OPEN ACCESS

GRS Journal of Multidisciplinary Research and Studies

Abbreviate Tittle- GRS J Mul Res Stud

ISSN *(Online)* - *3049-0561*

https://grspublisher.com/journal-details/GRSJMRS

Vol-3, Iss-6 (Jun)-2026

Climate-Smart Agricultural Technology Adoption and Intensity among Vegetable Farmers in Eswatini: Evidence from a Cragg Double Hurdle Model

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Article History

Received: 15.05.2026

Accepted: 10.06.2026

Published: 24.06.2026

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Abstract: Problem and Objectives: Trends reveal that in Eswatini, there are low quantities of vegetables produced locally and statistics show more volumes of vegetable imports which constitute about 70% of local consumption as a result of local production failing to meet domestic demand. The main objective of this study was to determine the factors affecting Climate Smart Agricultural Technology (CSAT) adoption and intensity among vegetable farmers in Eswatini.

Methods: The study used a descriptive quantitative research design to determine the factors affecting the adoption and intensity of adoption of climate-smart agriculture technology among smallholder vegetable farmers. A total of 200 vegetable farmers were purposively sampled from a population of 946 vegetable farmers registered with The National Marketing Board (NAMBoard) and were part of the Market Oriented Climate-Smart Agriculture Project. The study used survey to collect primary data through the use of a questionnaire. Data were analysed using descriptive statistics, and Cragg Double Hurdle model. The dependent variables of the model were adoption of CSAT and intensity of CSAT adoption. Adoption of CSAT was measured as a binary variable (1= adopter, 0 = non-adopter) and intensity of adoption of CSAT was measured as a proportion of adopted CSATs given the available CSATs.

Findings: The findings of the study indicate that significant factors affecting CSAT adoption decision include age, risk attitude, household size, off-income, and land quality. The results on factors affecting the intensity of CSAT adoption reveal that the adoption intensity is affected by age, access to inputs market, farm size, land quality and frequency of extension contact.

Conclusion and Recommendations: The study examined the factors affecting adoption and intensity of adoption of CSAT among vegetable farmers. The findings indicate that CSAT adoption decision depend on access and awareness while CSAT adoption intensity is constrained by structural and institutional factor.

The study recommends that more training be undertaken to sensitize farmers to adopt more CSAT and increase awareness of CSAT. It is recommended that the Ministry of Agriculture and the National Agricultural Marketing Board (NAMBoard) improve its extension services, capacitation of farmers through CSA workshop and diversify CSA interventions to other enterprises.

Keywords: *adoption, intensity of adoption, climate-smart technologies, Cragg Double Hurdle.*

Cite this Article

Sibandze, Sikelela, S., Olarinde, Luke, O & Dlamini, Daisy, D. (2026). Climate-Smart Agricultural Technology Adoption and Intensity among vegetable farmers in Eswatini: Evidence from the Cragg Double Hurdle Model. *GRS Journal of Multidisciplinary Research and Studies, Vol-3 (Iss-6). 18-30*

Introduction

The economy of Eswatini has been known to be largely dependent on agriculture with food security mostly dependent on subsistence farming, accounting for 54% of the GDP. A significant proportion of the manufacturing sector mainly focuses on value addition through processing of agricultural products including timber and sugar. Therefore, the sector has been of vital significance to the economy as a whole since it is the major employer of the rural households consisting of 70% of the population relying on agriculture for their incomes. The various activities include: sugar cane production, citrus fruits, vegetables, maize, livestock and poultry, and forestry (Thompson, 2024).

In the Kingdom of Eswatini, variability in weather patterns have resulted on unfavourable effects on food production, leading to insufficient production for domestic consumption. The country has experienced global impacts of climate change like most countries. The Kingdom suffers the effects of prolonged droughts which adversely affects agricultural productivity, water and food security. The recent droughts affected various sectors, mostly agriculture and food security due to water scarcity, resulting to 68% decrease in maize production (from the previous cropping season), drying of water sources, including boreholes across the country, however 317, 000 people received food assistance, with the overall impact costing 6.4% of the country's GDP. This has prompted a shift on the way agriculture is conducted, with a major focus on how to access available water, employ practices that conserve water, while ensuring that livelihoods are enhanced by agro-based economic activities. In addition, decreasing access to food markets and deficiency of value addition to agricultural processing has raised concerns pertaining to income and food security (Kunene, Ogunniyi & Masuku, 2018; Thompson, 2018).

Agricultural productivity in the Kingdom of Eswatini is low as a result of severe droughts, impact of HIV/AIDS and underinvestment in the agriculture sector (WorldBank, 2021). While 70% of the population are farmers. In the period between 2014 and 2016, the country experienced the El Nino drought and the outbreak of the Armyworm which affected a majority of cereal crops as well as vegetables which further worsened agricultural productivity (VAA, 2017). Most farmers in Eswatini produce maize in summer and vegetables in winter. NAMBoard receives only 11% of the vegetables from local production and the rest are imported from South Africa. Factors such as climate change on local vegetables have been the cause of higher imports experienced in recent years (Xaba & Masuku, 2013, Amoah, Debrah & Abubakari, 2014).

In response to the adverse effects of climate change, Climate-Smart Agriculture (CSA) has been one of the climate change adaptation strategies promoted by the government of Eswatini as an approach that integrates climate change mitigation, adaptation and increased productivity in agriculture. The ministry of agriculture through National Agricultural Marketing Board, Eswatini Development Enterprise (ESWADE) and other development agencies have been mandated to ensure the implementation of CSA through smallholder farmers in the country.

However, there is limited empirical evidence on the adoption as well as the factors affecting the adoption of Climate-Smart Agriculture Technologies (CSATs) and intensity of adoption of CSATs. The present study seeks to analyse the factors affecting the adoption and intensity of CSAT amongst smallholder vegetable farmers in Eswatini. The study contributes to the literature in three major areas. First, it is based on primary survey data which attempts to determine the adoption of CSATs and to elicit the factors affecting the adoption of CSATs among vegetable farmers in Eswatini. Secondly, this study assesses the intensity of adoption, measured by the number of CSATs adopted given the available CSATs. Thirdly, the study uses the Cragg Double Hurdle model to model the factors affecting both adoption of CSAT and the intensity of CSAT adoption. It uses the adoption and intensity of adoption equations and assumes that they are independent.

The remainder of this paper is organised as follows: Section 2 presents literature review, Section 3 deals with materials and methods, Section 4 presents the Results, Section 5 are the Discussions, while Section 5 are the Conclusions and Recommendations of the study.

Review of Literature

Determinants of CSAT adoption and intensity of CSAT adoption by smallholder farmers have been of great interest for scholars in the field of Agricultural Economics. In the context of Eswatini, there is limited literature on determinants of adoption of CSAT and intensity of CSAT adoption while a number of CSAT adoption studies have been conducted in Sub-Saharan Africa Region. This section of the paper presents a review of literature on the determinants of CSAT adoption and intensity of CSAT adoption. The literature reviewed on the determinants has been categorised into five categories being: socio-economic, social capital and information access, farm characteristics, financial farmers' perception on the technology and risk factors.

a) Farmers' socio-economic characteristics

The factors explored from literature under this category of socio-economic characteristics includes: marital status, age, gender, household size, educational level, farming experience etc. A variety of studies indicate ambiguous effects on the adoption of Climate-Smart Technology adoption. The overall effect of the socio-economic factors on the adoption of CSAT remains nuanced with differing results.

Farmers' socio-economic characteristics include educational levels, gender, household head age, marital status and household size. The gender of the household head has an important role in adoption of CSA technology. Some scholars report a higher level of technology adoption among male-headed households compared to their female counterparts because of the discrimination, that is, women have limited access to external inputs, services and information as a result of socio-cultural value (Martey et al., 2020; Amedu et al., 2020)

Gender has been found to positively affect adoption. Adoption is positively influenced because men in male-headed households in most societies are the ones who control productive resources e.g. labour, land and capital which are important for the adoption of new technology. On the other hand, female-headed households have limited adoption as a result of limited access to productive resources as well as access to training and extension services. Higher access to assets and information make such families better able to adopt the technology (Martey et al., 2020; Amedu et al., 2020).

Households' size has been found to be correlated to labour availability and determine the decision to adopt the technology depending on the labour requirements of the technology. Technology adoption has higher labour requirements and if family members are used then adoption is influenced positively. However, there is a high possibility that families with scarce labour to be non-adopters or partial adopters of labour-intensive technologies. A variety of scholars found a positive relationship between the adoption of labour-intensive CSA technologies e.g. intercropping and row marking and household size (Martey et al., 2020; Amedu et al., 2020).

Level of education has been found to have a positive effect on the adoption of CSAT. This is because education improves farmers' capacity to acquire, process, and use information related to agricultural practices (Makate et al., 2019; Abegunde et al., 2020; Obi & Maya, 2021; Oyawole et al., 2021; Sisay et al., 2023). Furthermore, Belay et al. (2022) found that a one year increase in the level of education improve adoption of CSA practices by 21.40% while Mthethwa et al. (2022) argued that education levels often hinders the adoption of CSA practices yet providing less clarity pertaining to their observed results.

Farming experience also has been found to significantly affect CSAT adoption. Farmers with remarkable experience exhibit better awareness on potential benefits of better management skills at farm level [40, 21]. This is evidence in the studies of Zamasiya et al., (2017) and Mutunga et al., (2018). In another study, Belay et al., (2022) found that a one year increase in farming experience increase the probability of adopting CSA practices by 3.90%. Furthermore, Ouedraogo et al. (2019) found that farmers with more years of experience are more likely to adopt CSA practices because of improved awareness and better tolerance on changes of farming practices. This practical experience enhances their ability to identify and understand the concept of CSA better[26].

b) Social Capital and Information Access Factors

Studies on CSA technology adoption has revealed that adoption is also affected by social capital and information access factors. These factors include, access to credit, group membership, access to extension, access to media or ownership of a phone, CSA awareness. A majority of these factors tend to positively influence the adoption of CSA practices.

Access to credit is another factor that significantly influence the adoption of CSA practices as indicated by previous studies on CSAT adoption. Improved household credit access decreases the income constraint on farmers and enables them to purchase inputs as well as hiring labour. Such is only realised when the credit is invested in agricultural activities as compared to leisure. In countries where female-headed households are discriminated against by credit institutions, low adoption rates have been reported as a result, they are unable to finance yield-improving technologies (Aryal et al., 2017). Access to credit positively and significantly influence adoption in the case of multiple CSA practices e.g. integrated soil fertility management and conservation agriculture (Zampaligré and Fuchs, 2019; Kangogo et al., 2021; Sisay et al., 2023).

Extension services connect innovators (researchers) and technology users (farmers) through the communication of information to farmers on the efficient use and merits of the new innovation. Extension officers scatter information through field visits, farmer meeting and making use of experienced farmers. Access to extension services is positively linked to adoption of technology due to provision of information by extension officer about the new technology and its capability. Furthermore, extension services aids in the implementation and diffusion of innovation hence closing the gap between farmers and the new innovation (Mwangi & Kariuki, 2015).

Membership in farmers associations improves social capital enabling trust, ideas and exchange of information about the new technology. The probability to adopt new technologies is increased especially when farmers involve themselves in community-based organisation which engage them in social learning about the technology. However, farmers' associations may also have an adverse effect on the adoption of technology, especially when opportunistic behaviour e.g. free-riding exists. Most researchers suggest an inverted U-shaped individual adoption curve, meaning that the effects of networks are positive at low adoption rates while negative at high adoption rates (Bandiera & Rasul, 2006). As more individuals participate in experimentation of new innovations, opportunistic behaviour in the form of free-riding may be predominant.

Awareness of CSA practices is a vital factor of CSA adoption. The major hindrance to the adoption of CSA the lack of awareness about the technology. In order to adopt CSA, one needs sufficient information to embrace the technology. According to Mountouama et al. (2022), a majority of farmers are not aware about CSA technologies. Findings from Teklu et al. (2022), indicate that CSA awareness increases chances of adoption of agroforestry, compost, row planting, water conservation and soil and water management by 6.70 to 33%.

c) Farmers Perception of the Technology

Consistent with the neo-classical model view that the rational economic agent maximizes utility, advantages enjoyed by an adopter together with the associated production costs have a significant role in the adoption of new technologies. Farmers show less interest in long term benefits than short term benefits. This is due to differences in perceptions of technologies between the farmer, scientists and extension agents. Such may provide a better understanding of technology adoption since farmers are the one dealing with technology frequently.

The differing perceptions are dependent on farmers' information and knowledge about the new technology and socio-economic situation. The amount of information is dependent on the level of education and training of the farmer that they get about the new technology. A study conducted in the Ethiopian highlands revealed that farmers' perceptions to adopt soil and water conservation technologies was significantly and positively affected by the education level and access to training (Moges & Tayes, 2017) .

The adoption of input-intensive technology for instance land-saving technology favours farmers with smaller land holdings [23]. Findings from studies revealed that technology adoption is positively influenced by the perceived advantages of CSA in terms of contribution towards productivity and income (Ntshangase et al., 2018; Ouedraogo et al., 2002).

d) Farm Related Factors

Factors that are farm related revealed by some studies which were found to affect CSAT adoption include farm size, land quality, distance to the market, and ownership of livestock and assets.

Farm size is an important factor affecting the adoption of CSA practices. Farmers owning large farms show an increased willingness to adopt CSAT due to sufficient space for practicing conservation agriculture, agroforestry, and integrated soil fertility management (Makate et al., 2019a & Sisay et al., 2023). Affording farmers normally own large farms and own more assets hence increasing the likelihood to adopt CSAT like terraces, stone bunds, stress-tolerant, livestock, and improved crop varieties due to possession of risk management resources (Zampaligré and Fuchs, 2019; Musyoki et al., 2022; Sisay et al., 2023) .

Soil quality is another factor influencing the adoption of CSAT. Findings from recent studies reveal that farmers with poor quality soils show an increased likelihood of adopting CSAT (Pangapanga-Phiri & Mungatana, 2021) .The adoption of row planting, agroforestry, and improved crop varieties was found to be positively influenced by poor soil fertility (Teklu et al., 2023).

Ownership of livestock assets positively influences technology adoption. Such implies that farmers possessing more assets have high chances of having income, equipment and materials needed for the technologies (Rosenstock & Nowak, 2019).

Distance to the market show mixed effects on the adoption of CSAT indicating a contradiction to the initial expectation of various studies of a negative impact. Longer distances to markets imply higher transaction costs hence discouraging the adoption of CSAT due to challenges in accessing inputs and output markets (Makate et al., 2019). Another study revealed the negative effect of distance from towns or markets on farmers' access to credit facilities, technologies, and information, hence escalating transportation costs and increasing difficulty in monitoring distance farms (Abegunde et al., 2020).

e) Financial Factors

On-farm income has a positive effect on the adoption of CSAT. Results from studies reveal that increased on-farm income increases the likelihood of CSAT adoption. Moreover, increased farm income minimises risk aversion and improves exposure to information (Abegunde et al., 2020). Furthermore, the correlation between CSAT adoption and on-farm adoption involves the sales of farm produce for generating income, implying that farmers involved in commercial farming have more chances to adopt CSA practices. Contrary, those involved in farming primarily for subsistence purposes show lower CSA adoption rates (Mthethwa et al., 2022).

Off-farm income shows nuanced effects on the adoption of CSAT. Average monthly off-farm income negatively affect the adoption of CSA practices, implying that over dependence on off-farm income activities as major income sources decreases the involvement in agricultural activities (Abegunde et al., 2020; Djido et al.,2022; Musyoki et al., 2022). Contrary, there exists a positive relationship between off-farm income and livestock diversity, echoing the importance of financial resources in the acquisition of inputs for production and the potential for larger land areas to cultivate various feeds, diminishing dependence on purchased feeds (Kurgat et al., 2020).

Access to subsidies show nuanced effects on the adoption of CSAT since it results to either an increase or decrease on the adoption of CSAT depending on the technology.

f) Risk Factors

Risk attitudes of farmers significantly affect the adoption of CSA technologies (Kangogo et al., 2021; Musyoki et al., 2022). . Risk-averse farmers are less likely to adopt CSATs e.g. ridges, terraces, and bunds, which may involve investments in terms of time, labour, and tools. The unwillingness emanates from their aversion to financial risks and the reluctance to utilise the available limited cash resources on the CSATs (Musyoki et al., 2022).

On the other hand, risk-taking farmers have more chances of adopting the various CSA practices, denoting their likelihood to get involved in new and innovative strategies. For example, a study propose that risk-taking has an important role in decisions related to irrigation and variations in cultivation calendars, emphasizing the importance of farmers' risk attitudes in modelling the landscape of CSA adoption .

The reviewed empirical literature indicate various factors having different effects on CSAT adoption and intensity of CSAT adoption. The reviewed literature group these factors into socioeconomic, social capital and information access, farm related, financial and risk factors. Some of these factors have a positive effect on CSAT adoption and some of them have a negative effect on CSAT adoption. On the other hand, some of these factors, particularly farmers socio-economic characteristics have nuanced effects (Makate et al., 2019; Abegunde et al., 2020; Kangogo et al., 2021; Sisay et al., 2023 ; Ntshangase et al., 2018; Ouedraogo et al., 2002; Zampaligré and Fuchs, 2019; Musyoki et al., 2022; Djido et al.,2022; Musyoki et al., 2022). Based on various literature on the subject and theoretical and analytical framework defined in this study, the following hypothesis was tested:

H_0: The smallholder vegetable farmers' characteristics (socioeconomic, social capital and information access, and farm characteristics factors) have no significant influence on the adoption of CSAT and intensity of CSAT adoption.

Materials and Methods

Econometric Framework and Estimation Strategies

In order to model the CSAT adoption decision and intensity of CSAT adoption, we applied the Cragg Double Hurdle model. We used Stata 14 software for the analysis.

Cragg Double Hurdle Model

The Cragg Double-Hurdle (DH) model was used to determine the factors affecting adoption and the intensity of adoption of Climate Smart Agriculture Technologies. The assumption of the study is that the farmer makes two sequential decision pertaining CSAT adoption. The first decision is to either adopt the CSAT or not and the second decision is on the intensity of adoption of the adopted CSAT. When estimating the double hurdle model, the first stage uses the probit regression utilising all the observations in determining the factors affecting the CSAT adoption decision [10].

The second stage involves using a truncated regression model on the participating farmers to analyse the intensity of adoption. It takes the value of zero if no climate smart agriculture technology (CSAT) adopted for vegetable production, and one if any CSAT is adopted for vegetable production. The one represents intensity of adoption, where in the current study is expressed as the number of adopted CSAT divided by the number of available climate-smart agriculture technologies. The intensity of adoption was determined as the proportion of adopted CSAT given the available climate-smart technologies that were adopted and then use ration formula to linearize it to be a continuous variable. The double hurdle model permits the use of a subset of data to pile up at some value without resulting to bias in estimating the determinants of the continuous dependent variable in the second stage [9] and hence all data in the remaining sample for participants is obtained.

The mathematical expression of the two stage DH model is as:

Decision to Adopt CSAT (hurdle 1)

$CSAT_i^* = \delta Y_i + \mu_i$ .. (3)

The Probit was estimated on the observed outcome as

$CSAT_i = 1\ if\ CSAT_i^* > 0$ And

$CSAT_i = 0\ if\ CSAT_i^* \leq 0$ .. (4)

In the above equation $CSAT_i^*$ is a latent variable taking the value of 1 if the vegetable farmer adopts the CSAT and 0 if otherwise, Y_i is a vector of explanatory variables affecting the CSAT adoption decision, δ is a vector of parameters to be estimated and μ_i is error term. $CSAT_i$

Decision on the intensity of adoption of CSATs to adopt (hurdle 2)

The unobserved latent value of the adoption intensity being Y_i^* which can be represented as:

$Y_i^* = \propto P_i + v_i$ .. (5)

The study used the proportion of adopted CSAT divided by the available CSAT that is Y_i since Y_i^* is a latent variable where;

$Y_i = Y_i^* = \propto X_i + v_i \ \ if \ Y_i^* > 0 \ and \ CSA_i^* > 0$

$Y_i = 0 \ otherwise$ .. (6)

Where Y_i was the observed proportion of adopted CSAT divided by the total available CSAT, that is, representing the intensity of CSAT adoption, X represents the vector of explanatory variable affecting the intensity of CSAT adoption, $\propto$, was a vector of the parameter to be estimated, where the error term is v_i.

μ_i and v_i are the error terms which are assumed to be independent of each other and are assumed to be normally distributed with constant variance and mean which is zero and distributed as;

$\mu_i \sim N(0,1)$

$v_i \sim N(0,1)$ .. (7)

Log- likelihood function of the double hurdle model is expressed as;

$LogL = \Sigma_0 ln\left(1 - \phi(\beta_i X_i)(\frac{\alpha Z_i}{\sigma})\right) + \Sigma ln\left(\phi(\beta_i X_i)\frac{1}{\sigma}\phi[\frac{A_i - \alpha Z_i}{\sigma}]\right)$ ..(8)

The model is equivalent to a univariate Probit model: equation 5 and equation 6, and the truncated regression model: equation 7, and equation 8 combined under the independence assumption between the error terms μ_i and v_i [10].

of the double hurdle model is expressed as;

LogL= Σ_0 ln(1-ϕ(β_i X_i)((αZ_i)/σ))+Σln(ϕ(β_i X_i) 1/σ ϕ[(A_i-αZ_i)/σ] ...(9)

The model is equivalent to a univariate Probit model: equation 5 and equation 6, and the truncated regression model: equation 7, and equation 8 combined under the independence assumption between the error terms μ_i and v_i 10.

Econometric Model Specification

The empirical model for farmer's decision to adopt CSA and the intensity of CSAT adoption are as specified for this study as follows:

Equation for decision to adopt

$D_i = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_4 X_4 + \alpha_5 X_5 + \alpha_6 X_6 + \alpha_7 X_7 + \alpha_8 X_8 + \alpha_9 X_9 + \alpha_{10} X_{10} + \alpha_{12} X_{12} + \alpha_{13} X_{13} + \alpha_{14} X_{14} + \alpha_{15} X_{15} + \alpha_{16} X_{16} + \alpha_{17} X_{17} + \alpha_{18} X_{18} \alpha_n X_n + \varepsilon_i \ldots$ (9)

Equation for the Intensity of CSAT adoption

$Y_i = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_4 X_4 + \alpha_5 X_5 + \alpha_6 X_6 + \alpha_7 X_7 + \alpha_8 X_8 + \alpha_9 X_9 + \alpha_{10} X_{10} + \alpha_{12} X_{12} + \alpha_{13} X_{13} + \alpha_{14} X_{14} + \alpha_{15} X_{15} + \alpha_{16} X_{16} + \alpha_{17} X_{17} + \alpha_{18} X_{18} + \alpha_n X_n + \varepsilon_i$.. (10)

Where:

There will be two dependent variables which include the CSAT adoption decision (1 = adopter, 0 = non-adopter) and the intensity of adoption which is the proportion of adopted CSAT given the available CSAT.

D_i = Decision to adopt CSAT

Y_i = Intensity of CSAT adoption

$X_1 \ldots \ldots X_n$ = Explanatory variables

$\alpha_1 \ldots \ldots . . \alpha_n$ = parameters to estimated

α_0 = y-intercept

ε_i = error term

Research design

The study uses a descriptive quantitative research design. Data were collected using a questionnaire validated by a panel of experts from the Department of Agricultural Economics and Management. It used surveys to collect primary data through face-to-face interviews.

Population and Sampling

The target population of the study comprise the Climate-Smart (CSA) vegetable farmers registered with the National Agricultural Marketing Board (NAMBoard). The sampling frame consists of all the vegetable farmers contracted with the NAMBoard. The total population (N) of the vegetable farmers contracted with NAMBoard is 946 across the four administrative regions of the country (NAMBoard, 2024). The study purposively sampled 200 CSA vegetable farmers who were part of the NAMBoard Market Oriented Climate Smart Agriculture Project. These consists of trained CSA vegetable farmers from three irrigation schemes (105) and trained CSA independent vegetable farmers (95).

Data Collection Methods

The study used cross sectional data which were collected using questionnaires from the sampled vegetable farmers in the Kingdom of Eswatini through face-to-face interviews. The questionnaire was divided into seven sections according to the data needed to assess the objectives of the study. The first section was the questionnaire identification, and the second section were the socio-economic characteristics of the vegetable farmers. The third section was on CSAT adoption, the fourth section was on the vegetable production information, the fifth section was on social capital and information access, the sixth section was on farm characteristics and the seventh section was on institutional access and resource endowments. It consists of open-ended and close-ended questions.

The instrument was forwarded for validation by the supervisory team and a panel of experts in the department of Agricultural Economics for face and content validity. It was tested for reliability and pre-testing using twenty-five farmers who were not included in the study sample. After pre-testing, the reliability of the questionnaire was calculated. The Cronbach alpha reliability coefficient was found to be 0.744 indicating an acceptable internal consistency among the items in the questionnaire.

The researcher conducted primary field surveys to collect data from the sampled vegetable farmers through face-to-face interviews using a questionnaire. This helped to reduce non-response error from the respondents.

Data Analysis

The data collected were analysed using Stata version 14 statistical packages. In determining the factors affecting the adoption decision and intensity of CSAT adoption, the study used the Cragg Double Hurdle model.

Table 1: Description of and Measurement of Variables used in the study

	Variable	Variable Description	Measurement
Dependent Variables			
1.	Adoption of CSAT(hurdle 1)	If household adopts CSAT (1= adopter, 0= non-adopter)	Binary
2.	Intensity of Adoption (hurdle 2)	Proportion of adopted technology given the available CSAT	Continuous
Independent Variables			
3.	Age	Actual years	Continuous
4.	Education level	Years of schooling (years)	Continuous
5.	Gender	1= male, 0=female	Dummy
6.	Household size	number of members	Continuous
7.	Marital status	1= married, 0=unmarried	
8.	Vegetable farming experience of the famer	Number of years in vegetable farming (years)	Continuous
9.	Distance To Output Market	Distance measured in Km	Continuous
10.	Access To Input Market	1=yes; 0=no	Dummy
11.	Access To Transport	1=yes; 0=no	Dummy
12.	Access To Market Information	1=yes; 0=no	Dummy
13.	Farm Size	Measured in Hactares (Ha)	Continuous
14.	Land Quality	1 = good, 0 = poor	Dummy
15.	Access To credit	1=yes; 0=no	
16.	Risk Attitude	2 = risk seeker, 1 = risk neutral, 0 = risk averse	
17.	Frequency of Extension Contact	Measured in number of times	Continuous
18.	Off-farm income	1=yes; 0=no	Dummy

Source: Author

Table 2: Hypothesis Explanation and expected signs of the variables used in the study

S/N	Variable	Explanation	Expected signs
1.	Age	May increase adoption through experience but reduce it due to risk aversion and resistance to new technologies	+/-
2.	Education level	Enhances information processing and technical capacity, thereby increasing adoption and intensity of CSAT use.	+
3.	Gender	Differences in access to resources and services may influence adoption and intensity of CSAT use.	+/-
4.	Household size	Provides labour for CSAT implementation but may reduce investable surplus due to higher consumption needs	+/-
5.	Marital status	Improves labour availability and household stability, thereby enhancing adoption and intensity of use	+
6.	Vegetable farming experience of the famer	Increases awareness of climate risks and expected benefits, thus promoting adoption and intensity	+
7.	Distance To Output Market	Increases transaction costs and reduces profitability, thereby discouraging adoption and intensity.	-
8.	Access To Input Market	Reduces input access constraints and facilitates implementation, thereby increasing adoption and intensity	+

9.	Access To Transport	Lowers transaction costs and improves market access, thereby encouraging adoption and intensity	+
10.	Access To Market Information	Improves decision-making and profitability expectation, thereby increasing adoption and intensity	+
11.	Farm Size	Increases capacity to experiment and scale up CSAT, thereby enhancing adoption and intensity.	+
12.	Land Quality	Raises expected returns to investment, thereby encouraging adoption and intensity of CSAT use.	+
13.	Access To credit	Relaxes liquidity constraints and enables investment, thereby increasing adoption and intensity.	+
14.	Risk Attitude	Risk tolerance encourages experimentation while risk aversion discourages adoption and intensity.	+/-
15.	Frequency of Extension Contact	Improves awareness and technical knowledge, thereby increasing adoption and intensity.	+
16.	Off-farm income	May ease financial constraints or divert labour from farming, thus exerting an ambiguous effect on adoption and intensity	+/-

Table 3: Summary of the CSAT adopted by NAMBoard Farmers: Market Oriented Climate-Smart Agriculture Project

S/N	Climate-Smart Agricultural Technologies (CSAT)
1.	Drip irrigation
2.	Climate-Smart Agriculture Equipment (ripper, planter, & boom sprayer)
3.	Permaculture
4.	Protected Production
5.	Agroforestry
6.	Conservational Agriculture

The smallholder vegetable farmers who were part of the NAMBoard Market Oriented Climate-Smart Agriculture Project in the study area were presented with a plethora of CSATs to improve productivity in vegetable production under the era of climate change. The CSATs are presented on Table 3 above which includes drip irrigation, CSA equipment, permaculture, protected production, agroforestry, and conservational agriculture.

Diagnostic Tests

Before implementing the Double Hurdle model some preliminary diagnostics of the variables to be used were done which include multicollinearity and test for omitted variables. Multicollinearity was tested using the Variance Inflation Factor (VIF). The results of the multicollinearity test show a mean VIF of 1.12 indicating that there was no serious linear relationship among the explanatory variables since. The test for omitted variables in the Double Hurdle model used the Ramsey Reset test. The results of the test failed to reject the null hypothesis that the model has no omitted variables.

When choosing the best model that fits the determining of factors affecting the adoption and intensity of adoption of CSAT, the Double Hurdle model was tested against the Tobit model for model specification. The Akaike Information Criteria (AIC) was used to test for the goodness of fit between the two models. The AIC test statistic for the Double Hurdle model .indicate a lower value of -2117.383 compared to the AIC test statistic for the Tobit regression model of -334.013. This shows that the Double Hurdle model is preferable for determining the factors affecting the adoption and intensity of adoption of CSAT among smallholder vegetable farmers.

Results

Household Characteristics of Vegetable Farmers in Eswatini

The socio-economic characteristics of adopters and non-adopters of CSAT are presented in table 4. These characteristics include those that are continuous, namely: age, farming experience, vegetable farming experience, years of schooling, household size, frequency of extension services contact, farm size, and distance to output market.

Table 4 also indicate the test of the difference of means between adopters and non-adopters. An independent t-test was done to test if the difference between the means is statistically significant. Statistically significant mean differences at ten percent were found to be years of schooling and household size, while age was found to be statistically significant at five percent level. These farmers' characteristics are very important in stimulating the adoption of CSAT.

The mean age for adopters was found to be 44.6 with a statistically significant mean difference of 3.5. The average farming experience was found to be 10.3 years. The mean age and farming experience for the adopters was found to be more than that of non-adopters. This can be explained by the fact that more experienced farmers will tend to adopt avail technologies to improve their productivity. The mean household size for adopters was found to be more than that of non-adopters. A larger household size mean more family labour available to utilise the available adopted CSAT. Adopters frequently contacted extension services compared to non-adopters. Increased extension contacts increase the likelihood of CSAT among smallholder farmers.

Table 4: Household Characteristics of Vegetable Farmers in Eswatini

Variables	Overall	Adopter	Non-adopter	Mean Difference
Age	43.82(14.61)	44.60(14.65)	41.1(14.19)	3.5(0.0523)**
Farming Experience	10.02(8.31)	10.3(8.5)	8.9(7.38)	1.4(0.1779)
Vegetable Production Experience	7.29(7.46)	7.53(7.95)	6.44(5.31)	1.09(0.236)
Years of schooling	10.57(4.28)	10.38(4.42)	11.27(3.65)	0.89(0.089)*
Household size	7.5(3.6)	7.6(3.6)	6.9(3.3)	0.7(0.066)*
Frequency of Extension contact	2.25(2.05)	2.27(1.95)	2.16(2.37)	0.11(0.644)
Farm size	2.52(1.26)	2.52(1.26)	2.53(1.22)	0.01(0.910)
Distance to Output Market	27.82025(59.841)	27.8(59.257)	27.89(62.216)	0.09(0.990)

Source: Authors computation from sample survey (2024)) *** = P < 0.01; ** = P < 0.05; * = P < 0.10 p-value (SD in parenthesis in column 2,3,4; p-value in parenthesis in column 5).

Factors affecting the adoption Decision of Climate Smart Agriculture Technologies

The table below presents results from the double hurdle model for the adoption decision (first hurdle). Table 5 below indicate that the CSAT adoption decision is positively influenced by age, household size, risk attitude and off-farm income and negatively influenced by land quality. The coefficients presented on the table show how each of the explanatory variables affect the probability of adoption decision of CSAT.

Table 5 Results of the Double Hurdle Model Estimation of Factors Affecting CSAT Adoption

	Probit Regression		Marginal Effects	
Factors	**Coefficient**	**Std. Err.**	**Dy/dx**	**Std. Err.**
Gender	0.045	0.147	0.046	0.147
Age	0.014**	0.006	0.014**	0.006
Marital Status	-0.213	0.156	-0.212	0.156
Household size	0.040*	0.022	0.041*	0.021
Climate-Smart Awareness	0.330*	0.180	0.329*	0.179
Vegetable farming Experience	-0.004	0.010	-0.004	0.011
Distance To Output Market	0.00080	0.00124	0.00080	0.001
Access To Input Market	-0.310	0.024	-0.309	0.242
Access to Transport	0.212	0.186	0.213	0.186
Access To market Information	0.291	0.179	0.293	0.179
Farm Size	-0.023	0.059	-0.022	0.059
Land Quality	-0.347**	0.163	0.345**	0.163
Access To credit	0.035	0.146	0.034	0.145
Risk Attitude	0.211**	0.105	0.212	0.105
Frequency of Extension Contact	0.00145	0.0323	-0.0145	0.0323
Off-farm income	0.263*	0.147	0.264	0.147
_cons	-0.831	0.540	0.046	0.147

Factors Affecting the Intensity of adoption of Climate Smart Agriculture Technologies

The results of the second hurdle of the Cragg Double Hurdle model on the factors affecting the intensity of CSAT adoption among smallholder vegetable farmers are presented on Table 6 below. The factors presented in the previous section are identified as those factors affecting the probability of CSAT adoption decision and were estimated using the probit regression model. However, it does not necessarily imply that all the significant factors in the first hurdle, that is, factors affecting the CSAT adoption decision are capable of passing to the second hurdles, that is, factors affecting the intensity of CSAT adoption.

This implies that variables and the level of intensity of the effect at which each variable affects both CSAT adoption decisions and intensity of CSAT adoption is different. Thus, this section focuses on the results of the truncated regression model estimating the factors affecting the intensity of CSAT adoption.

These results indicate that the intensity of CSAT adoption is positively and significantly influenced by, access to inputs market, farm size, land quality and frequency of extension contact while age has a negative and significant effect on the intensity of CSAT adoption. This indicates the combined role of individual socioeconomic farmers' characteristics, farm characteristics, and social capital and information access factors.

Table 6 Results of the Double Hurdle Model Estimation of Factors Affecting intensity of CSAT Adoption

	Truncated Regression	
Factors	Coefficient	Std. Err.
Gender	0.009	0.026
Age	-0.002*	0.001
Marital Status	-0.044	0.029
Household size	0.001	0.004
Climate-Smart Awareness	0.053	0.037
Vegetable farming Experience	0.002	0.002
Distance To Output Market	0.00018	0.00049
Access To Input Market	0.130*	0.048
Access to Transport	0.029	0.037
Access To market Information	0.020	0.036
Farm Size	0.028***	0.011
Land Quality	0.068**	0.033
Access To credit	-0.0001	0.026
Risk Attitude	-0.020	0.017
Frequency of Extension Contact	0.046***	0.0176
Off-farm income	0.003	0.267
_cons	-0.118	0.110

Log likelihood= -22.181, Wald chi2 (16) =26.78, Prob>chi2 = 0.0440

*** = P < 0.01; ** = P < 0.05; * = P < 0.10

Discussions

Factors Affecting Climate Smart Agriculture Technology Adoption

The first hurdle of the Cragg Double hurdle model used the probit regression model, to identify the determinants influencing the likelihood of adopting CSATs among vegetable farmers. The marginal effects were also computed to determine the extent to which each explanatory variable changes the probability of adoption. The results indicate that age, household size, climate-smart awareness, access to inputs markets, land quality, risk attitudes, and off-farm income significantly influence the likelihood of adoption of CSATs.

Age positively and significantly influenced the adoption of CSATs at the 5% significance level. The marginal effect (dy/dx = 0.014) implies that a one year increase in age of the farmer increases the probability of adopting climate-smart technologies by approximately 1.4%, holding other factors constant. This finding suggests that older farmers are more likely to adopt CSATs due to accumulated farming knowledge, practical experience, and better understanding of climate variability and adaptation strategies. Older farmers may also possess greater authority in household decision-making and increased access to productive resources, which facilitate technology adoption. In addition, this could be explained by the fact that older farmers are much experienced and exhibit better awareness on potential benefits of better management practices at farm level [21].

The household size also positively influences the adoption of CSAT among vegetable farmers. The marginal effect indicates that an additional household member increases the likelihood of adopting CSATs by approximately 4.1%. Larger households are likely to have more labour available for implementing labour-intensive CSATs such as mulching and conservation agriculture. Household labour availability reduces reliance on hired labour and lowers production costs associated with technology adoption. A smaller household size has increased chances of not adopting or partially adopting labour intensive CSA technologies.

The awareness of the CSAT is positively correlated to the adoption decision as indicated by the results of the study. The marginal effect (dy/dx = 0.329) suggests that farmers who are aware of

CSATs are approximately 32.9% more likely adopt such technologies compared to farmers with limited awareness. The major limiting factor to the adoption of climate smart technologies is lack of awareness about a given technology. In order for farmers to adopt CSAT, knowledge and sufficient information is required for them to embrace the technology. Farmers who understand the relationship between climate variability and agricultural productivity are more inclined to adopt adaptation and mitigation strategies that improve resilience and productivity. Teklu et al.[33] also found similar findings indicating that CSAT awareness increases the likelihood of CSAT adoption.

The land quality negatively and significantly influences CSAT adoption decision at 5 percent level. The marginal effect (dy/dx = 0.345) suggests that poor land quality decreases the probability of adopting CSATs by approximately 34.5%. Farmers cultivating degraded or less fertile land may be discouraged from investing in CSATs because expected returns are uncertain or relatively low. In contrast, farmers with fertile and productive land are more likely to invest in sustainable agricultural innovations due to higher anticipated productivity gains. The results are inline to the findings of Pangapanga-Phiri [30] which revealed that poor soil quality decreases the probability of CSAT adoption.

The farmers risk attitude positively and significantly affects the adoption decision of CSAT. The results show that the vegetable farmers are risk seekers which is positively correlated to CSAT adoption. The marginal effect indicates that farmers with a greater willingness to take risks are approximately 21.2% more likely to adopt CSATs. Adoption of innovative agricultural practices often involves uncertainty regarding costs, productivity outcomes, and profitability. Farmers with positive risk attitudes are generally more willing to experiment with new technologies and are less constrained by fear of potential losses associated with innovation. These findings are contrary to Musyoki et al.[22] who found a negative relationship between adoption and farmers risk attitudes. Musyoki et al.[22] argued that the negative relationship between technology adoption and farmers risk attitudes originates from their aversion to financial risks and resistance to employ the CSAT at their disposal.

Lastly, the results indicate that the CSAT adoption decision is positively influenced by off-farm income. The marginal effect (dy/dx = 0.264) implies that farmers with off-farm income sources are approximately 26.4% more likely to adopt CSATs than those without supplementary income. The implication of these results is that the diversification of income sources increases available financial resources and hence increases the likelihood of CSAT adoption by the farmers. In addition, off-farm income improves household liquidity and enhances farmer’s ability to finance the acquisition of agricultural inputs, irrigation systems, and other CSATs. Additional income sources also reduce financial constraint and provide a safety net against production risks associated with climate variability. Abegunde et al.[1] & Djido et al. [11] found contrasting results, for instance, a negative relationship between the adoption decision and off-farm income. This can imply that farmer heavily depend on off-farm income sources which reduces engagement in on-farm income generating activities. These findings concur with Kurgat et al. [13] who also found a positive relationship between off-farm income and CSAT and further emphasized the significance of financial resources in the acquisition of production inputs.

Factors Affecting the Intensity of Climate Smart Agriculture Technology Adoption

The results show that factors affecting the intensity of CSAT adoption include age, access to inputs market, farm size, land quality and frequency of extension contact.

Age negatively and significantly affects the intensity of adoption of CSAT amongst the smallholder vegetable farmers at 5 % level. This suggests that older farmers tend to apply CSAT at lower intensity levels compared to younger farmers. The results may imply that this finding may reflect lower adaptability to new technologies, risk aversion and shorter planning horizons among older farmers. From an economic perspective, the result implies that human capital dynamics particularly generational differences in learning and innovation uptake, play a significant role in shaping the depth of CSAT adoption. Policy interventions aimed at strengthening lifelong learning and targeted training for older farmers may therefore enhance inclusive intensification of CSAT adoption.

Access to inputs market positively and significantly influences the intensity of adoption of CSAT at 5% level. The results indicate that farmers with better access to input markets are more likely to intensify CSAT adoption. The finding underscores the importance of market accessibility in reducing transaction costs and ensuring timely availability of key agricultural inputs required for CSAT. Economically, this suggests that CSAT adoption is partially constrained by input market inefficiency. Strengthening rural input distribution systems and improving market infrastructure could therefore substantially enhance the effectiveness and scale of CSAT adoption. Hassan & Nhemachena [49] argued that access to inputs markets also minimise information exchange with different services providers and further ensures access to improved agricultural inputs.

The results further indicate that farm size positively and significantly influences the intensity of adoption. This implies that larger farms are associated with higher levels of CSAT adoption. The result is inconsistent with the notion that larger landholdings provide economies of scale, greater resource flexibility, and higher capacity to absorb risks associated with new technologies. Larger farms are also better positioned to experiment with and diversify CSATs across their plots. From a policy standpoint, this finding suggest the need for inclusive strategies such as farmer group models or cooperative-based approaches to enable smallholder to achieve comparable intensity levels. These results are similar to Makate et al. [15] & Sisay et al.[32] who found that farmers owning large farms show eagerness in CSAT adoption due to available land for the adoption of CSAT. The affording farmers are capable to purchase more assets which increases the probability to adopt more CSAT.

Land quality positively and significantly affect the intensity of adoption of CSAT. Farmer operating on higher quality land tend to adopt CSAT more intensively likely due to higher expected returns from soil-responsive technologies. This result highlights the role of farm characteristics in shaping the profitability and feasibility of sustainable agricultural practices. It suggests that degraded land conditions may act as a constraint of intensification, thereby calling for complementary investments in soil fertility management and land rehabilitation programs to enhance equitable adoption outcomes.

Frequency of extension contact positively and significantly influences the intensity of adoption of CSAT. This indicates that increased interactions with extension agents enhance farmers' understanding, awareness, and technical capacity to implement CSAT more intensively. The finding reinforces the critical role of agricultural advisory services in knowledge dissemination and behavioural change. It further suggests CSAT are information intensive and require continued technical support for effective adoption. Strengthening extension systems and increasing farmer-extension contact frequency would therefore be a key policy lever for improving CSAT adoption intensity. Extension services also help in the implementation and diffusion of innovation hence, breaching the gap between farmers and the new innovation Mwangi & Kariuki[23.]

Conclusions and Recommendation

The findings on intensity of CSAT adoption indicate that while the initial CSAT adoption decision may depend on access and awareness, deeper intensification is largely constrained by structural and institutional factors. The findings on intensity of CSAT adoption reveal that the intensity of adoption is jointly shaped by a combination of farmers' socio-economic characteristics (age), social capital and information access factors (frequency of extension contact), and farm characteristics (farm size and land quality). Hence, the null hypothesis which states that the smallholder vegetable farmers' characteristics have no significant influence on the intensity of adoption of CSAT was rejected in favour of the alternative hypothesis.

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