6.0245
gap_poor	ATT	15.16504	17.55156	-2.38652***	15.11539	19.2008	-4.08541***
	ATE			-3.53853			-3.67514
gap2_poor	ATT	6.912348	8.268428	-1.35608***	6.895379	9.396444	-2.50107***
	ATE			-2.16712			-2.16168

Source: Authors' own analysis of IHS3 dataset

The study used four matching estimators to check consistency of PSM results. All matching algorithms estimated poverty incidence at 46% for treated groups and at 52% for control groups. However, poverty incidence was estimated at 50% for the control group using Mahalanobis estimator. In the same line, ultra poverty was estimated at 18.8%, poverty gap at 15.1%, and poverty severity at 6.9 percent in all estimators for the treated group. This shows consistent estimation of PSM. Furthermore, all matching estimators showed statistically significant differences in poverty measures between treated and control groups, implying that small-scale irrigation reduces poverty of participating households relative to non-participating households. However, it should be noted that poverty incidence among irrigating households is observably higher even though it is statistically less than that of non-irrigating households.

The following results interpretation has been based on Kernel based matching since it provided the best match. For the treated group, poverty incidence was estimated at 46% and at 52% for the control group. Thus, irrigation reduces the incidence of being poor by about 6.5 percent. Poverty incidence was estimated to reduce by about 4.5 percent for any randomly selected rural smallholder farmer. Furthermore, the study found that irrigation lowered the proportion of the ultra-poor within the treated group by 6 percent. In addition, poverty gap was estimated at 15.1% for the treated and at 19% for the control group. The estimate of poverty gap implies that it would take MWK28.31/day (poverty gap multiplied by poverty line[1]-MWK187.50/day) per capita to eliminate poverty within irrigating farmers and MWK35.63/day per capita to eliminate poverty within non-irrigating farmers. This would translate to MK10, 333.15 per capita per annum for irrigating farmers and MWK13, 004.95 per capita per annum for non-irrigating farmers. Results of this study also show that participation in irrigation agriculture has a positive impact on poverty severity of rural households. For the treated group, irrigation reduces poverty severity by about 2.5 percent.

To further strengthen these findings and take care of unobserved heterogeneity, a double difference technique was employed to compare poverty status between program target and non-target groups as specified in the analytical section. Table A-1 in the appendix shows fixed effects estimates of poverty severity. The major interest in the model is the sign of the "program target" variable. Even though it was not significant, results of the study show a negative program target coefficient implying that the targeted population had less cases of extreme poverty as compared to non-targeted population. It can, therefore, be concluded that irrigation agriculture helped to reduce cases of extreme poverty in among irrigating households as compared to non-irrigating households in Malawi within the study period.

These findings prompted the need to analyze other poverty related variables including crop productivity, crop income, and food security situation of households under study. In the subsequent sections, similar analytical approaches to what has been presented in the foregoing section were applied.

[1]Poverty line estimated at US$1.25/day = MK187.5/day. Exchange rate at MK150/US$ between March 2010 and March 2011.

3.3 Impact of Irrigation on Crop Productivity

Crop productivity was defined as maize yield per hectare (Kg/ha). The analysis was based on plot level data. This was done to account for the dynamics of production at plot level. For this analysis, maize was selected because of its dominance in the production systems of smallholder irrigation farmers. To empirically assess the impact of irrigation on crop productivity, PSM was employed taking maize crop productivity as the outcome variable. Similarly, various matching methods were employed to find the method that best matched treated and control groups. The selection criteria was based on balancing tests about the mean for treated and control groups. Common support and balancing tests have been presented in appendix table A2 and A3. Suffice to say that matching went on well and that common support was satisfied. Of all matching methods, Mahalanobis matching technique produced the less amount of bias after matching. After this, ATT and ATE were estimated using PSM and mean difference in ATT between the treated and control group was estimated. Table 8 below shows the results.

Table 8: ATT and ATE of Irrigation on Maize Productivity

	Sample	Treated	Controls	Difference	S.E.	T-stat
NNM	ATT	1806.035	1423.046	382.9889*	201.856	1.9
	ATE			726.2296	.	.
KBM	ATT	1806.035	1357.362	448.6731**	150.7848	2.98
	ATE			536.345	.	.
Mahalanobis	ATT	1788.321	1555.853	232.4681*	197.374	1.18
	ATE			385.5864	.	.
LLR	ATT	1809.655	1306.716	502.9393**	204.0493	2.46
	ATE			640.9192	.	.
Observations		3029	181			

**=significant at 95%, *=significant at 90%.

Tests were conducted on the difference in mean maize productivity of irrigating and non-irrigating households. The study found that irrigating households had statistically and significantly higher mean maize productivities than non-irrigating farmers. The mean maize productivity was estimated at 1.8 tons per hectare for the treated group using NNM, KBM and LLRM. However, since Mahalanobis matching produced provided the best match, its results can be relied upon for interpretation. Results of the study show that irrigation raises mean maize productivity of participant farmers by about 232kg/ha as compared to non-participant farmers. Furthermore, for any randomly selected farmer in a community, irrigation would raise the mean maize productivity about 385kg/ha.

A double difference fixed effects model was run to compare maize crop productivity between targeted and non-targeted groups to provide more robust results. Table A-1 shows fixed effects estimates of crop productivity. The study shows that the targeted population had higher mean maize crop productivity as compared to non-targeted population at 90% level of significance. It can therefore be concluded that crop productivity was higher within irrigating farmers as compared to non-irrigating farmers. In conclusion, the null hypothesis that crop productivity of irrigating famers was less than that of non-irrigating farmers is rejected in support of the alternate hypothesis that irrigating farmers had a statistically significantly higher mean maize productivity as compared to non-irrigating famers.

3.4 Impact of Irrigation on Crop Income

The third part of the analysis looked at the impact of irrigated agriculture on crop income. The analysis on crop income was based on plot level maize data because deferent crops have different cost outlays. Crop income was calculated as gross margin (the difference in revenue and variable costs of production). Variable costs included the cost of renting a piece of land for cultivation, cost of buying inputs like fertilizer, chemicals, seeds, cost of transporting inputs from source to the farm, and cost of labor for farm activities. This was done for rain fed and irrigated maize. However, it should be noted that some costs which are specific to irrigation including cost of drawing water, cost of maintaining irrigation systems were not captured in the dataset. As such, the estimates of crop income may be biased. However, the estimated crop income gives a picture of how gross margins for maize are in Malawi.

Various matching algorithms were employed to match treated and control groups. As in other models above, the best matching techniques was selected based on the quality of match produced. Table A4 as well as figures A1 and A2 in the appendix show regions of common support before and after matching. It can be seen that there was sufficient overlap between treated and control group in terms of their propensity scores. Balancing tests for means in the various matching techniques were also employed. Table A5 in the appendix shows that Mahalanobis matching method produced the best match as seen by an insignificant after match p-value and the least bias. Thereafter, PSM was used to estimate ATT and ATE. Table 9 shows the ATT, and ATE of participation in irrigated agriculture on maize crop income.

Table 9: ATT and ATE of Irrigation on Maize Crop Income

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
NNM	ATT	11204.76	10423.78	780.9878	1452.474	0.54
	ATE			1462.292	.	.
KBM	ATT	11204.76	10344.73	860.0325	1208.073	0.71
	ATE			562.0714	.	.
Mahalanobis	ATT	10907.88	9389.448	1518.432	797.5656	1.9
	ATE			1958.783	.	.
LLRM	ATT	11268.92	10228.55	1040.364	1471.141	0.71
	ATE			937.9458	.	.

Table 9 above shows consistent, maize crop income of about MWK 11, 000.00 per plot per season for irrigating farmers and about MWK10, 000.00 per plot per season for non-irrigating farmers. The mean difference in ATT between treated and control groups was tested and it was found that irrigating farmers do not have statistically significantly higher mean maize crop income as compared to non-irrigating farmers. However, since Mahalanobis matching produced the best match, its results are relied upon. The mean maize crop income for irrigating farmers was estimated at MWK10, 907.88 per plot per season and that of non-irrigating farmers was estimated at MWK 9389.45 per plot per season. If any farmer would be selected at random, the study found that their maize crop income would increase by MWK3, 573.64 per plot per season. The lack of statistical significance may arise because of a biased variable cost component of gross margin analysis arising from absence of other variables that add to cost of production including cost of obtaining water for irrigation, value of family labor employed in farm production, and cost of maintaining irrigation systems. Secondly, most smallholder farmers are subsistence oriented to the extent that very little maize is offloaded to the market. As such, the impacts on maize crop income may not be significant.

In addition to the above, a fixed effect model of the double difference was employed to provide more proof on the results as shown in table A-1 in the appendix. A positive and significant coefficient of the program target variable was observed. This implies that the targeted population had higher maize crop income as compared to the non-targeted population. The main explanation rests in the fact that green maize is more lucrative than dry maize. People buy more green maize in the dry season because it is in high demand at that time than in the rainy season when most households can harvest from their own gardens. So, it can be concluded that participation in irrigated agriculture improves crop income even though PSM results did not show statistically significant differences in mean maize incomes.

3.5 Impact of Irrigation on Food Security

The food security outcome of households was analyzed in line with the Food Security Continuum. Matching algorithm was employed to estimate the mean difference in food security outcomes of irrigating and non-irrigating farmers. Kernel based matching technique produced better estimates as compared to other matching techniques as confirmed by balancing tests and region of common support shown in appendix tables A4 and A5. Kernel based matching showed that there were no significant different in variables after matching implying that matching was successful. In addition, it gave the least percentage of bias as compared to other matching techniques. It also showed that there was sufficient overlap between treated and control groups after matching. PSM was then employed to estimate the impact of irrigation on food security outcomes of households. Table 10 shows ATT and ATE for the food security outcome.

Table 10: ATT and ATE of Food Security Outcome

Food security	**Sample**	**Treated**	**Controls**	**Difference**	**S.E.**	**T-stat**
NNM	ATT	1.714286	1.666954	0.047332**	0.020943	2.26
	ATE			0.039101	.	.
KBM	ATT	1.714286	1.668209	0.046076**	0.014792	3.12
	ATE			0.054078	.	.
Mahalanobis	ATT	1.714286	1.669535	0.04475**	0.020335	2.2
	ATE			0.042033**	.	.
LLR	ATT	1.714655	1.674069	0.040586**	0.020957	1.94
	ATE			0.037762	.	.
Observations		1162	8045			

**=significant at 95%,

The mean difference in ATT between treated and controls group was tested and it was found that irrigating farmers had statistically significantly higher food security outcomes as compared to non-irrigating farmers. The mean food security situation of irrigating farmers was estimated at 71% and that of non-irrigating farmers was estimated at 67%. Furthermore, the study shows that the food security outcome of any randomly selected household in a community was positive implying that irrigation benefits the larger community than merely benefiting individual participating farmers.

Results presented above were based on a seven days recall period. However, almost equal proportions of households from both groups reported experiencing food shortages within a 12 months recall period (p-value=0.3460).

Table11: Proportion of Households Reporting Food Shortages within 12 Months Recall Period

Treatment	Food secure	Food insecure	Total
Untreated	52.5	47.5	100
Treated	53.9	46.1	100
Pooled	**52.7**	**47.3**	**100**

Thus, even in the presence of irrigation farming, there were some households who still faced the problem of food insecurity. A probable explanation would be found in the land holding sizes for irrigation. Most farmers in Malawi hold on average 0.5 hectares of land under irrigation. This is very small to produce enough food and effectively hedge against food insecurity. The Ministry of Agriculture, Irrigation and Food Security (GoM, 2011) estimated that an average Malawian household with five members would require about 1.5 hectares of cultivated land to maintain subsistence levels of food consumption in a year.

A double difference method was also employed to compare food security outcomes between targeted and non-targeted populations. A fixed effects logistic model, to take advantage of the binary nature of the dependent variable, yielded a significant overall model. Food security outcomes of targeted and non-targeted population indicated that the targeted population was more food secure as compared to the untargeted population. It is evident from this that irrigation agriculture improved the food security situation of participating farmers.

4. Discussion

This study reveals that the variables age and education level of household head have negative influence on the decision participate in irrigation. The coefficient on the age variable implies that as household heads grow older, they have a disincentive to participate in irrigation. This can be explained by the fact that small scale irrigation agriculture is more labor intensive than rain-fed agriculture. The coefficient on the education variable implies that as household heads become more educated, they tend to move away from smallholder irrigation. This could be because of the high income earning potential that education brings about. The coefficient on the gender variable implies that male headed households have an incentive to participate in irrigation relative to female headed households. This result is consistent with findings of Nkhata, (2014) in which it was also found that male headed households had a higher likelihood of participating in irrigation as compared to female headed households. This difference can be explained by gender based roles to which each group is exposed during child development stages.

Estimates of poverty imply that irrigation farming has a positive impact on poverty incidence, ultra-poverty, poverty gap, and poverty severity. Furthermore, the NSO, (2010) estimated poverty incidence and ultra-poverty in rural Malawi at 56.6% and 28.1% respectively. It also estimated poverty gap at 21.4% and poverty severity at 10.6%. In addition, Mangisoni, (2008) estimated the average poverty incidence at 39% for treadle pump adopters and at 61% for non-adopters, poverty gap at 16.8% for adopter and 38.6% for non-adopters, and poverty severity at 9.5 percent for adopters and 22.2% for non-adopters. This implies that treadle pump irrigation reduced the incidence of being poor by 22%, poverty gap by 21.8% and poverty severity by 12.7%. Mangisoni's,

(2008) study shows huge impacts of irrigation on poverty reduction. The current study shows that irrigating farmers are statistically and significantly less poor than non-irrigating farmers. It has to be noted, however, first that statistical significance does not imply program significance (Edriss, 2013). Even though there are noticeable differences in poverty levels between irrigating and non-irrigating smallholder farmers in rural Malawi (statistical significance), the impact is not huge enough to be counted worthy of the resources committed to irrigation. 45% poverty incidence is still high relative to the resources that have been put into irrigation agriculture. Secondly, the difference in poverty of irrigators and non-irrigators is not as huge as is proposed by Mangisoni, (2008). This explains why literature shows that poverty is still rampant in Malawi. Thus, if Malawi is to significantly reduce poverty levels among smallholder irrigation farmers, then more has to be done beyond the conventional practice.

In terms of crop productivity, Nkhata, (2014) found that irrigating farmers produced a mean of 1050kg/ha of maize while non-irrigating farmers produced a mean of 1514.4kg/ha of the same crop. This implies that irrigating farmers' crop productivities were slightly lower than those of non-irrigating famers. This result may not be surprising because the comparison was made between dry season cultivators (participant) and rainy season cultivators (non-participant). In general, one would expect rainy season cultivation in Malawi to be more productive as compared to dry season cultivation because of abundance of moisture during the rainy season and the availability of subsidized fertilizer. The current study found a similar scenario in that when maize productivity was analyzed based on the season of cultivation; rainy season cultivation had higher productivity as compared to dry season cultivation. However, when the comparison was based on participation status regardless of the season of cultivation, irrigating farmer's maize productivities were significantly higher than those of non-irrigating farmers.

The current study also found that participation in irrigated agriculture positively, though not statistically significantly, improved crop income. These findings hold with the findings of Oxfam (2011) and IFRC (2012) which reported that irrigation improves crop income as was observed by the ability of farmers to build new houses, pay medical expenses and school fees. However, Mangisoni (2008) and Nkhata (2014) found positive and significant improvement of net farm incomes for irrigating households as compared to non-irrigating households. Mangisoni (2008) found mean farm incomes of MWK7, 137.69 for irrigators and MWK10, 697.33 for non-irrigators in Blantyre district, and MWK24, 366.47 for irrigators and MWK6, 090.04 for non-irrigators in Mchinji district. Meanwhile, Nkhata (2014) estimated maize and rise crop incomes at MWK 114,438 for the treated group and MWK 22,990 for the control group. These results are different from result of the current study because they considered more than crop in the analysis

Lastly, this study established a statistically significant impact of irrigating on food security outcomes of irrigation farmers as compared to non-irrigating farmers. In line with this finding, Mangisoni (2008) found that 91% of treadle pump adopters were food secure in Blantyre and Mchinji districts. However, the impact established in the current study is not profound enough because, as the study has shown, both groups experienced food shortages in the months of January and February. These finding agree with the finding of Ferguson and Mulwafu (2005) who noted that even though irrigation famers are not among the poorest in Malawi, many of them remain vulnerable and face hunger between the month of January and March.

5. Conclusion

This study provides insights into the impact of small-scale irrigation initiatives on poverty reduction in rural Malawi. Using various methods, this study has provided ample evidence that irrigation has positive and significant impacts on poverty reduction, crop productivity, and food security of participating households. However, the impact on crop income is not statistically significant even though is it positive. Furthermore, the impact on poverty reduction is not huge enough even though it is statistically significant. This implies that small scale irrigation improves crop productivity, crop income and food security but this translates into minimal poverty reduction.

6. Policy implications

The following policy implications were made from the findings of this study.

1) There is need to encourage farmers to participate in irrigation agriculture because this study has found small scale irrigation to be poverty reducing, crop productivity enhancing, crop income raising, and has the potential to improve food security.
2) The Government should consider establishing large scale irrigation schemes along the lakes and big rivers where water is abundantly available. The study has found that small-scale irrigation initiatives are not very effective in reducing poverty, even though they increase crop productivity, crop income, and food security. If there is to be significant improvements in all the variables of interest under this study, the way to go is commercial farming in large scale irrigation schemes. This should be coupled with the creation of infrastructure in transport and communication to aid distribution and marketing of the crops

to be produced. Such a system would make sure that all Malawians have access to safe and sufficient food all year round.

3) Even though the study found significant food security impact of irrigation, there were still pockets of irrigating farmers who faced food insecurity problems. To sufficiently improve food security, there is need to increase cultivable area under irrigation. The average 0.5 ha has been deemed inadequate to meet food security needs of households. The other way round is to increase the number of times crops are grown in a year up to the level that meets household food requirements.
4) There is need to conduct a similar study using panel data so that changes can be observed over time. The current study failed to utilize panel data because it was unavailable at the time of the study.

Acknowledgements
We would also like to thank the African Economic Research Consortium (AERC) for funding part of studies at Bunda and University of Pretoria. Many thanks to the Food and Agricultural Organization of the United Nations and the Natural Resources Department at Bunda College for funding to complete the study.

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Journal of Economics and Sustainable Development
ISSN 2222-1700 (Paper) ISSN 2222-2855 (Online)
Vol.8, No.4, 2017

Appendix

Table A-1 : Fixed Effect Estimates of Poverty Severity, Crop Productivity,Crop Income, and Food Security between Targeted and Non-Targeted Populations

Poverty Severity		*Crop Productivity*	*Crop Income*	*Food Security*
Group variable: urban		Group variable: urban	Group variable: urban	Group variable: urban
R-sq: within	= 0.6237	R-sq: within = 0.0112	R-sq:wi thin = 0.0085	R-sq: overall = 0.0246
Number of obs.	9918	Number of obs = 2329	Number of obs =	Number of obs = 7205
Prob > F=	0.0000	Prob > F = 0.0035	Prob > F =0.0001	Prob > F =0.0000
gap2_poor	**Coeficient**	**lnYieldperHectare**	**TotalMaizeRev**	**FoodSecurity**
Progtarget	-2.446569	0.791048*	2125.29***	0.184432***
	6.146526	-0.464119	876.9178	0.055872
Hhsize	(-0.4543367)***	-0.0068		0.007103***
	0.1608396	-0.019282		0.002309
head_age	(-0.0353604)*	0.001044	(-12.7672)***	(-0.00068)***
	0.0198305	-0.002621	4.805245	0.000331
head_gender	-0.7320837	0.037216	(-323.536)*	0.092021***
	1.034444	-0.102683	183.3596	0.012984
head_edlevel	0.6030128	0.197259***	58.97603	(-0.04157)***
	0.4560483	-0.05639	103.6952	0.007154
head_marital	(2.264056)***			
	0.6099757			
Lnrexpaggcap	(-57.43463)***			
	0.5210273			
TotalLandPlanted		0.029547	(729.5935)***	
		-0.132082	252.5665	
TotalSeedplanted		-9.10E-08	0.271351	
		-2.47E-07	2.828581	
TotalLabor		0.000124	0.566616	
		-8.15E-05	1.96526	
TotalOrgFertApplied		3.13E-05		
		-3.79E-05		
TotalFert			1.883872***	
			0.94988	
AccesstoExt		0.257251***		
		-0.099326		
MaizeProductivity				(-0.000025)***
				3.92E-06
Constant	(654.7174)***	3.806208***	-948.367	0.054358
	8.281891	-0.486324	924.515	0.058819
F test that all u_i=0:		F test that all u_i=0:	F test that all u_i=0:	F test that all u_i=0:
F(1, 9909) =	0.33	F(1, 2317) = 11.07	F(1, 3691) =	F(1, 7197) = 3.06
Prob > F = 0.5666		Prob > F = 0.0009	Prob >F =0.1391	Prob > F = 0.0803

Table A2: Common Support for crop productivity outcome

Common	**NNM**	**KBM**	**Mahalanobis**		**LLR**		
Support	On support	On support	Off support	On support	Off support	On support	Total
Untreated	3,029	3,033	12	2,976	12	2,976	2,988
Treated	181	183	1	179	1	179	180
Total	3,210	3,216	13	3,155	13	3,155	3,168

Table A3: Balancing tests for crop productivity outcome model

Algori Thm	**Sample**	**Ps R2**	**LR chi2**	**p>chi2**	**MeanBias**	**MedBias**	**%Bias**	**%Reduction**	**%Var**
NNM	Unmatched	0.074	103.04	0.000	14.5	12.4	77.7*	1.14	38
	Matched	0.029	14.61	0.553	6.8	6	40.3*	0.72	25
KBM	Unmatched	0.07	97.67	0.000	14.3	12.2	76.3*	1.09	38
	Matched	0.026	12.98	0.738	7.9	7.5	37.7*	0.71	25
Mahal	Unmatched	0.074	104.51	0.000	14.9	13.2	74.6*	1.49	38
	Matched	0.016	8.15	0.963	3.3	1.3	29.3*	1.68	13
LLR	Unmatched	0.077	106.17	0.000	14.8	13.3	78.9*	1.21	38
	Matched	0.031	15.24	0.507	6.9	5.8	41.4*	0.72	13

*if B>25%, R outside [0.5; 2]

Table A4: Common support for crop income model

assignment	On support	On support	On support	On support	On support	Total
Untreated	1,517	1,517	3,111	0	1,487	1,487
Treated	144	144	449	2	142	144
Total	1,661	1,661	3,560	2	1,629	1,631

Table A5: Balancing tests for crop income model

	Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
NNM	Unmatched	0.047	45.14	0.000	11.2	7.1	45.4*	6.56*	33
	Matched	0.041	16.06	0.378	8.5	5.9	41.6*	6.08*	22
KBM	Unmatched	0.047	45.14	0.000	11.2	7.1	45.4*	6.56*	33
	Matched	0.044	17.39	0.296	9.8	5.8	42.7*	7.02*	22
Mahalanobis	Unmatched	0.022	58.96	0.000	6.6	3.4	39.2*	1.04	33
	Matched	0.023	29.14	0.033	3.4	1.3	28.9*	15.36*	11
LLRM	Unmatched	0.042	39.75	0.000	11	6.5	44.3*	5.20*	33
	Matched	0.037	14.17	0.513	8.8	5.1	40.1*	4.81*	22

*if B>25%, R outside [0.5; 2]

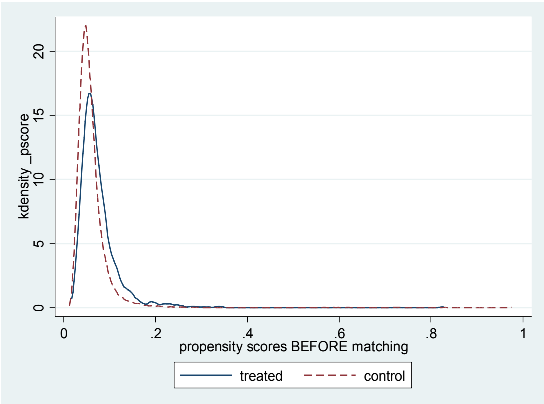

Figure A1: PSM kdensity before matching (Crop income)

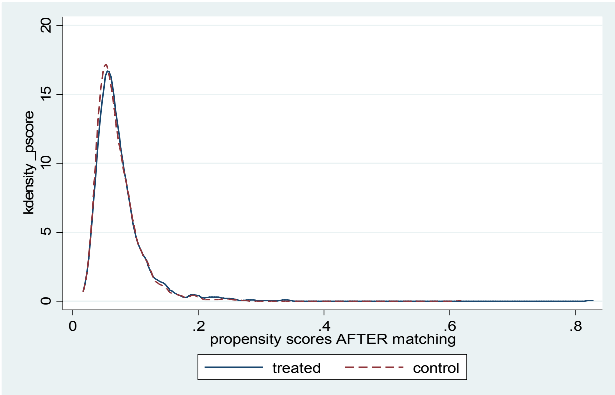

Figure A2: PSM kdensity after matching (crop income)

Table A6: Common support for food security outcome

Common	NNM	KBM	Mahal	LLR		
Support	On Support	On-support	On-support	Off-support	On-support	Total
Untreated	8,045	8,045	8,045	5	8,005	8,010
Treated	1,162	1,162	1,162	1	1,160	1,161
Total	9,207	9,207	9,207	6	9,165	9,171

Table A7: Balancing tests for food security outcome model

Algorithm	Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
NNM	Unmatched	0.073	510.9	0.000	11.6	6	73.2*	1.46	57
	Matched	0.009	27.39	0.053	4.9	5.1	21.7	0.87	43
KBM	Unmatched	0.073	510.9	0.000	11.6	6	73.2*	1.46	57
	Matched	0.006	18.19	0.377	2.7	1.6	17.8	0.75	29
Mahal	Unmatched	0.073	510.9	0.000	11.6	6	73.2*	1.46	57
	Matched	0.022	71.9	0.000	4.7	0.5	35.0*	1.26	57
LLR	Unmatched	0.077	537.77	0.000	11.4	6.1	75.0*	1.48	57
	Matched	0.009	28.36	0.041	5	5.2	22.2	0.87	43

*if B>25%, R outside [0.5; 2]