African Journal of
Agricultural and Resource Economics
Volume 20, Number 2 (2025), pp 207–219

Impact of sustainable intensification technologies on farm income among rural households: Empirical evidence from Dedza district, Malawi

Isaac Maviko*
Lilongwe University of Agriculture and Natural Resources, Lilongwe, Malawi; Department of Agricultural and Applied Economics, Bunda College. E-mail: isaacmavikoh@gmail.com

Charles B.L. Jumbe
Lilongwe University of Agriculture and Natural Resources, Lilongwe, Malawi; Department of Agricultural and Applied Economics, Bunda College. E-mail: charlesjumbe@yahoo.com

Kennedy Machira
Lilongwe University of Agriculture and Natural Resources, Lilongwe, Malawi; Department of Agricultural and Applied Economics, Bunda College. E-mail: kmachila30@gmail.com

* Corresponding author

Received: June 2025
Published: June 2025

DOI: https://doi.org/10.53936/afjare.2025.20(2).12

Abstract

This study examined the effect of sustainable intensification (SI) technologies, specifically the use of improved maize seed varieties, of improved bean seed varieties (Nua45), crop rotation, maize-legume intercropping and doubled-up legume systems on farm income in Dedza district, Malawi. A Multistage sampling method was applied to sample 330 smallholder farmers. The propensity score matching (PSM) method was used to assess the causal effect of SI adoption on farm income. The results from the PSM analysis reveal that adoption of SI practices increased farm income by MWK 35 424.32 (US$ 48.45) per 0.57 hectares in 2020. Based on the findings, the study recommends increased investment in agricultural extension services through the recruitment and training of more extension officers in rural areas to enhance farmers' access to timely and practical knowledge of SI technologies. In addition, the development and scaling-up of affordable credit schemes, such as input loans and microfinance packages tailored to smallholders, are essential to facilitate the uptake of improved seed and other SI-related inputs. Lastly, strengthening market linkages through the promotion of farmer cooperatives and contract farming arrangements is key to ensure access to quality inputs at fair prices and to secure reliable markets for produce.

Key words: sustainable intensification, climate change, impact, PSM, livelihoods

1. Introduction

Climate change poses a significant threat to Malawi's agriculture sector, which remains the cornerstone of the national economy and a primary source of income and food security for rural households (Government of Malawi [GoM], 2024). Despite its central role, agricultural productivity faces significant challenges due to climate and weather variability, declining soil fertility and limited access to modern technologies. Smallholder farmers, who constitute the majority of the agricultural workforce, are particularly vulnerable to the challenges, which threaten livelihoods and reduce their ability to sustain agricultural output. Most farmers cultivate on small plots of less than one hectare, rely on rain-fed agriculture and have limited access to quality inputs, extension services, credit facilities and reliable markets. The constraints have contributed to a persistent decline in agricultural productivity, with far-reaching socio-economic consequences, most notably among them rising poverty levels. According to the World Bank Poverty Assessment report of 2022, 51.7% of Malawians live below the poverty line of MWK 137 428.00 (US$ 187.96) per person per year (GoM 2017; World Bank 2022). The figure underscores the adverse effects of agricultural inefficiencies on household income and national development.

The pathway out of poverty trap in Malawi relies largely on the performance of the agricultural sector, since agriculture is the predominant sector underpinning the livelihoods of poor households in rural areas (GoM 2024). Thus, increasing agricultural productivity is key to getting more people out of poverty. Agricultural productivity cannot be achieved without adopting productivity-enhancing technologies. This is due to the fact that it is no longer possible to meet the needs of an increased population by expanding land under crop production. Therefore, the promotion of agricultural practices that boost production is an important strategy to reduce poverty levels and meet food demand with minimal disturbance of the natural resources.

In this regard, improved agricultural technologies that best fit smallholder farmers are needed to the enhance income and food security of small-scale farmers. The adoption and intensive use of sustainable intensification (SI) technologies are therefore regarded as a means to enhance farm income, as well as ecosystem services in agro-based economies (Martey *et al*. 2021; Vatsa *et al*. 2023). Sustainable intensification is defined as the process of increasing agricultural productivity from existing farmland, while minimising pressure on the environment and enhancing the use of natural resources and ecosystem services (Pretty & Bharucha, 2014). The approach emphasises the efficient use of natural, human and economic resources to achieve productivity gains without expanding cultivated land or degrading the environment. Key SI technologies promoted among smallholder farmers include crop rotation, intercropping, conservation agriculture, use of improved seed varieties, biological fixation of nitrogen and pest and disease control.

The practices have been recommended extensively by various stakeholders to deal with the problems that arise as a result of the over-use of irrigation and chemical fertiliser, which increase the cost of production on the farm (Asante *et al*. 2024). Some of the technologies have the potential to improve residue retention and, to a certain extent, increase crop biodiversity, reduce soil disturbance and provide the extra benefit of improving the fertility of the soil and crop production (Shani *et al*. 2024). Several studies have recommended the use of SI technologies to achieve both increased agricultural productivity and environment protection by improving the fertility of the soil and increasing farm yield on the same piece of land with minimal pressure on natural resources (Gebre *et al*. 2021; Xie & Haung 2021).

In an effort to improve the income of farmers from agricultural production, Lilongwe University of Agriculture and Natural Resources (LUANAR), with financial support from the United States Agency for International Development (USAID), has been promoting yield-enhancing practices since 2016 with the aim of improving the welfare of rural households. Research has shown that the adoption of such technologies ensures efficient use of resources, especially for resource-constrained farmers who cannot manage to purchase inorganic or chemical fertiliser. In addition, the technologies help to reduce the high risk of financial losses associated with drought-induced crop failure (Kotu *et al*. 2017; Biru *et al*. 2019). However, little research has been conducted to assess the effect of adopting such production-enhancing technologies on farm income in Malawi.

Although some studies elsewhere have linked the adoption of SI technologies to improvements in the livelihoods of farmers, including household income, many of these studies have focused predominately on individual technologies in isolation (Manda *et al*. 2018; Martey *et al*. 2021). However, in practice, smallholder farmers often adopt a combination of SI technologies simultaneously to address complex production challenges, including climate change variability and unexpected shocks (Asante *et al*. 2024). Aseres *et al*. (2019) argue that evaluating the impact of a single technology yields biased or incomplete estimates of welfare outcomes, given the complementary and interactive effects of multiple practices.

Despite the growing promotion of newly introduced technologies, such as the doubled-up legume system, there remains limited empirical evidence of the combined effect of such SI technologies on household income, particularly in the Malawian context. Furthermore, much of the existing research has focused on broader outcomes, such as food security and poverty reduction, with a predominant emphasis on maize production (Takahashi *et al*. 2019).

This study was therefore designed to address these knowledge gaps by investigating the aggregate effect of adopting multiple SI practices, including doubled-up legume technology, bean improved seed (Nua45) crop rotation, maize hybrid seed and intercropping on farm income in Dedza district, Malawi. In doing so, it contributes to the empirical literature by providing a more holistic understanding of how resource-constrained farmers adopt integrated strategies to improve productivity and income. By applying the propensity score matching (PSM) approach, the study controls for selection bias and estimates the net effect of SI adoption, thereby yielding more reliable and policy-relevant findings. In addition, by generating context-specific evidence from Malawi, where data on income effects of bundled SI practices remains scarce, this study offers valuable insights to inform the design and implementation of agricultural policies and interventions aligned with national development priorities, such as the National Agriculture Policy and Malawi Vision 2063.

2. Methodology of the study

2.1 Theory of random utility

The adoption of SI practices can be analysed through the lens of random utility theory, as illustrated in the conceptual framework presented in Figure 1. Perception, attitude and knowledge are key factors that influence the decision-making process. Farmers are likely to adopt SI practices if they perceive the benefits, such as increased yields, cost savings and environmental sustainability, as outweighing the associated costs and risks (Ahmed *et al*. 2017). According to utility maximisation theory, farmers adopt SI practices when the expected utility (benefits) exceeds the cost within the constraints they face, such as financial resources.

In this regard, a farmer is exposed to a number of SI practices (crop rotation, maize-legume intercropping, improved bean varieties, drought-resistant varieties and doubled-up legume systems) from which he/she must adopt based on perceived benefits. A farmer makes the choices at random and in any combination. For a given farmer, the probability of choosing a given SI practice is affected by the choices made on any of the other practices. Therefore, farmer *i,* from a given number of *N* households chooses SI practices denoted by $j = 1, 2,3,4,5$, where *1, 2, 3, 4, 5* are the choices of SI practices, namely hybrid maize seed, intercropping, crop rotation, doubled-up legumes and Nua45.

Farmer *i* attains utility level U_{ij} from any combination of the SI practices chosen. However, choices made are discrete, such that a farmer selects or chooses a combination of SI technologies that maximise utility (i.e. give the highest output), such that $U_{ij} > U_{ik}$. Thus, *ceteris paribus*, the utility derived from a given practice *j* yields more utility than practice *k*. However, the utility derived by the farmer is not observable, but the observable attributes associated with it can be decomposed into deterministic (V_{ij}) and random (ε_{ij}) parts (Train 1998). Mathematically, this can be expressed as follows:

$$U_{ij} = V_{ij} + \varepsilon_{ij}, \forall j = 1, 2, \ldots \ldots, 5 \tag{1}$$

In the above equation, $V_{ij} = \delta_j X_{ij}$ represents the utility; parameter X_{ij} denotes a vector of observable variables; δ_j denotes a vector of parameters that are not known; and ε_{ij} denotes unobserved variables that affect the utility attained. Since ε_{ij} is not observed, it is difficult to exactly predict the farmer's choice, but the likelihood of any particular outcome can be derived.

2.2 Conceptual framework

In this study, a conceptual framework was developed to illustrate the relationship between the adoption of sustainable intensification (SI) practices and farm income (Figure 1). The framework draws upon Rogers' diffusion of innovations theory (Rogers 2003), which explains how, why and at what rate new ideas and technologies spread within a social system. According to this theory, technology adoption follows a process that begins with awareness, followed by interest, evaluation, trial and eventual adoption. However, not all farmers are equally positioned within this process. In contrast to the assumption that all rural farmers are aware of new technologies, Rogers' model recognises the existence of adopter categories – from innovators and early adopters to laggards – thus highlighting the variability in access to information and readiness to adopt.

In the Malawian context, new agricultural technologies are typically disseminated through participatory approaches, such as on-field or on-station trials, demonstrations, and farmers' field days. However, actual awareness and adoption are shaped by a farmer's individual characteristics (e.g., age, sex, education level, household size), farm-level attributes (e.g., land size, perceived soil fertility) and institutional factors (e.g., access to credit, training, extension services, and membership of farmer organisations). These determinants are consistent with both the diffusion of innovations theory and elements of the theory of planned behaviour (Ajzen 1991), which emphasises the role of attitudes, subjective norms and perceived behavioural control in shaping intention and behaviour.

Attitudes and perceptions regarding SI practices also play a key role in influencing adoption decisions. Farmers who perceive SI practices as beneficial through increased productivity, income gains, cost efficiency and environmental sustainability are more likely to adopt them. In contrast, negative perceptions about complexity, cost or risks act as barriers. These psychosocial dimensions are informed by personal experiences, cultural norms and peer influence, again reinforcing the relevance of the theory of planned behaviour. Thus, promoting SI adoption requires more than just the availability of technologies; it involves targeted extension and education strategies that improve knowledge, shift perceptions and build capacity among smallholder farmers. Recognising the heterogeneity of farmers and the complexity of behavioural change, the framework provides a realistic and evidence-based foundation for analysing the relationship between SI adoption and farm income in Dedza district.

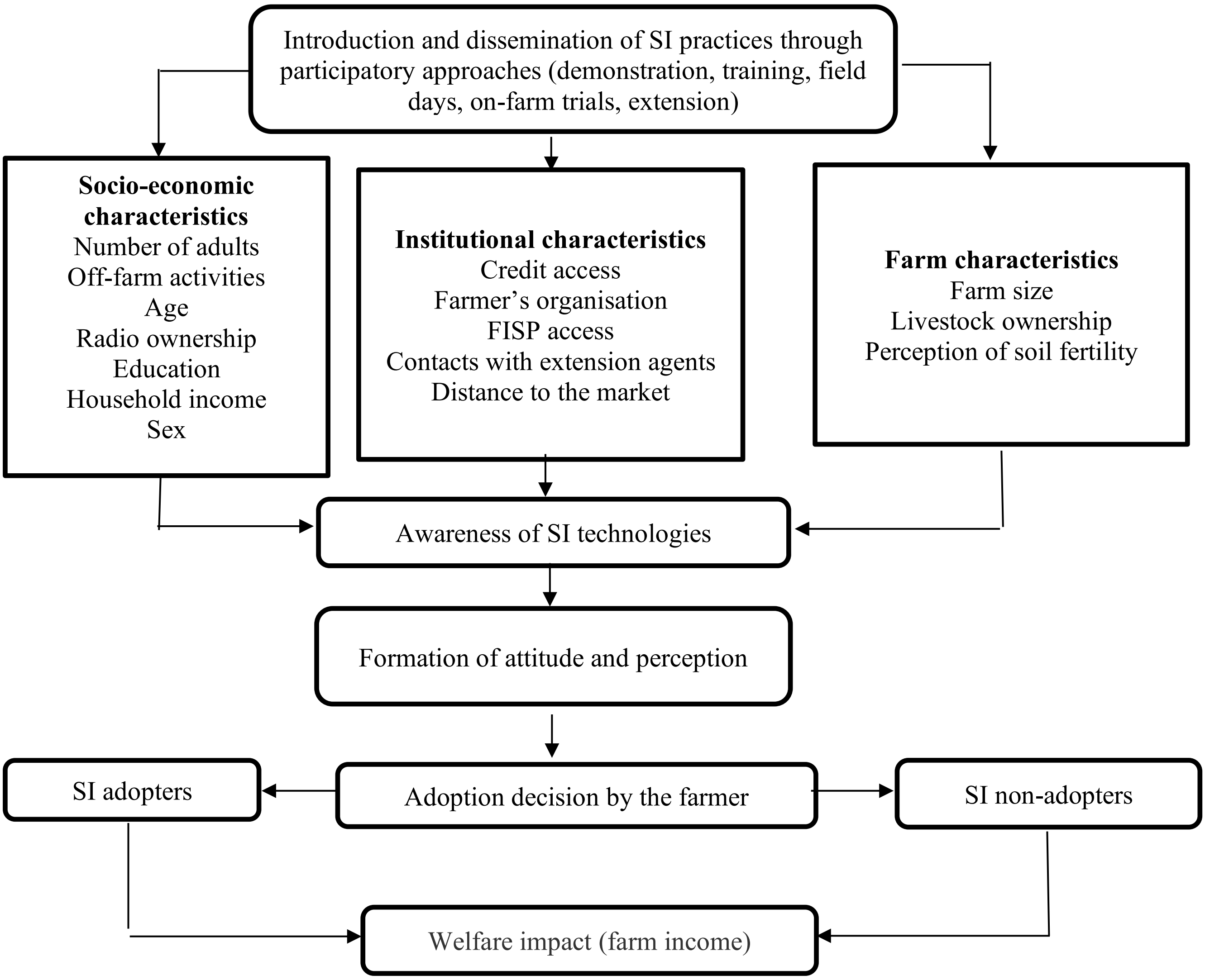

Figure 1: Impact of SI practices on farm income
Source: Adapted and modified from Neupane *et al*. (2002)

2.3 Study area and sampling technique

The study area was the Linthipe extension planning area (EPA) in Dedza district.[1] The study area was selected because it represents a region where various agricultural technologies are actively practised, providing an ideal setting to assess the impacts of SI practices on farm income. A multistage sampling technique was employed to sample smallholder farmers in the study area. Smallholder farmers were selected using the probability proportional to size (PPS) method, which ensured that a larger number of respondents were drawn from villages with higher populations. The approach enhanced the

[1] In Malawi, the agricultural vertical administrative structure starts with the ministry as the top layer, then agricultural development divisions (ADD), which are divided into district agricultural offices (DAO). The DAOs are subdivided into extension planning areas (EPA). Finally, the EPAs are subdivided into sections.

representativeness of the sample. A well-structured sampling frame was used to systematically identify farmers, thereby minimising selection bias and ensuring sufficient data. The random sampling technique was employed to select both adopters and non-adopters in each village. The study employed the formula shown below to determine the sample size of smallholder farmers (Cochran 1977).

$$n = \frac{z^2\, p(1-p)}{e^2} \tag{2}$$

In the equation above, n = the size of the sample, t = the z-value. taken as 1.96 (at 95%), p = 50% and represents the proportion of adopters of SI practices, and e = 8% and it denotes margin of error.

$$n = \frac{1.96^2 * 0.5(1-0.5)}{0.08^2} = 150 \text{ farmers} \tag{3}$$

Taking into account non-responses, which were 10%, and using 2 as a design effect, the sample size was adjusted as follows:

150*1.1*2 = 330 smallholder farmers.

Hence, the sample size increased to 330. The design effect was used to reduce the high variance of estimators likely to be caused by intra-cluster correlation due to clustering (Scott & Holt 1982).

2.4 Empirical models

2.4.1 Propensity score matching

The impact of technology adoption varies depending on the method used to construct the counterfactual (Khandker *et al*. 2010). The fundamental challenge in impact evaluation is the counterfactual problem, which arises from the inability to observe the same individual in both the treatment (adoption) and control (non-adoption) states simultaneously. With impact evaluation techniques, the aim is to find what would have happened to that individual in the absence of the intervention. According to Ravallion (2008), this can best be achieved through the use of non-experimental approaches such as PSM.

In practice, adoption of agricultural technologies on the farm is rarely random (Khandker et al*.,* 2010). Farmers self-select into adoption based on observable characteristics such as education, land size, access to credit and extension services. The non-random selection introduces selection bias, making simple comparisons between adopters and non-adopters potentially misleading. The strength of the PSM approach is that it relaxes the randomisation assumption by matching treated and untreated units with similar observable characteristics, thus mimicking a randomised experimental design.

Furthermore, the study lacked baseline data**,** which ruled out the use of panel-based methods such as difference-in-differences. Given these data constraints, and the objective of estimating the average treatment effect on the treated (ATT), the PSM method was the most appropriate technique. It allowed for a statistical estimation of the income effect of adopting sustainable intensification (SI) practices by comparing adopters with a matched group of non-adopters who shared similar characteristics. This ensured that differences in outcomes could be attributed to the adoption of SI technologies, rather than pre-existing differences between the two groups of farmers.

The ATT was used to measure the impact of the adoption of SI practices on farm income. According to Khandker *et al*. (2010), the ATT that is attributed to adoption can be presented as shown below:

$$ATT_{PSM} = E_{P(X)}\{E(Y_1|D = 1, P(X)) - E(Y_0|\, D = 0, P(X))\} \tag{4}$$

In the equation above, the probability with respect to the distribution of the propensity scores estimated is represented by $E_{P(X)}$, Y_1 is the outcome variable for the adopters of SI practices, while Y_0 is the outcome for the non-adopters of SI practices. Furthermore, D is the adoption variable and its binary; in other words, it takes the value 1 for adopters and 0 for non-adopters. The ATT_{PSM} in the equation indicates the difference between the treated and the non-treated groups and depends on the estimates of the propensity scores, which are estimated on the covariates that are observed, hypothesised by vector X.

3. Results and discussion

3.1 Descriptive statistics of farm households

Table 1 presents the demographic and socioeconomic characteristics of the sampled farm households. In terms of age, there were significant differences across all technology categories in mean age between adopters and non-adopters of SI practices. The overall mean ages for adopters and non-adopters were 42 and 43, respectively. In terms of sex composition, the results revealed that male-headed households dominated across all the technology categories compared to female-headed households. The results further show statistically significant differences between adopters and non-adopters of crop rotation and doubled-up legume technologies.

The average household size for adopters and non-adopters was 4.7 and 4.4, respectively, which is not very different from the nation's average household size of 4.3, as reported by NSO (2018). In terms of differences between adopters and non-adopters, Table 1 shows significant differences in household size between the adopters and non-adopters of hybrid seed and crop rotation, at the 5% and 10% level of significance, respectively. It is worth noting from Table 1 that adopters across all the technologies have a larger household size compared to non-adopters.

The number of adults (more or less equal to 18 years) in the household entails the amount of household labour available (Manda *et al*. 2018). The average number of adults for adopters and non-adopters was 2.46 and 2.17, respectively. Furthermore, the results reveal significant differences in the number of adults in the household between adopters and non-adopters. The results further show a large number of adults for adopters in the study area across all the technologies compared to non-adopters. The availability of land increases the likelihood of farmers adopting land-intensive technologies. Table 1 shows that the average land size for adopters and non-adopters was 0.57 ha and 0.41 ha, respectively, and the difference was significant. The results are in line with the NSO (2018) report, which states that the average farm size for smallholder farmers in Malawi is less than one hectare.

Non-farm activities help to ease farm activities by hiring labour for the farm. The results in Table 1 reveal that, of the total number of adopters, 53.79% engaged in off-farm activities. Similarly, 65.78% of the total non-adopters were involved in non-farm activities. Overall, there is a significant difference between adopters and non-adopters in terms of proportions of farmers involved in non-farm activities. Livestock ownership is one of the major complementary sources of income in rural areas (Teklewold & Mekonnen 2017). Considering that some of the technologies, such as Nua45, doubled-up legume cultivation and improved maize seed, are input intensive, livestock ownership helps to reduce the financial constraints faced by small-scale farmers. The results in Table 1 show that, of the total number of adopters, 61.38% owned livestock.

Table 1: Descriptive statistics of the sampled households

Variables	SI technologies											
	Improved maize varieties		Maize-legume intercropping		Crop rotation		Doubled-up legume		Nua45		Overall	
Continuous variables (mean)	**Adopters (102)**	**Non-adopters (230)**	**Adopters (104)**	**Non-adopters (228)**	**Adopters (100)**	**Non-adopters (232)**	**Adopters (73)**	**Non-adopters (259)**	**Adopters (64)**	**Non-adopters (268)**	**Adopters (145)**	**Non-adopters (187)**
Age	41.10 (14.36)**	43.6 (16.75)	42.60 (14.73)	43.03 (16.75)	41.10 (13.47)**	43.7 (17.04)	43.1 (12.12)	42.9 (16.48)	42.3 (14.99)	43.3 (16.89)	42.3 (14.99)**	43.3 (16.69)
Household size	4.8 (1.51)[a]**	4.4 (1.77)	4.7 (1.65)	4.5 (1.72)	4.8 (1.58)[a]**	4.4 (1.74)	4.6 (1.55)	4.5 (1.74)	4.7 (1.30)	4.5 (1.73)	4.7 (1.53)	4.4 (1.81)
Number of adults	2.41 (0.09)	2.24 (0.07)	2.41 (0.09)	2.24 (0.07)	2.50 (0.10)[a]**	2.21 (0.04)	2.42 (0.11)	2.26 (0.62)	2.29 (0.12)	2.30 (0.06)	2.46 (0.08)[a]***	2.17 (0.07)
Land size (ha)	0.54 (0.67)	0.48 (0.24)	0.83 (1.01)[a]*	0.38 (0.73)	0.45 (0.11)[a]**	0.23 (0.03)	0.49 (0.30)	0.31 (0.91)	0.63 (0.46)[a]***	0.49 (0.05)	0.57 (0.10)[a]*	0.41 (0.34)
Distance to market	1.87 (0.20)[a]*	2.66 (0.27)	2.45 (0.45)	2.40 (0.20)	2.53 (0.47)	2.36 (0.20)	2.84 (0.61)	2.29 (0.19)	3.36 (1.12)	2.31 (0.18)	2.20 (0.33)	2.58 (0.24)
Contacts with extension agents/year	4.84 (0.01)[a]***	2.12 (0.24)	4.72 (0.61)[a]***	2.15 (0.23)	5.57 (0.66)[a]***	1.83 (0.20)	5.77 (0.70)[a]***	2.16 (0.25)	5.76 (1.06)[a]***	2.16 (0.26)	4.66 (0.50)[a]***	1.63 (0.20)
Dummy variables (percentage)												
Gender (male)	79.41	72.61	77.88	73.25	83	71.12[b]**	82.19	72.59[b]*	70.59	75.17	77.93	72.19
Off-farm activities (yes)	53.92	63.48	50.96	64.91[b]**	62	59.91	63.01	59.85	58.82	60.74	53.79	65.78[b]**
Livestock (yes)	61.76	50.87[b]*	67.31	48.25[b]***	68	48.28[b]***	65.75	50.97[b]**	76.47	51.68[b]***	61.38	48.66[b]**
Credit access (yes)	38.24	34.35	37.5	34.65	42	32.76	38.36	34.75	61.76	32.55	39.31	32.62
Training in SI practices (yes)	32.35	13.91b***	25.96	16.67[b]**	36	12.5[b]***	52.05	10.42[b]***	41.18	17.11[b]***	68.97	10.70[b]**
Access to FISP (yes)	21.57*	15.65	21.15	15.79*	29	12.5	31.51	13.51	32.35	15.77	22.07	13.90

Notes: Figures in parentheses are standard deviation of continuous variables; [a] indicates t-test, [b] indicates chi-square test; * = significant at 10% ($p < 0.1$), ** = significant at 5% ($p < 0.05$), and *** = significant at 1% ($p < 0.01$).

Access to the farm input subsidy programme (FISP) entails government efforts to support rural farm households to easily have access to productive resources. Table 1 shows that very few farm households in the study area are beneficiaries of FISP. Across all the technologies, adopters benefitted more from FISP compared to non-adopters. With regard to the number of contacts with agricultural extension agents, the results reveal that adopters of different technologies have more contacts with agricultural extension agents (4.66) than non-adopters (1.63).

The results in Table 1 indicate that there are significant differences in terms of access to training on sustainable intensification (SI) practices between adopters and non-adopters. Specifically, adopters reported significantly higher access to training across all the SI technologies considered in the study. Training equips farmers with the necessary skills and knowledge to effectively implement and manage SI technologies, enabling them to make informed decisions that enhance productivity and sustainability (Tanti *et al*. 2022).

3.2 Effect of adoption of SI technologies on farm income

3.2.1 Choosing a matching algorithm

Choosing a matching algorithm involves the selection of the best-matching algorithm to balance the distribution of covariates between adopters and non-adopters of sustainable intensification practices. Following Haji and Legesse (2017), the study tested commonly used the matching estimators of nearest neighbour, radius and kernel matching, as shown in Table 2.

The best matching algorithm is the one that reduces standardised mean bias, produces a large number of matched sample size, returns small pseudo-R^2 and produces a large number of insignificant variables after matching (Li 2012). It is apparent from Table 2 that kernel matching satisfies the proposed criterion at a bandwidth of 0.03, and it was therefore used to estimate the average treatment effect on the treated of the adoption of SI technologies. The kernel matching indicated a small pseudo-R^2, a large, matched sample size, a large number of insignificant variables after matching and a small standardised mean bias, as shown in Table 2.

Table 2: Balancing of propensity scores

Algorithm	Matching parameters	Number of insignificant variables after matching	Pseudo-R^2	Matched sample size	Mean bias
Kernel	Bandwidth 0.01	16	0.017	330	5.1
	Bandwidth 0.03	16	0.007	330	3.5
	Bandwidth 0.25	16	0.015	330	4.1
Nearest neighbour	Integer 4	16	0.014	330	5.2
	Integer 6	16	0.012	330	4.4
	Integer 9	16	0.011	330	4.7
Calliper matching	Radius 0.2	16	0.026	330	7.5
	Radius 0.3	16	0.026	330	7.5
	Radius 0.4	16	0.026	330	7.5

3.2.2 Matching quality

After matching, the quality of matching achieved was assessed to ensure that every household with the same X values had an equal positive chance of being both participant and non-participant (Caliendo & Bonn 2008). This forms the verification of the common support or overlap assumption. Figure 2 shows the distribution of the estimated propensity scores and overlap between adopters and non-adopters of SI technologies.

Visual inspection of the graph shows that common support was achieved, as there is a sizeable overlap in the distribution of estimated scores between SI technologies adopters and non-adopters. It is also clear that there are no sizeable differences between the maximum and minimum values of the propensity score density distributions for both groups.

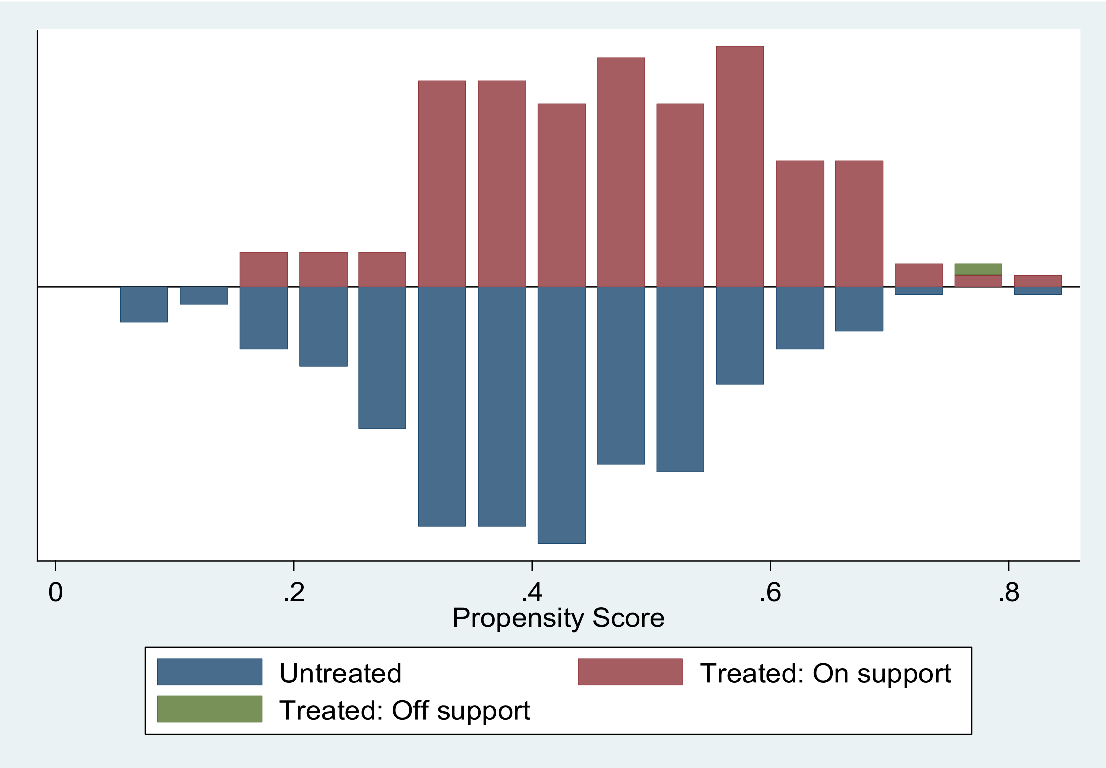

Figure 2: Matching quality

3.2.3 Estimating the average treatment effect on the treated (ATT)

After satisfying the common support assumption, the study calculated the average treatment effect on the treated. The difference in the outcome variable is now attributed to the adoption of SI technologies, since adopters and non-adopters have been matched in all observable covariates (Haji & Legesse 2017). The number of sales of farm produce was used as a proxy for farm income and was an outcome variable of this study.

Before matching, the average farm income for the adopters of SI technologies was MWK[2] 62 384.88 (US$ 85.32), while the average farm income for non-adopters was MWK 26 966.34 (US$ 36.88), with a difference of MWK 35 418.54 (US$ 48.44). After matching, the average amount of farm income for SI adopters was MWK 62 505.60 (US$ 85.48), while that for non-adopters was MWK 27 081.28 (US$ 37.04). The difference of MWK 35 424.32 (US$ 48.45) after matching is the average treatment effect on the treated (ATT), and this was significant at the 1% significance level, as shown in Table 3.

Table 3: Estimating the causal effect of adoption of SI technologies on farm income

Outcome	Sample	Treated	Controls	Difference	Std. error	t-value
Farm income	Unmatched	62 384.88	26 966.34	35 418.54	9 904.21	3.58***
	ATT	62 505.60	27 081.28	35 424.32	11 131.75	3.18***

[2] Malawian kwacha

The implication is that the adopters of SI technologies had higher farm income compared to non-adopters, and the difference is ascribed to their participation status. Therefore, the null hypothesis – that adoption of SI technologies by smallholder farmers does not influence farm income – is rejected and the study concludes that the adoption of SI technologies has a positive impact on farm income.

3.2.4 Sensitivity analysis

Estimates in impact studies are prone to unobserved heterogeneity, hence the need for sensitivity analysis (Khandker *et al*. 2010). The sensitivity analysis answers the question, "what would the unmeasured covariates have to be like to alter the findings of the study?" Table 4 shows that the mean standardised bias (SB) was 10.9% before matching, and it was reduced to 3.5% after matching. The 67.89% reduction in mean bias shows the strong balancing power of the estimation.

In addition, the mean bias of 3.5% is within the acceptable range of 3% to 5% bias after matching, as recommended by Caliendo and Bonn (2008). The common support restriction was imposed on the observations during matching. This involved dropping the treatment observations of which the p-score was higher than the maximum or less than the minimum p-score of the controls (Michaleck 2012; Haji & Legesse 2017). Consequently, only one case was lost due to common support imposition, representing a 0.3% loss, which is reasonably low (Michaleck 2012).

The study followed Rosenbaum (2002) and estimated sensitivity analysis through the rbounds package in Stata. The results in Table 4 show that the gamma values ranged from 1.3 to 2.0. A gamma value of 1 indicates no hidden bias (unobserved heterogeneity). The results therefore mean that the unobserved variables should have to increase the odds ratio of adoption of SI technologies 30% to 100% before they would affect the estimated effect of participation. As such, the results of this study are robust, despite the presence of unobserved heterogeneity (Michaleck 2012).

Table 4: Indicators of matching quality and robustness of results

Outcome variable	$SB_{\text{-unmatched sample}}$	$SB_{\text{-matched sample}}$	Cases lost	Pseudo-R^2	Critical values of gamma (Γ)
Farm income	10.9	3.5	1	0.007	1.3–2.0

3.2.5 Limitations of the study

While the study provides important insights into the impact of sustainable intensification (SI) practices on smallholder farmers' income, it is not without its limitations. The analysis relied on cross-sectional data, which limits the ability to establish causal relationships over time. Future studies should consider using panel data to capture dynamic effects and control for time-varying unobserved heterogeneity. Furthermore, although propensity score matching (PSM) was employed to minimise selection bias, it cannot completely eliminate the influence of unobserved variables that may affect both the likelihood of adopting SI and farm income. Future research could apply more robust quasi-experimental methods, such as difference-in-differences or instrumental variable approaches.

4. Conclusion

The study examined the effect of sustainable intensification (SI) practices on farm income in Dedza district, Malawi using a propensity score matching (PSM) model. The results reveal that the adoption of SI practices led to a significant increase in farm income, of MWK 35 424.32 (US$ 48.45) per 0.57 hectares in 2020, underscoring the potential of these practices to boost the livelihoods of resource-constrained farmers. These findings affirm that SI technologies are not only viable pathways to improving agricultural productivity, but also offer a critical tool for building climate resilience and reducing rural poverty among rural farm households.

Building on the findings, it therefore is important to scale up the adoption of sustainable intensification (SI) practices by increasing investment in agricultural extension services. This can be done by recruiting and training more extension officers, particularly in rural areas. This will improve farmer access to timely and practical knowledge on SI technologies. Secondly, there is need develop and scale up affordable credit schemes tailored to smallholder farmers, including input loans and microfinance packages that support the purchase of improved seed and other SI-related inputs. In addition, both input and output market linkages should be strengthened by establishing farmer cooperatives and contract farming arrangements to enable farmers to access quality inputs at fair prices and secure reliable markets for their produce.

This study has implications for other agrarian societies in sub-Saharan Africa that face similar structural challenges, including land degradation, small farm sizes, erratic weather patterns driven by climate change, and limited access to modern agricultural technologies. In such contexts, sustainable intensification (SI) presents a practical and scalable approach to sustainably enhance agricultural productivity without necessitating the expansion of cultivated land. The positive income effects observed in Malawi suggest that, with appropriate support mechanisms, SI practices can similarly transform smallholder agriculture in other sub-Saharan countries facing comparable constraints.

References

Ahmed MH, Geleta KM, Tazeze A & Andualem E, 2017. The impact of improved maize varieties on farm productivity and wellbeing: Evidence from the East Hararghe Zone of Ethiopia. Development Studies Research 4(1): 9–21.

Ajzen I, 1991. The theory of planned behaviour. Organizational Behaviour and Human Decision Processes 50(2): 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Asante BO, Ma W, Prah S & Temoso O, 2024. Farmer's adoption of multiple climate-smart agricultural technologies in Ghana: Determinants and impacts on maize yield and net farm income. Mitigation and Adaptation Strategies for Global Change 29: 16.

Aseres ME, Liu A & Mwalupaso GE, 2019. Adoption of sustainable intensification practices and its effect on smallholders' food security in Ethiopia. Applied Ecology and Environmental Research 17(3): 6681–700. https://doi.org/10.15666/aeer/1703_66816700

Biru WD, Zeller M & Loos TK, 2019. The impact of agricultural technologies on poverty and vulnerability of smallholders in Ethiopia: A panel data analysis. Social Indicators Research 147: 517–46. https://doi.org/10.1007/s11205-019-02166-0

Caliendo M & Bonn I, 2008. Some practical guidance for the implementation of propensity score matching. Journal of Economic Surveys 22(1): 31–72.

Cochran GW, 1977. Sampling techniques. third edition. New York: John Wiley and Sons.

Gebre G, Mawia H, Makumbi D & Rahut D, 2021. The impact of adopting stress tolerant maize on maize yield , maize income and food security in Tanzania. Food and Energy Security 10(4): e313.

Government of Malawi (GoM), 2017. Malawi growth and development strategy. Lilongwe: Ministry of Finance and Ministry of Economic Planning and Development.

Government of Malawi (GoM), 2024. Annual progress report 2021–2022: Malawi 2063 first 10-year implementation plan (MIP-1). Lilongwe, Malawi: National Planning Commission. https://npc.mw/wp-content/uploads/2023/02/MIP-1-Progress-Report-2023.pdf

Haji J & Legesse B, 2017. Impact of sedentarization program on the livelihood and food security of Ethiopian pastoralists. Journal of Arid Environments 136: 45–53.

Khandker SR, Koolwal GB & Samad HA, 2010. Handbook on impact evaluation: Quantitative methods and practices. Washington, DC: The World Bank.
Kotu BH, Alene A, Manyong V, Hoeschle-Zeledon I & Larbi A, 2017. Adoption and impacts of sustainable intensification practices in Ghana. International Journal of Agricultural Sustainability 15(5): 539–54.
Li M, 2012. Using the propensity score method to estimate causal effects: A review and practical guide. Organizational Research Methods 16(2): 188–226. https://doi.org/10.1177/1094428112447816
Manda J, Gardebroek C, Kuntashula E & Alene AD, 2018. Impact of improved maize varieties on food security in Eastern Zambia: A double robust analysis. Review of Development Economics 22(4): 1709–28.
Martey E, Etwire P & Mockshell J, 2021. Climate-smart cowpea adoption and welfare effects of comprehensive agricultural training programs. Technology in Society 64: 101468. https://doi.org/10.1016/j.techsoc.2020.101468
Michaleck J, 2012. Counterfactual impact evaluation of EU rural development programmes: Propensity score matching methodology applied to selected EU member states. Volume 2: A regional approach. Rome: Joint Research Centre, Institute for Prospective Technological Studies.
Neupane RP, Sharma KR & Thapa GB, 2002. Adoption of agroforestry in the hills of Nepal: A logistic regression analysis. Agricultural Systems 72(3): 177–96. https://doi.org/10.1016/S0308-521X(01)00066-X
NSO, 2019. 2018 Malawi population and housing census main report. Zomba, Malawi: National Statistics Office.
Pretty J & Bharucha ZP, 2014. Sustainable intensification in agricultural systems. Annals of Botany 114(8): 1571–96. https://doi.org/10.1093/aob/mcu205
Ravallion M, 2008. Evaluating anti-poverty programs. In P Schultz & John Strauss (eds.), Handbook of development economics, Volume 4: 3787–846.
Rogers EM, 2003. Diffusion of innovations. Fifth edition. New York: Free Press.
Rosenbaum PR, 2002. Observational studies. New York: Springer.
Scott AJ & Holt D, 1982. The effect of two-stage sampling on ordinary least squares methods. Journal of the American Statistical Association 77(380): 848–54. https://doi.org/10.2307/2287317
Shani F, Joshua M & Ngongonda C, 2024. Determinants of smallholder farmers' adoption of climate-smart agricultural practices in Zomba, eastern Malawi. Sustainability 16(9): 3782.
Takahashi K, Muraoka R & Otsuka K, 2019. Technology adoption, impact, and extension in developing countries' agriculture: A review of the recent literature. Agricultural Economics 51(1), 5231–45. https://doi.org/10.1111/agec.12539
Tanti P, Jena P, Aryal J & Rahut D, (2022). Role of institutional factors in climate-smart technology adoption in agriculture: evidence from an Eastern Indian state. *Environmental challenges*, https://doi. org/ 10. 1016/j. envc. 2022. 100498.
Teklewold H & Mekonnen A, 2017. The tilling of land in a changing climate: Empirical evidence from the Nile Basin of Ethiopia. Land Use Policy 67: 449–59. https://doi.org/10.1016/j.landusepol.2017.06.010
Train KE, 1998. Recreation demand models with taste differences over people. Land Economics 74(2): 230–9.
Vatsa P, Ma W, Zheng H & Li J, 2023. Climate-smart agricultural practices for promoting sustainable agrifood production: Yield impacts and implications for food security. Food Policy 121: 102551. https://doi.org/10.1016/j.foodpol.2023.102551
World Bank, 2022. Malawi – Fourth social action fund project assessment report – Environmental assessment. Lilongwe, Malawi: World Bank Independent Evaluation Group.
Xie H & Huang Y, 2021. Influencing factors of farmers' adoption of pro-environmental agricultural technologies in China: Meta-analysis. Land Use Policy 109: 105622. https://doi.org/10.1016/j