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Assessing the Effectiveness of Climate-Smart Irrigation Practices in Improving Household Income Among Smallholder Maize Farmers in Botswana

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Abstract: The growing impacts of climate change have adversely affected smallholder farmers across the world, leading to low output, decreased incomes, and high levels of food insecurity. As a result, farmers have been advised to find alternative ways of dealing with this phenomenon. The low adoption of climate-smart irrigation technology in Botswana warrants an investigation into the factors and the impact of adoption. This study used a semi-structured questionnaire to collect data from 271 smallholder maize farmers, who were selected through a multi-stage sampling approach. Descriptive statistics, probit regression, and propensity score matching technique (PSM) were employed to analyze the data. The results revealed that the majority of the respondents (55%) were male and 62% of farmers were above 50 years. The majority (62%) of the participants had a farm size of less than 5 ha and were heavily reliant on family labour for farm operations. Despite high (66%) awareness of climate-smart irrigation technology, many (52%) farmers did not adopt smart irrigation in Botswana. Age, gender, and access to credit had a statistical and negative influence on adoption. However, level of education and farming experience had a positive influence on adoption. The result of the propensity score matching model indicated that farmers using climate-smart irrigation techniques experienced positive and significant improvement in crop yield compared to dryland farmers. The study recommends that relevant institutions in Botswana should design a strategy that will be tailored to addressing issues of access to credit, facilitate training and education on advanced irrigation methods, and encourage more young farmers to engage in farming activities.

Keywords: adoption; climate-smart agriculture; climate-smart irrigation; PSM model; ATT; Botswana

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1. Introduction

Climate change is emerging as an unprecedented threat to global agriculture. In Africa and other developing countries, where agriculture is the main livelihood of most of the population, the impacts are dire because agriculture in these regions heavily relies on rain-fed systems [1–3]. Consequently, shifts in climate patterns pose significant risk to both food production and security [4]. Studies highlight the detrimental impacts of climate change on agriculture, including reduced crop yields, increased vulnerability to diseases and more frequent extreme weather events [4]. Addressing these challenges is critical in ensuring food security and agricultural sustainability.

To mitigate the impacts of climate change, there has been growing emphasis on adopting climate-smart agriculture (CSA) strategies [5]. Among these, climate-smart irrigation (CSIT) has garnered significant attention worldwide. Climate-smart irrigation encompasses sustainable and adaptive approaches to agricultural water management designed to improve water-use efficiency, improve production and minimize the impact of climate change [6]. Consequently, significant advancements have been made in irrigation systems, which researchers are continuously exploring. Climate-smart irrigation strategies empower smallholder farmers to enhance, automate, and optimize traditional agricultural practices, leading to improved agricultural productivity and a more streamlined farming system [7]. The implementation of smart irrigation systems such as drip irrigation can significantly reduce the total amount of water required to produce field crops. Empirical evidence suggests that automated drip irrigation system can save 26% more water and enhance high crop productivity compared to traditional irrigation methods [8]. Additionally, Yang et al. [9] reported that during water shortage, drip irrigation not only saves water but it also maintains crop yields better compared to other types of irrigation methods.

Despite the potential benefits of climate-smart irrigation technology, its adoption remains low among smallholders in many developing countries [10–12]. Botswana serves as notable example of this trend. In this country, the majority of economically disadvantaged rural communities are directly or indirectly involved in crop production, which is crucial for poverty alleviation, employment, and income generation. However, crop production in Botswana is highly vulnerable to climate-related shocks, with rising temperatures and erratic rainfall patterns threatening crop productivity, household income and food security [13]. Therefore, policies that boost and improve irrigation management and encourage the adoption of climate-smart irrigation technology should be considered [14]. Considering this, since independence the government has implemented several policies and support programmes to guide, boost, and improve the production and productivity of various agricultural sub-sectors [15], which include arable agricultural programmes such as the Integrated Support Programme for Arable Agriculture Development (ISPAAD) and the Arable Land Development Programme (ALDEP). However, these policies did not improve the nation's food security situation, so the Ministry of Agriculture (MoA) of the Government of Botswana created a new initiative called the Temo Letlotlo Programme and Horticulture Impact Accelerator Subsidy (IAS) fund. Despite the increasing recognition of climate change's impact on agriculture in Botswana, all these programmes fail to encourage smallholder crop farmers to adopt climate-smart irrigation strategies directly. Hence, this paper investigates the drivers of climate-smart irrigation adoption and its impacts in this context.

2. Conceptual Framework on the Adoption of Climate-Smart Irrigation Technology

The conceptual framework of this study, as illustrated in Figure 1 below, has four main components. The first components is climate change and its vulnerability. Second, there is the adaptation process to mitigate climate change and vulnerability, which is CSIT; third is the determinant of the CSIT. The last component is the outcome of the adoption decision in terms of crop yield and the income of the farmers.

Climate change leads to climate vulnerabilities, such as droughts, dry spells, and irregular rainfall, leading to shortage of agricultural water that adversely affects crop yield. Without interventions, many rural farmers are at a risk of losing their livelihoods due to the devastating effects of climate change [16]. Climate-smart irrigation technologies (CSIT) enhance smallholder farmers' resilience to climate change [17] as a sustainable and adaptive solution for agricultural water management. The main objective of CSIT is to increase crop yield and enhance farms' income [18] by mitigating climate risks and ensuring the availability of sufficient water for agricultural production. Therefore, the farmers who decided to adopt CSIT improved their crop productivity and farm income. In contrast, if farmers prefer either not to adopt CSIT, or to adopt a traditional way of watering, then CSIT may increase the risks and expose their crops to extreme weather, which may have adverse impacts on farm income through reducing per-crop yields or crop loss. Figure 1 shows the relationship between the variables discussed.

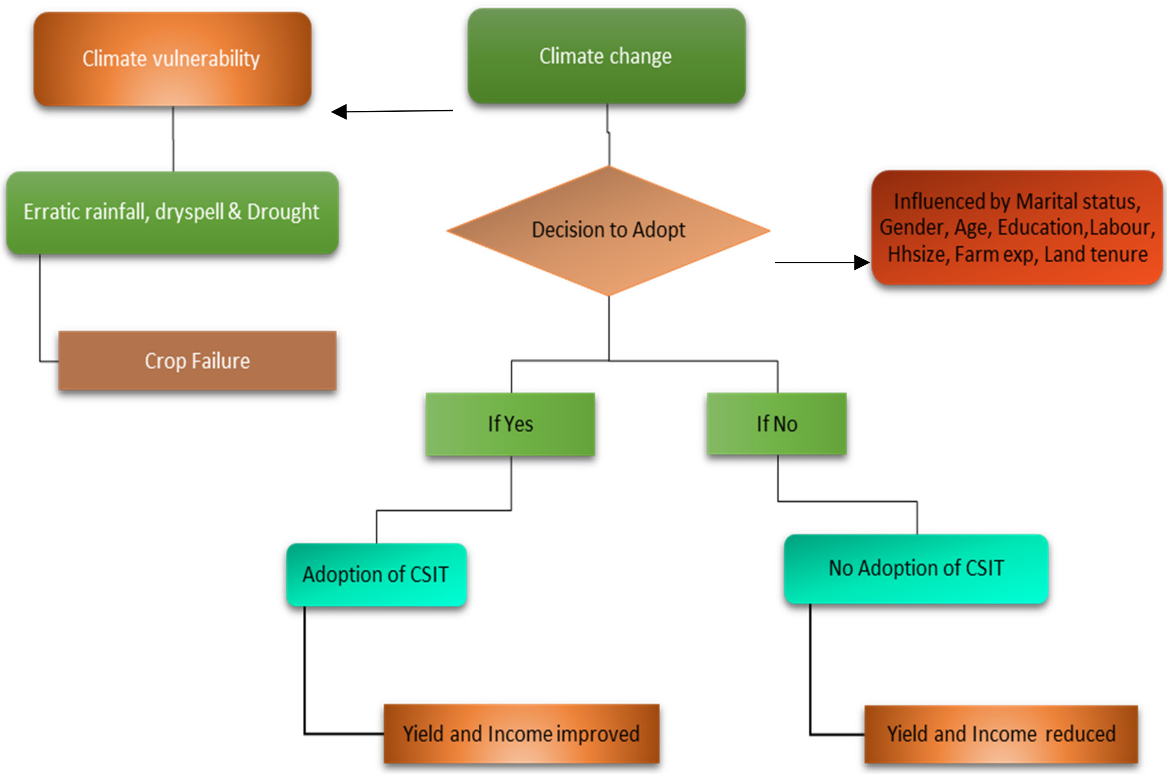

Figure 1. Conceptual framework of climate-smart technology adoption by smallholder farmers. Source: Adapted and modified from Abegunde, Melusi and Obi, 2019 [2].

3. Methodology

3.1. Description of Study Area

Botswana is a landlocked country primarily characterized by the Kalahari Desert, which stretches west of the eastern hardveld and covers 84% of the country. The country is situated between longitudes 20 and 30 degrees east of Greenwich, and latitudes approximately 18 and 27 degrees south of the Equator [19]. Botswana is one of the smallest countries on the African continent and is home to 2.7 million people. It shares borders with South Africa to the South and East, Namibia to the West, and Zimbabwe to the East. According to World Bank [20]. Botswana is one of the most unequal countries in the world. Botswana is divided into 10 districts, each with its own unique characteristics and cultural heritage. The study was conducted only in the five districts in Botswana, namely Central, Kgatleng, South-East, Southern and Kweneng, and these areas were randomly chosen.

The central district at 24.0480° S, 26.7747° E latitude and longitude is sandveld, with a mean annual rainfall of 350 mm and high temperatures exceeding 35 °C [21]. The south-east district experiences a blend of average winter temperatures, rainfall, and summer temperatures; with a mean annual rainfall of 450 mm and high temperatures of 32 °C [22]. The Southern district at 25.0559° S, 26.0121° E latitude and longitude experiences highly variable rainfall patterns, averaging about 450 mm annually [23]. During the summer season, the district experiences average daily high temperatures of 32 °C. Kweneng and Kgatleng districts in Botswana have contrasting climates. Deep Kalahari sandy soils primarily cover Kweneng, while Kgatleng has loamy clay soil. The semi-arid climate has annual rainfall ranging from 350 to 600 mm, with mean daily temperatures ranging from 25 °C to 32.6 °C. Kgatleng experiences annual rainfall between 450 and 550 mm, with winter temperatures ranging from 6 °C to 20 °C [24]. As a result of these climate conditions, crops grown in Botswana include maize, wheat, sunflower, and groundnuts. In addition, the country is also known for citrus, cotton, and dairy products.

3.2. Sampling Procedure, Sample Size, and Data Collection

The study utilized cross-sectional survey data from smallholder maize farmers in Botswana, who were selected using a multi-stage sampling approach. The study used primary and secondary data. Primary data from 271 smallholder maize farmers from five districts in Botswana were collected using a structured questionnaire from December 2023 to January 2024. The survey questionnaire was developed in English and Setswana, and included a broad array of information, encompassing demographic, social-economic, farm, and institutional characteristics that affect the adoption of new technology. Trained research assistants, who were knowledgeable about the rural farming system and proficient about in the local language, administered the questionnaire to prevent misinterpretations or misunderstanding of words or questions. The survey collection tool was administered to 10 respondents prior to the actual data collection to assess its validity and reliability. The unit of analysis for this study was farmers. Additionally, secondary data were obtained from government documents, peer-reviewed journals, and books.

3.3. Data Analysis

Following the collection of primary data from smallholder farmers, the information was coded, cleaned, and organized into a Microsoft Excel spreadsheet. Subsequently, the coded data were imported from an MS Excel (365 MSO version 2409) spreadsheet to STATA version 13 for analysis. This study employed descriptive statistics, probit regression, and propensity score matching to analyze the data. The details of how the analytical tools were applied is provided below.

3.3.1. Descriptive Statistics

The study employed descriptive statistics to characterize the demographic, socio-economic and institutional attributes of smallholder maize farmers in the study area. Tools for descriptive statistics included frequency tables for categorical variables and calculation of average mean, maximum, minimum, and standard deviation for continuous variables.

3.3.2. Propensity Score Matching Model (PSM)

Propensity score matching (PSM) is a non-experimental method for causal inference that aims to equate the treatment groups by balancing them on confounding factors to make them comparable [25]. The model is designed to reduce self-selection bias caused by observable features, by pairing a group that participates in adoption activities with a group that does not share similar observable traits [26]. As a result, it helps to minimize the potential bias that can come from differences in individual characteristics between the treated and untreated groups. Propensity score matching involves linking individuals in the treatment group with individuals in the control group based on their estimated likelihood of being in the treatment group determined by their observable features. As the name suggests, propensity score matching computes the propensity scores for each observation through a first-stage regression analysis, employing either a probit or a logistic regression model. These scores reflect each farmer's likelihood of adopting CSIT. The propensity score (p-score) generated from the probit in the first-stage regression ranges from 0 to 1. A score closer to 1 indicates a higher likelihood of adopting CSIT practices, while a score closer to 0 suggests a lower likelihood. This estimated propensity score on the treated (ATT), matched treated, and non-treated farming households were calculated using probit regression in the first stage and was used to estimate the average treatment effect in the third stage of PSM. In the second stage, two balanced groups were created based on their estimated propensity score. This study employed various matching methods, including kernel matching, nearest neighbour matching, and radius matching, to achieve balance between the groups.

3.3.3. Probit Regression Model

Smallholder households in Botswana often operate under uncertainty, impacting their capacity to produce agricultural products effectively. As a result, the probit model assumes that smallholder farmers make adoption decisions with a goal of maximizing their utility [27]. The theoretical framework of the probit model is grounded in random utility theory (RUT). In this context, let U0 represent the expected benefits from non-adoption, and Uj denote the expected benefits from adopting CSIT. According to the RUT, a farmer i chooses to adopt CSIT, if the expected benefit from adoption surpass those from non-adoption [28,29]. The utility functions for adoption and non-adoption are defined as follows:

$$U_{i1} = \beta_1 X_i + \varepsilon_{i1} \qquad \text{(for Adoption)} \tag{1}$$

$$U_{i0} = \beta_0 X_i + \varepsilon_{i0} \qquad \text{(for Non-Adoption)} \tag{2}$$

The decision-making framework can be expressed as follows:

$$y_i = \begin{cases} 1\ if\ u_i\ \geq 0 \\ 0\ if\ u_i < 0 \end{cases} \tag{3}$$

The probability of a smallholder farmer i's decision to adopt CSIT is determined by the utility of that alternative compared to the utility of the current alternative ($U_{i1} > U_{i0)}$. Therefore, for the smallholder farmer i, the probability of adoption is indicated by:

$$P\ (y_1) = P\ (U_{i1} > U_{i0}) \tag{4}$$

$$P\ (y_1) = P\ (\beta_1 X_i + \varepsilon_{i1} > \beta_0 X_i + \varepsilon_{i0}) \tag{5}$$

$$P\ (y_1) = P\ (\varepsilon_{i1} - \varepsilon_{i0} < \beta_1 X_i - \beta_0 X_i) \tag{6}$$

$$P\ (y_1) = P\ (\varepsilon_i < \beta X_i) \tag{7}$$

$$P\ (1) = F\ (\beta X_i) \tag{8}$$

where, U_{i1} = the utility derived from the technology by a farmer from the CSIT; U_{i0} = the absence of utility obtained from CSIT; P (1) = probability of adopting CSIT technology; β_0 to β_1 = estimated parameters; X_i = independent variables; F = is the cumulative distribution function of the standard normal distribution. ε_i = disturbance term.

3.3.4. Average Treatment Effect on the Treated (ATT)

In the third stage of the propensity score matching model, the average outcomes for the *two groups* were estimated. The estimated impacts of CSIT interventions are determined by calculating the difference in average outcomes between the group that adopted CSIT practices and the group that did not implement CSIT interventions. This difference is referred to as the PSM estimator of average treatment effect on the treated households (ATT), represented as follows:

$$ATT = E\{Y_{1i} - Y_{0i} \mid A_i = 1\} \tag{9}$$

$$= E\ E\{Y_{1i} - Y_{0i} \mid A_i = 1, p(Xi)\} \tag{10}$$

$$= E\ [E\{Y_{1i} \mid A_i = 1, p(Xi)\} - E\{Y0i \mid Ai = 0, p(Xi)\} \mid Ai = 1 \tag{11}$$

where y_1 and y_0 represent the outcomes for households that have adopted CSIT practices and the controlled group, respectively. $A_i = 1$ indicates adoption of CSIT, and $A_i = 0$ refers to comparison group does not. Table 1 presents a summary of the explanatory variables used in this study, specifying the measurement type and outlining the theoretical relationship posited between these variables and the dependent variable studied. Data collection for this study was conducted from December 2023 to January 2024.

Table 1. Explanatory variables used in the probit model and their expected outcome.

Variable Name	Type of Measurement	Prior Expectations
Adoption (Yes/No)	Dependent variable	
Gender of HH	Farmer's sex (female = 0; male = 1) (Dummy)	+
Marital status	Marital status of the farmer (single = 0;married, divorced, widowed = 1) (Dummy)	+/−
Age of a farmer	Actual number in years (Continuous)	+
Education	Level of education (Categorial)	+
Labour	Availability of labour (Continuous)	+/−
Household size	Total number of individuals living in a unit (Continuous)	+
Farming Experience	Number of years in farming (Continuous)	+/−
Land tenure	The type of land ownership (Categorical)	+
Land size	Number of hectares that each household owns (Continuous)	+/−
Access to credit	If a farmer has access or not (Yes = 1; No = 0) (Dummy)	+
Frequency of extension visits	Measures how often farmers receive visits from extension officers (Continuous)	+
Main occupation	Measured the main occupation of the farmers (Categorical)	−
Access to electricity	If a farmer has access or not (Yes = 1; No = 0) (Dummy)	+
Districts	Different districts in which the farmers come from (Categorical)	+/−

+/− represents the direction of influence (either positive or negative) Source: Author, 2024.

4. Results and Discussion

4.1. Demographic and Socio-Economic Profile of the Smallholder Maize Farmers in Botswana

The demographic and socio-economic characteristics of farmers were assessed using a structured interview process. Information was gathered from the farming household heads, who provided the required information on behalf of their families. Key characteristics assessed included age, gender, level of education, marital status, household size, and involvement in off-farm activities, among others. As presented in Table 2, the sample consisted of both those who adopted and those who did not adopt climate-smart irrigation technology. Based on the results from the survey, 48% of the respondents are those who adopted improved irrigation methods as a mechanism to cope with the changes in climatic conditions, while 52% selected for study relied on rainfed systems for farming. More than half of the respondents' reliance on rainfed agriculture highlights a potential vulnerability. Furthermore, these farmers face increased risks of crop failure due to insufficient rainfall.

Gender is a very crucial aspect in a household for decision-making, especially in rural areas [30]. Table 2 indicates that the study participants were dominated by males (55%) rather than females (45%). This finding is a clear indication that agriculture in Botswana is still a male-dominated activity, with females participating in non-agricultural activities. The findings of this study are consistent with those of Gayo [31]. This indicates that farming households are predominantly male due to the physically demanding nature of farming. Additionally, in many African cultures, men are typically responsible for farming, while women often handle household chores.

Table 2. Socio-economic and demographic profile of sampled farmers in Botswana.

Variable	Frequency (*n*)		Percentage (%)	
Gender				
Male	150		55.35	
Female	121		44.65	
Marital status				
Single	150		55.35	
Married	121		44.65	
Adoption status				
Adopters	131		48.34	
Non-adopters	140		51.66	
Land tenure				
Own	182		67.16	
Lease	89		32.84	
Level of education				
No education	47		17.34	
Primary education	62		22.88	
Secondary education	80		29.52	
Tertiary education	43		15.87	
Others	39		14.39	
Access to credit				
Yes	24		8.86	
No	247		91.14	
	Mean	**Max**	**Min**	**SD**
Age	50.981	74	23	12.394
Household size	4.40	10	1	2.31
Farm size	1.811	9	1	1.436
Farming experience	3.394	6	1	1.294
Income	577	35,325	157	4723

Abbreviations: Max, Min, and SD; maximum, minimum, and standard deviation Source: Survey data (2024).

Descriptive statistics reveal that only 45% of farmers were married, and 55% were single (Table 2). The result also indicated that 31.37% of the farmers were above 60 years, and 30.26% were in the age range from 51 to 60 years; meaning that only 20% of the population were in younger age groups (below 40 years), and around 62% of the respondents were aged above 50 years. This means that many farmers in Botswana are well experienced in farming (see Table 2), although older farmers will negatively impact on the supply of family labour force and agricultural production. In addition, older farmers with many years of experience are not always willing to abandon old tactics in favour of new ones, while young farmers are more flexible. Therefore, there is a need to encourage youth participation in agriculture to improve the adoption of climate-smart irrigation practices. This argument is supported by many scholars, such as Ruiz Salvago et al. [32] and Alrawashdeh et al. [33] to mention a few. Furthermore, the study demonstrated that a greater proportion (36.53%) of the respondents have 31 to 40 years of farming experience, and only 8.12% have fewer than 5 years of experience. These statistics imply that the respondents have many years of farming experience.

The farmers were also queried about their educational levels; classified as formal versus no formal education. The results presented in Table 2 show that a total of 17.34% of farmers had no formal education, while 22.88% had completed primary education. Interestingly, 29.52% of farmers had secondary education, and 15.87% had acquired tertiary qualifications. The statistics confirm that a greater proportion of the respondents (69.74%) possess a lower level of education. Level of education has a direct influence on the adoption of sustainable irrigation practices, leading to crop productivity. This was confirmed by Das, AB and Sahoo, D [34]. The findings show that the highest percentage (72%) of farmers belongs to a family with a maximum of five members, and 28% of the respondents had 6 to 10 members in the family. An increase in the number of households may lead to the adoption of more intensive and sustainable agricultural irrigation practices due to the increase in demand for food. Contrary to that, other studies have found that larger farm households are more likely to use labour-intensive agricultural practices due to insufficient labour supply [35]. However, the reality is that with smart irrigation, no or less human involvement is required [36].

Off-farm activities are "dummy variable", showing whether the household head participates in off-farm activities or not. It is expected to impact adoption positively as engaging in off-farm activities can solve liquidity problems [37]. Approximately 46.86% of the respondents reported participating in off-farm activities, primarily due to low agricultural income and the seasonal nature of jobs in the agricultural sector [38].

Farmers were engaged in different income-generating activities such as engaging in small businesses selling vegetables, and other types off-farm activities such as "Ipelegeng" which is a short-term employment support scheme in Botswana by the government. The majority of the respondents (83.39%) considered farming as the main source of income, while only 16.61% reported their main source of income as coming from business and other types of employment. Access to and ownership of land is an important factor in farming. A total of 67.16% of farmers reported that they cultivated their own farm, while the rest (32.84%) were either renting or leasing the land.

4.2. Determinants of Climate-Smart Irrigation Technology

To investigate the research question regarding the adoption of climate-smart irrigation technology, a probit regression model was applied, with the results summarized in Table 3. The probit model indicate that various socio-economic and institutional factors influenced the adoption of climate-smart irrigation technology at different levels. Among the fourteen variables that were included in the model, seven were found to significantly influence the adoption of climate smart-irrigation technology. The model's performance is evidenced by the value of Pseudo R^2 of 67%, the log-likelihood of -59.79 and an LR Chi2 that is significant at 5% level, demonstrating a good fit to the data. Additionally, the model showed no multicollinearity issues because it had a low average variance inflation factor (VIF) of 1.54.

The probit model regression results reveal that age was significant at the 1% level and negatively influenced farmers' decision to adopt irrigation technology. Specifically, an increase of one year in farmers' age is associated with a 9% decrease in their likelihood of adopting climate-smart irrigation technology. This negative relationship is corroborated by studies from Van der Berg [39], Lebeta [40]. Kurgat et al. [41], and Aryal et al. [42]. This indicates that older farmers are generally reluctant to adopt new innovations. Additionally, household size negatively impacted the decision to adopt climate-smart irrigation technology, with a significant level of 10%. This suggests that, as a family size increases, the likelihood of adopting climate-smart irrigation technology increases by 20%. Farming experience was found to have negative and significant effect on adopting climate-smart irrigation technology with a significance level of 1%. This finding is supported by research from Serote et al. [43] and Tanti [44]. The negative relationship suggests that, as farming experience increases, the likelihood of adopting climate-smart irrigation technology decreases. This trend may be attributed to older farmers, who typically possess more experience but are less willing to take risks associated with investing in new irrigation technologies due to their shorter planning horizon [45,46]. Land Tenure (land tenure = −0.726) negatively and significantly impacts the adoption at 1%. The negative coefficient suggests that the probability of adoption decreases by 10% for those who use their own property. This may be because those who use leased property are more serious about maximizing productivity within a limited timeframe compared to those who own land. On contrary to that Maíra [47], Wondmu [48] and Schuck, et al. [49] reported that an enterprises with the most owned land are most likely to invest in more efficient irrigation systems during severe droughts. Gender significantly influences farmers' decision to adopt climate-smart irrigation technology at the 5% level, with the probability of males adopting this technology increasing by 44% compared to females. This finding is consistent with that of Abdulkareem and Azahinli [50], reflecting cultural biases that grant men exclusive rights to make farm decisions regarding short-term and long-term adjustments [43]. Level of education (Education = 0.075) is significant at 1% and directly impacts farmers' awareness and understanding of improved irrigation techniques. Those with higher education levels are generally more informed about the benefits and operations of advanced irrigation systems. Conversely, lower educational attainment can lead to misconceptions about these technologies or a lack of confidence in using them effectively. Supporting this view, Schultz [51], Ali and Byerlee [52], and Hojo [53] reinforced the notion that education enhances a farmer's capacity to respond swiftly and efficiently to technological changes. The availability of labour (Labour = 0.2633) is regarded as an important factor that influences technology adoption among smallholder farmers; this is confirmed by Adeoti [54], Feder et al. [55], Quan and Doluschitz [56], and the availability of labour directly impacts a farmer's ability to implement and maintain an irrigation system. Access to credit positively influences the likelihood of farmers adopting climate-smart irrigation technology as anticipated. This finding is consistent with Yohannes' [57] study, which demonstrated that credit access enhances farmers' financial capacity to invest in modern farming technologies.

Table 3. Estimating the determinants of CSIT adoption by maize farmers using probit regression.

Adoption	**Coef.**	**Std.Err**	**Z**	**p > ∣Z∣**
Maritalstatus	0.0535	0.19099	0.28	0.779
Gender	0.4493 **	0.19538	2.30	0.021
Age	−0.2851 ***	0.09660	−2.95	0.003
Education	0.0752 ***	0.02053	3.67	0.000
Labour	0.2633 ***	0.07674	3.43	0.001
HHsize	−0.3355 *	0.20117	−1.67	0.095
Farm_Exp	−0.3105 ***	0.07649	−4.06	0.000
Land tenure	−0.7267 ***	0.21526	−3.38	0.001
Access_credit	0.4126	0.34399	1.20	0.230
-cons	1.262	0.57478	2.20	0.028
Number of obs = 269 LR chi2(9) = 134.21 Prob > chi2= 0.0000 Pseudo R2 = 0.3603 Log Likelihood = −119.12591				

* Significant at 10%, ** significant at 5%,and *** significant at 1%. Source: Survey data (2024).

4.3. Impact of Climate-Smart Irrigation Technology (CSIT)

The impact of climate-smart irrigation technology (CSIT) was assessed by comparing the differences in "Gross Production" and in "Gross Value" between those who have adopted the CSIT and those who have not. This evaluation was performed using the propensity score matching model and the average treatment effect on the treated (ATT) analysis.

4.3.1. Estimation of Propensity Score

The impact of adopting climate-smart irrigation technology on "Gross Production" and "Gross Value" was estimated using the propensity score matching (PSM) method, implemented through the Pscore and PSMatch2 commands in STATA version 15.1. The propensity score indicates the likelihood of receiving a treatment based on observed factors. Researchers can build comparable treatment and control groups by matching people who have similar propensity scores.

4.3.2. Matching Effect Analysis

The effectiveness of propensity score matching approach relies on two requirements; namely, (i) the balancing test and (ii) the common support test. Rosenbaum [58] examined the balance of the covariate between the treated and the controlled groups both before and after matching using the standardized bias as a measure. The success of the balance is determined by the percentage reduction in covariates bias and the changes in t-statistical significance levels before and after matching [59]. The balancing test requires that after matching, there are no systematic differences in covariates between the treated and non-treated groups. As shown in Table 3, after matching, the standardized bias of all covariates were fewer below 5%, and most control variables were significant before matching. Additionally, the *p*-values of the t-statistics of all control variables were greater than 5% after matching, indicating that these variables are negligible after matching. This suggest that the matching process effectively reduces disparities in the distribution of explanatory variables between the control group and the treatment groups. Furthermore, the pseudo R^2 decreased after matching, indicating that the differences in controlled variables between the treated and untreated groups have been minimized. A lower psuedo R^2 value suggests that the treatment and control groups became more comparable after matching for the variables and reduced the risk of confounding bias (see Table 4). Overall, these results affirm the quality of the matching.

Table 4. Balance test results of propensity score matching (PSM).

Variable	Unmatched Matched	Mean Treated	Mean Control	%bas	%Reduced |bias|	*t*-Test t	*t*-Test P > |t|
Marital Status	U	0.4651	0.4214	8.8	20.2	0.72	0.473
	M	0.4651	0.4302	7.0		0.56	0.575
Gender	U	0.6589	0.4642	39.9	95.2	3.26	0.001
	M	0.6589	0.6495	1.9		0.16	0.874
Age	U	2.2636	3.1357	−81.7	99.2	−6.70	0.000
	M	2.2636	2.2709	−0.7		−0.05	0.959
Education	U	12.07	7.0429	102.0	97.0	8.31	0.000
	M	12.07	11.917	3.1		0.30	0.265
Labour	U	1.845	1.0786	61.4	59.3	5.05	0.000
	M	1.845	2.157	−25.0		−1.61	0.109
Hhsize	U	1.2636	1.3429	−16.6	−48.5	−1.36	0.174
	M	1.2636	1.3813	−24.8		−2.02	0.044
Farm_Exp	U	2.938	3.8143	−71.7	53.4	−5.89	0.000
	M	2.938	3.346	−33.4		−2.48	0.014
Landtenure	U	0.51938	0.82143	−67.6	81.4	−5.57	0.000
	M	0.51938	0.46335	12.5		0.90	0.370
Access_Credit	U	0.14729	0.03571	39.3	83.3	3.26	0.001
	M	0.4729	0.16594	−6.6		−0.41	0.682

Table 4. *Cont.*

Variable	**Unmatched Matched**		**Mean Treated Control**		**%bas**	**%Reduced |bias|**	***t*-Test** t	P > |t|
Sample	**Ps R2**	**LR chi2**	**p > chi2**	**MeanBias**	**MedBias**	**B**	**R**	**%var**
Unmatched	0.360	134.21	0.000	54.3	61.4	165.5 *	0.89	20
Matched	0.046	16.54	0.056	12.8	7.0	51.3 *	1.40	20

Source: Survey data (2024).

4.3.3. An Average Treatment Effect on the Treated (ATT) Analysis

Once the propensity scores have been estimated, the next step is to conduct an average treatment effect on the treated (ATT) analysis. This analysis focuses specifically on evaluating the impact of the treatment, which is the adoption of CSIT, on those smallholder maize farmers who actually participated in it. We estimated the impact of CSIT on gross production and gross value using three comparison techniques: Nearest neighbour (NN) matching, radius matching, and kernel matching and Bootstrap standard errors are used to make estimations. The estimations from all matching methods showed that CSIT had a favourable and significant influence on maize production in the treated groups.

As shown in Table 5, in the case of gross production, the average treatment effect on treated (ATT) ranges from 650 kg to 2489 kg per hectare of land, whereas the average treatment effect of CSIT on gross value ranges between BWP 1186 to 2944. Therefore, the study found that the adoption of CSIT has a significant relationship with gross production and gross value, which determines the farm income of the farmers.

Table 5. Average treatment effect of CSIT on gross production and gross value.

	NN Matching	**Kernel Matching**	**Radius Matching**
ATT	2489 ***	650 ***	938 ***
SE	551	178	198
ATT	1186 ***	2039 ***	2944 ***
SE	711	409	623

Source: Survey data (2024). *** significant at 1%.

5. Conclusions and Recommendations

Climate-smart irrigation technology has attracted substantial interest due to the increase in demand for enhanced water usage efficiency. Smart irrigation may conserve irrigation water and boost production at the farm level, thus contributing to better food security for the needy and household income for smallholder farmers.

This study mainly investigated the adoption and effectiveness of climate-smart irrigation technology among smallholder farmers in Botswana. The findings from descriptive statistics highlighted the ageing farming population, male domination and educational barriers. Additionally, the findings show that adoption of climate-smart irrigation technology is still low in Botswana. The results of the probit model indicated that age, household size, farm experience, and land tenure negatively and significantly impacted on the adoption decision, meaning that all these factors lower the probability of adopting CSIT among the smallholder maize farmers in Botswana, as expected. In contrast, gender, education, labour force, and access to credit lead to an increase in the likelihood of adoption among the farmers. Other variables such as marriage status, land tenure, frequency of extension visits, access to credit and region were insignificant in the adoption of climate-smart irrigation technology. While these factors were not significant drivers of adoption, they may be crucial in understanding the broader context of Botswana's farming sector. Further studies may reveal new insights regarding these issues. using propensity score matching model (PSM) and average treatment effect on the treated (ATT), the results show that the adoption of

CSIT is economically and financially viable, pro-poor, and can mitigate the adverse effects of climate change on maize production in Botswana. Given the findings above, the study recommends the following regarding the adoption of climate-smart irrigation technology:

- The concerned institutions in Botswana should work to improve access to credit for farmers;
- Support should be strengthened to facilitate training and improve the educational attainment of farmers for farmers, to understand better the potential the benefits of adopting climate-smart irrigation technology;
- Encourage more young farmers to engage in farming activities and ensure frequent extension services to encourage irrigation farming;
- Gender-sensitive programmes that address unequal access to resources such as land should be prioritized.

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