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Adaptation through Climate-Smart Agriculture: Examining the Socioeconomic Factors Influencing the Willingness to Adopt Climate-Smart Agriculture among Smallholder Maize Farmers in the Limpopo Province, South Africa

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Abstract: Agriculture contributes to the South African economy, but this sector is highly vulnerable to climate change risks. Smallholder maize farmers are specifically susceptible to climate change impacts. The maize crop plays a crucial role in the country's food security as is considered a staple food and feed. The study aimed at examining the socioeconomic factors influencing smallholder maize farmers' willingness to adopt climate-smart agriculture in the Limpopo Province, South Africa. It was conducted in three different areas due to their specific agro-ecological zones. A multipurpose research design was used to gather data, and multistage random sampling was used to choose the study areas. Subsequently, 209 purposefully selected farmers were interviewed face-to-face using structured questionnaires and focus discussion groups. Descriptive results revealed that 81%, 67%, and 63% farmers in Ga-Makanye, Gabaza, and Giyani were willing to adopt CSA. Using the double-hurdle model, the *t*-test was significant at 1%, Prob > chi2 = 0. 0000, indicating a good model. At a 5% confidence level, education, crop diversification, and information about climate-smart agriculture (CSA) positively influenced adoption, while household size and agricultural experience negatively influenced it. It is recommended that the Department of Agriculture, Land Reform, and Rural Development provide CSA workshops and educational programs to farmers to enhance their knowledge and decision-making processes regarding adaptation strategies.

Keywords: smallholder maize farmers; climate-smart agriculture; adaptation strategies; vulnerability assessment; willingness to adopt

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1. Introduction

The agricultural sector plays a significant role in the South African economy, as it contributes 4.2 percent of the gross domestic product (GDP) [1]. Considering the fact that the agricultural system is rain-fed and has low adaptive capacity [2,3], the economic impact of climate change on agriculture in South Africa has caused the sector to decline in the GDP, leading to losses in job opportunities and foreign exchange earnings [4]. Thus, climate variability is a major emerging factor confronting agricultural expansion [5]. Climate is defined as short-term changes in the atmosphere over longer periods of time, usually defined as 30 years or more [6,7], whereas climate variability refers to variations in the prevailing state of the climate on all temporal and spatial scales beyond that of an individual weather event [6,7]. It is not only agriculture that is subjected to climate change (extreme weather and unreliable rainfall), as smallholder farmers are also exposed to climate change as they have limited access to resources and capacities to adapt to these risks [8,9]. Overall, there has been a sharp decline in annual rainfall, while there has been a rise in the frequency of extremely hot days. Research shows that agriculture in developing countries can be the main solution to poverty reduction and food security [10]; however, this will only happen if there is an investment in agriculture to develop a resilient system to feed the increasing population. Mall, Gupta, and Sonkar [11] argued that climate change brings higher temperatures and more extreme weather, such as floods and droughts, and that this will cost millions in crop failure. For rain-fed agricultural output, seasonal rainfall periods have declined and are often unpredictable, as there are very hot humid temperatures with little rainfall [12]. Farmers are seeing an increase in the frequency of dry spells and droughts during the summer. These dry spells are described as long stretches of time without rain during the rainy season [13,14]. The amount of water available is also impacted by differences in rainfall, which raises temperatures, especially on hot days when most farmers in the area rely on rainfall for irrigation. Additionally, the high temperatures due to climate change have led to insect and pest outbreaks, such as with stalk borer and fall army worm infestations in the study area [15,16]. This could make it more difficult to control insect and pest infestations, particularly among peasant smallholder farmers. In South Africa, the maize crop plays a crucial role in the country's food security, as it is considered a staple food for households and a source of feed for livestock [17].

Maize contributes to household consumption because it is cheap and easily accessible [17]. Subsequently, the crop contributes to poverty alleviation through the provision of income for rural households and the improvement of livelihoods [18–20]. Maize production depends on climatic elements to guarantee productivity, profitability, and quality of life [21]. Therefore, climate change poses key hazards to agricultural production, as it alters precipitation, temperature, carbon dioxide, climate variability, and nutrient uptake [22]. This necessitates that smallholder farmers assess the impact of these risks and address them through various improved adaptation strategies. Smallholder farmers can be made more resilient through improving local knowledge, training, awareness, access to resources, and risk management by using climate-smart agriculture (CSA) strategies. CSA is an approach to developing the technical, policy, and investment conditions to build a sustainable food system under climate change [23]. This includes increased system productivity and a resilience approach through the adoption of new technologies and management practices. This will require an improvement in soil fertility and water management, as well as more crop and livestock development, which is considered sustainable for a fragile ecosystem [24].

CSA is a strategy to support agricultural systems globally while concurrently addressing three challenge areas: enhancing agriculture's resilience to climate change, mitigating its effects (by enabling the farming sector to seize greenhouse gases), and guaranteeing global food security through creative financing, policies, and practices [25–28]. Thus, CSA is the key to ensuring food systems remain sustainable, considering the impact of climate change and that it can lead to a 20% or more increase in global hunger and child malnutrition by 2025 [29]. The literature has indicated that CSA is a key solution towards reducing the risks imposed and the challenges caused by climate change, and therefore farmers need to adopt the practice of CSA [30,31]. However, it has been reported that the adoption rate of these adaptation strategies (CSA) remains relatively low by smallholder maize farmers due to the high costs associated with the adoption and limited knowledge about these CSA practices [32–35]. Additionally, there is no doubt that climate change-related challenges dictate that smallholder farmers must adopt CSA practices; however they have limited access to land and land ownership [36,37] that permits them to do so. Hence, it is imperative to understand social and economic factors that can hinder successful adoption of CSA practices, as other scholars have stated that the adoption of these CSA practices is influenced by interrelated factors such as farm size, access to weather information, and extension services [38,39]. Therefore, the study aimed at examining the willingness to adopt CSA among smallholder maize farmers and the socioeconomic factors influencing their willingness to adopt CSA in the selected areas of the Polokwane, Tzaneen, and Giyani Municipalities of the Limpopo Province, South Africa. Farmers' adaptive response to climate change is limited due to socioeconomic factors influencing the available adaptation options [40]. The study examines socioeconomic factors such as age, education, gender, farm size, farming experience of farmers, information about climate-smart agriculture, exposure to climate risks, and farmers' sensitivity towards the risks. The research null hypothesis that guided this study was that smallholder maize farmers' socioeconomic factors do not influence their willingness to adopt CSA in the selected areas of the Polokwane, Tzaneen and Giyani Municipalities of the Limpopo Province, South Africa.

2. Research Methodology

2.1. Description of the Study Areas

The study was conducted in three selected areas: Ga-Makanye in the Polokwane Municipality, Gabaza in the Greater Tzaneen Local Municipality, and Gabaza in the Greater Giyani Municipality in the Limpopo Province, South Africa as shown in Figure 1. Ga-Makanye is a small village situated outside Polokwane, and it has a total population of 9536 and 2256 households [41]. However, the study chose 37 farmers, as these were the only available maize farmers in the areas due to others relocating to urban areas for better job employment. It is dominated by black and Sepedi-speaking individuals. Gabaza is also a small village outside Tzaneen town dominated by black people, mainly consisting of different tribes. It consists of a 2413 total population with 671 households. The area is dominated by Xitsonga-speaking individuals constituting 78% of the population. Giyani is a town situated in the eastern part of the province featuring a 25,954 total population with 8096 households; it is dominated by the Xitsonga tribe [41]. The study chose these three areas due to their location in different agro-ecological zones [42,43]. Ga-Makanye is characterized by a humid subtropical climate which influences the monsoon winds (seasonal winds). The area experiences very dry winters and very hot summer days. Likewise, Gabaza is suited within Tzaneen, and it also experiences monsoons; thus, it is also classified as a humid subtropical climate. There are hot and humid summers with frequent rainfall, unlike in Ga-Makanye, and dry winters which are hot. Giyani experiences different and unique climatic conditions. It is a subtropical climatic zone characterized by very hot and dry summer and winter days. The area can reach the peak temperature of 43 degrees Celsius, which is extremely hot. This harsh temperature results in heatwaves that are unbearable, even during winter, and the area experiences harsh temperatures.

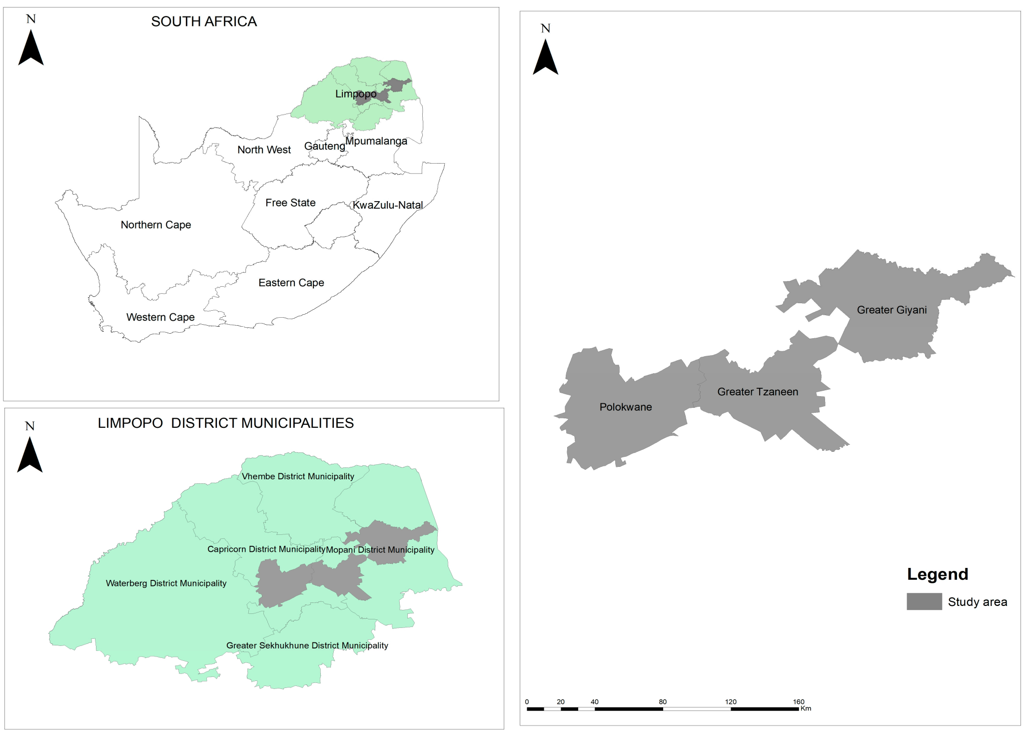


Figure 1. South African map showing five districts in the Limpopo Province. Source: Author's compilation (2024).

2.2. Research Design

The study used a multipurpose research design to validate both qualitative and quantitative methodologies. The multipurpose research design is essential because it does not only afford the integration of quantitative and qualitative data but also provides an opportunity for researchers to use the strengths of one dataset to mitigate the weaknesses of the other dataset [44]. Measures of dispersion (descriptive statistics) and the double-hurdle model estimated using the Probit and Tobit regression models were utilized to analyze factors influencing the willingness to adopt CSA among farmers.

2.2.1. Sampling Method (s) and Sample Size

The study employed a multistage sampling technique combining both non-probability and probability sampling techniques. In the first stage, the Limpopo Province was purposefully selected as the main area because of the prevalence of smallholder rural maize farming, which contributes to food security within the province and country. Secondly, two districts were purposefully selected, Capricorn (dry sub-humid) and Mopani (semi-arid), due to their different agro-ecological climate zones. Thirdly, Ga-Makanye village was purposefully selected from the Capricorn District in the Polokwane Municipality, and two areas, Gabaza and the Giyani Municipality, were purposefully selected from the Mopani Municipality. Because researchers were unfamiliar with the study region and there was not a larger maize farmer population, households were used as a proxy because most rural households in South Africa grow maize for consumption and income generation. Subsequently, the study used a 209 sample size of maize farmers that was selected randomly and proportionate to household sizes in each village. The study used Yamane's formula to select the sample size for each area.

$$\mathrm{n} = \frac{\mathrm{N}}{1 + \mathrm{N}(\mathrm{e})^2}$$

The sample size calculation is as follows:

Ga-Makanye (n) = $\frac{37}{1+37\left(\frac{10}{100}\right)^2} = 26$

Gabaza (n) = $\frac{671}{1+671\left(\frac{10}{100}\right)^2} = 87$

Giyani (n) = $\frac{8096}{1+8096\left(\frac{10}{100}\right)^2} = 96$

2.2.2. Data Collection

The study used primary, cross-sectional data. The data were collected using both qualitative and quantitative methods to understand farmers' willingness to adopt CSA and factors influencing adoption [45]. The study used structured questionnaires, focused group discussions (FGDs), and Likert scales to collect data from the respondents. The collected data were used to describe the socioeconomic factors of maize farmers, such as age, educational level, gender, household size, farm size, agricultural experience, as well as factors influencing their willingness to adopt (WTA) CSA. The study used IBM SPSS 29.0 to conduct a multicollinearity test on a binary expected outcome regression model. The test used the variance inflator factor (VIF) to analyze the total effect of each independent variable against all independent variables.

2.2.3. Model Specification

The study used double-hurdle regression model estimated using Probit and Tobit (truncated). The model used is as follows:

$$p^{*}i = \mathrm{C}^{*}i\ \alpha + \varepsilon i \text{ (adoption decision)} \tag{1}$$

$$p^{*}i = 1 \text{ if } p^{*}i > 0 \text{ and } 0 \text{ if } p^{*}i < 0 \tag{2}$$

$$WTACSA = X'_{i}\beta + u_i \text{ (Factors affecting the adoption)} \tag{3}$$

$$y_i = x'_i + u_i \text{ if and } y^*_i > 0. \quad (4)$$

- p^*i is considered the variable that explains the decision to adopt CSA by smallholder maize farmers;
- p_i is the variable that is observed adoption decision and takes the value of 1 if the smallholder farmer is willing to adopt at least three CSA practices; it is 0 if otherwise;
- $WTACSA$ is a dormant variable used to describe the decision on factors affecting the adoption of CSA practices;
- y_i is observable variable of adoption measured as the number of CSA practices to adopt;
- C and X gives the direction for independent variables for the decision to adopt;
- α and β are the parameters to be estimated.

The equation below was used to calculate the direction of the relationship of the indicators. This gives rise to the Ordinary least squares equation for the variables. It is as follows.

$$Y = B_0 + B_1X_1 + B_2X_2 + \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots + B_kX_k + \in \quad (5)$$

$$\begin{gathered} WTAi^* = B_0 + B_1FS + B_2EL + B_3GND + B_4AG + B_5AE + B_6HS + B_7ID + \\ B_8CD + B_9AES + B_{10}ICSA + B_{11}E + B_{12}S + B_{13}IS + B_{14}CM + \in \end{gathered} \quad (6)$$

$$WTAi^* = \begin{Bmatrix} 1\ if\ WTAi^* > 0 \\ 1\ if\ WTAi^* < 0 \end{Bmatrix}$$

2.2.4. Analytical Techniques

Descriptive Statistics

Descriptive statistics were used to present a summary of the sample and its measures. Specifically, descriptive statistics was used to analyze the central tendencies, which include mean values, median and mode to address and describe the socioeconomic characteristics of smallholder maize farmers in Ga-Makanye, Gabaza, and Giyani. A *t*-test was used to explain the statistical difference between continuous variables such as age and experience, household size and farm size. The *t*-test is an inferential statistic used to determine if there is a statistically significant difference between the mean of two variables [46]. The *t*-test was between three different groups, with Ga-Makanye constituting 26 samples, Gabaza having 87 samples, and Giyani featuring a 96 sample size.

Double-Hurdle Regression Model

The study used the double-hurdle model on the presumption that CSA adoption willingness involves two separate judgments [47]. According to Cragg [48], the double-hurdle model implies that smallholder farmers would make two consecutive decisions on whether to adopt CSA [49,50]. Equations (6) and (7) reflect the first hurdle, the CSA adoption (Yes/No) factor, which was estimated using a Probit model. A truncated count distribution model was used in the second hurdle to find factors that affect adoption willingness.

In the double-hurdle model, the regression analysis of the probability to adopt CSA is estimated using a truncated regression procedure given by the following equation [50]:

$$\text{P}\ (WTACSA > 0) = \Phi\ \ (\text{C} * \text{i}\ \alpha)\ \Phi\begin{pmatrix} Xi\ \beta \\ \sigma \end{pmatrix} \quad (7)$$

$$E(WTACSA > 0) = \Phi(\frac{X_i\beta}{\sigma})^{-1} \quad (8)$$

Contingent Valuation Method

Contingent valuation is a method used to gauge the perceived value individuals place on a certain commodity by asking them if they would be willing to accept or pay for the good [47]. Smallholder maize farmers in the study area were asked to place or state their preference on the CSA by selecting at least three CSA practices they are most likely to adopt given the opportunity and by indicating which CSA practices they prefer to adopt to address climate change risks. The CSA practices considered include crop insurance, rainwater harvesting, drought-tolerant maize seeds, crop rotation, crop diversification, site-specific nutrient management, conservation agriculture, and others. Through structured questionnaires and Likert scales, the contingent valuation method was used to assist farmers in at least choosing three CSA practices to indicate their willingness to adopt CSA given the opportunity. When a farmer chose less than three, it indicated that they were unwilling to adopt CSA (the minimum of three was indicating the willingness to adopt). Farmers were also grouped in FGDs to participate in choosing an effective strategy; however, there was a lack of awareness about CSA and what CSA is about, as it was never promoted or implemented within the study areas. This clearly shows that a lack of information and awareness about CSA contributes greatly to obstacles that limited the effective adoption of CSA in Ga-Makanye, Gabaza, and Giyani.

3. Results

3.1. Descriptive Results

3.1.1. Smallholder Maize Farmers' Willingness to Adopt CSA in Ga-Makanye, Gabaza, and Giyani

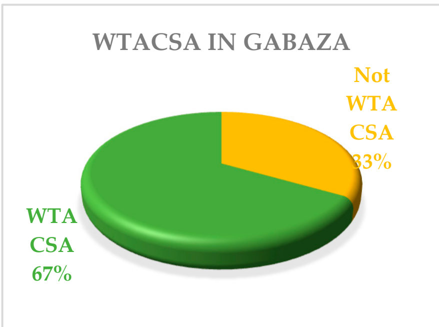
Table 1 shows the list of explanatory variables which are socioeconomic factors influencing the willingness to adopt CSA. It gives the description of the regressors used in the double hurdle model. While Figure 2a shows sampled smallholder maize farmers' decision to adopt CSA in Ga-Makanye, Gabaza, and Giyani. From the results, a larger proportion (81%) of sampled smallholder maize farmers in Ga-Makanye are willing to adopt climate-smart agriculture (CSA). These farmers were willing to adopt CSA as an adaptation strategy to mitigate the risks posed by climate change. Conversely, a small number (19%) expressed an unwillingness to adopt CSA practices. Furthermore, Figure 2b shows the sampled smallholder maize farmers' decision to adopt the CSA in Gabaza. About 67% of these farmers were willing to adopt CSA, and 33% of them were unwilling to adopt these adaptation strategies due to illiteracy levels and limited capacity to understand new information, as they felt like these practices would be challenging to learn. Figure 2c indicates about 63% of smallholder maize farmers' decision to adopt CSA in Giyani, and 37% of them exhibited a reluctance to adopt CSA as their adaptation strategy. Farmers in the three selected study areas mentioned that adopting CSA will require high capital investment, more costs associated with production, and limited resources; hence, they were not willing to adopt the practice.

Table 1. Description of model variables for double-hurdle regression model.

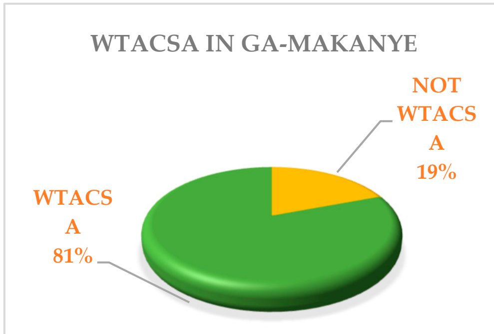
Dependent Variable		**Description and Unit of Measurement**	
Willingness to adopt CSA	WTA*i	Binary: 1 = farmer is willing to adopt climate-smart agriculture 0 = otherwise	
Variable label	**Variable type**	**Description**	**Expected sign**
Farm size (FS)	Continuous	Size of the farm in hectares	+/-
Educational level (EL)	Continuous	Number of years spend in school	+
Gender (GND)	Dummy	1 = if the farmer is a female, 0 = otherwise	+
Age (AG)	Continuous	Age of the farmers in years	+/-
Agricultural experience (AE)	Continuous	Number of years practicing agriculture	+/-
Household size (HS)	Continuous	Number of household members	+/-

Table 1. *Cont.*

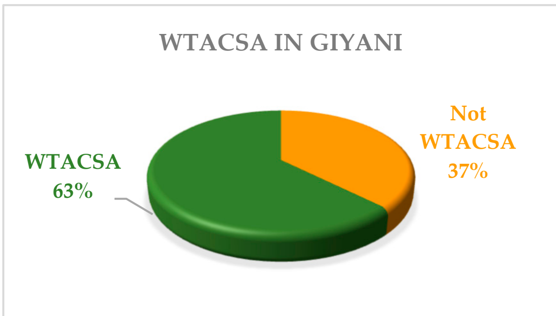
Income diversification (ID)	Dummy	1 = farmer diversify their level of income, 0 = otherwise	+
Crop diversification (CD)	Dummy	1 = farmer diversify their crop production, 0 = otherwise	+
Access to extension services (AES)	Dummy	1 = farmer has access to extension services, 0 = otherwise	+
Information about climate-smart agriculture (ICSA)	Dummy	1 = farmer has access to information, 0 = otherwise	+
Exposure of the farm to climate risks (E)	Dummy	1 = farmer is exposed to climate risks, 0 = otherwise	+
Sensitivity to climate risks (S)	Dummy	1 = farmer is sensitive to climate risks, 0 = otherwise	+/-
Insurance (IS)	Dummy	1 = farmer has insurance, 0 = otherwise	-
Cooperative membership (CM)	Dummy	1 = farmer is cooperative member, 0 = otherwise	+/-



(**a**) Willingness to adopt CSA in Ga-Makanye



(**b**)Willingness to adopt CSA in Gabaza



(**c**) Willingness to adopt CSA in Giyani.

Figure 2. Sampled smallholder maize farmers' decision to adopt CSA in Ga-Makanye, Gabaza, and Giyani. Source: Author's compilation (2024).

Table 2 presents the sampled smallholder maize farmers' decision to adopt CSA in Ga-Makanye, Gabaza, and Giyani. According to Table 2, the gender distribution is equal in Ga-Makanye, while there are more female farmers in Gabaza and Giyani—roughly 77% and 70.8%, respectively. These results seem to contradict the studies of Kassa [51], which stated that, in South Africa, small-scale farming is mainly practiced by males as compared to females. The study is in line with studies of Mfundo [52], which showed that South African small-scale farming is mainly conducted by females, especially with the maize crop. In Ga-Makanye, smallholder maize farmers had moderate to acceptable levels of education, with roughly 42% and 15.4% of farmers having completed secondary and university school, respectively. Nonetheless, a higher percentage of farmers—33.3% in Gabaza and 42.7% in Giyani—had no formal education, indicating lower levels of literacy. The study shows that there are more uneducated farmers in the study area. This should indicate the need for a major intervention, as education is believed to improve an individual's reasoning capability and increase the awareness of variable technologies that can be adopted [53]. There was high exposure and awareness of climate risks, which implies that most farmers in the study areas experienced different agro-ecological zones and climate change risks, and they were also found to be highly sensitive to these risks.

Table 2. Categorical descriptive results of sampled smallholder maize farmers in Ga-Makanye, Gabaza, and Giyani.

Socioeconomic Variable	Ga-Makanye (%)	Gabaza (%)	Giyani (%)
Gender			
Female	50	77	70.8
Male	50	23	29.2
Educational level			
No education	15.4	33.3	42.7
Primary	26.9	24.1	35.4
Secondary	42.3	27.6	11.5
Tertiary	15.4	14.9	10.4
Access to extension services	59.3	66.7	49
Access to Information about CSA	50	44.8	45.8
Exposure to climate risks	85	86	85
Sensitivity to climate risks	73	63	67

3.1.2. Measures of Dispersion of the Sampled Smallholder Maize Farmers in Ga-Makanye, Gabaza, and Giyani

Table 3 demonstrate the measures of dispersion of the sampled smallholder maize farmers in Ga-Makanye. The study found a significant difference in maize farmers' ages and experiences in Ga-Makanye in a sample size of 26. The results showed that older farmers (83 years) having more experience and younger ones having less was significant. The average age of a farmer was 60, and they lived with five people and had four hectares of land. Additionally, the results imply that the farmers started being actively involved in agriculture around 13 years of age. This shows that they started early in practicing farming, and it gave them more experience observed throughout the years. The two-tailed *t*-test showed that older farmers had more experience, while younger farmers had less experience, and it was statistically significant at the 5% level. The standard deviation of age and experience are high, which means that there is correlation between the two variables.

According to the survey, the average age and level of expertise among smallholder maize farmers varies greatly. The mean difference between farmers aged 23 to one year and those with more years of experience was found to be quite significant. The average farmer had five family members and two hectares of land (see Table 3). The findings indicate that older farmers have more field experience than younger farmers.

Table 3. Measures of dispersion of the sampled smallholder maize farmers in Ga-Makanye.

Socioeconomic Variable	Mean	St. Deviation	Min	Max	*t*-Test (Sig. 2-Tailed)
Age (years)	60	18.57	21	83	51.7 **
Experience (years)	24	20.59	3	70	78.9 **
Household size (per head)	5	2.21	2	11	93.2 **
Farm size (hectares)	4	4.63	0, 50	19	60.7 **

** indicates statistical significance at 5%.

Table 4 presents measures of dispersion of sampled smallholder maize farmers in Gabaza. The study reveals that, among a sample of 87 smallholder maize farmers, the average age of a farmer was 67 years and they had 25 years of agricultural experience (See

Table 4). The youngest farmer was 25 years, while highest number of years in farming was 70 years. The oldest farmer was 94 and had the highest experience of 75 years. This implies that the farmer started farming at the age of 19 years. The production started earlier because of factors such as patriarchy systems, which enabled the limitation of education but saw an uptake in domestic work, including farming in the backyard. The average farmer lived with six people and had two hectares of land. The results show that the *t*-test values are smaller than the 95% significance level, indicating that the mean values of farmers' ages and experience do not significantly differ from one another.

The results sampled at Giyani saw 96 farmers interviewed. The average age of a smallholder maize farmer was 64 years with 27 years of experience in agriculture (refer to Table 5). These results indicate that an older farmer would have more experience in terms of years involved in the production of certain crops. A smaller farmer in the area was aged 30, while an older farmer was 85 years with 50 years' experience. These results indicate that the farmer started late in farming enterprise at the age of 35 years. The implication could be that the farmer was involved in other economic activities, such as the manufacturing industry, then opted for farming due to social reasons. Additionally, the average number in the farmers' households was six with farm size of two hectares. The implication is that more people living with a farmer will result in a larger farm size. The standard deviations of the age and experience were high, indicating that there is correlation between the variables.

Table 4. Measures of dispersion of the sampled smallholder maize farmers in Gabaza.

Socioeconomic Variable	Mean	St. Deviation	Min	Max	*t*-Test (Sig. 2-Tailed)
Age (years)	67	14.75	23	94	37.9 **
Experience (years)	25	19.57	1	75	16.2 **
Household size (per head)	5	3.04	1	14	28.5 **
Farm size (hectares)	2	1.20	0.25	8	60.3 **

** indicates statistical significance at 5%.

Table 5. Measures of dispersion of the sampled smallholder maize farmers in Giyani.

Socioeconomic Variable	Mean	St. Deviation	Min	Max	*t*-Test (Sig. 2-Tailed)
Age (years)	64	13.75	30	85	17.0 **
Experience (years)	27	16.04	12	50	95.9 **
Household size (per head)	6	2.37	0	12	3.2 **
Farm size (hectares)	2	1.99	0.25	12	78.7 **

** indicates statistical significance at 5%.

3.2. Econometric Results

3.2.1. Test for Multicollinearity

Table 6 presents the variance inflation factors (VIFs) of the regressors used for multicollinearity test. The study excluded insurance and age variables due to potential autocorrelation and heteroscedasticity problems. The results indicate that there is sufficient evidence that all variables had a VIF that was less than 2 and <10 (0.4–0.1), with a mean VIF of 1.2885 for the sampled variables (n = 209). These results indicate that there is no multicollinearity problem in the model for the sample.

Table 6. Variance inflation factors (VIFs) of the regressors.

Explanatory Variables	Collinearity Statistics	
	VIF	**1/VIF**
Farm size (in hectares)	1.097	0.911
Educational level	1.805	0.554
Gender of a maize farmer	1.069	0.935
Agricultural experience	1.900	0.526
Household size	1.058	0.945
Income diversification	1.332	0.750
Crop diversification	1.200	0.833
Access to extension services	1.169	0.855
Information about CSA	1.201	0.833
Exposure to climate risks	1.263	0.792
Sensitivity to climate risks	1.335	0.749
Farmers' cooperative membership	1.033	0.968
Mean VIF	1.2885	

VIF—refers to Value inflator factor.

3.2.2. First Hurdle: Probit Regression Model of Results of Sampled Smallholder Maize Farmers in Ga-Makanye, Gabaza, and Giyani (n = 209)

The double-hurdle regression results are presented in Tables 7 and 8. The regression model's Wald statistics was significant at 1% suggesting a good fit of the model, Prob > chi2 = 0.0000, which gives the study sufficient evidence to reject the null hypothesis that all regression coefficients in each hurdle are jointly equal to zero.

Table 7. First hurdle: Probit regression model.

	Coef.	**Std. Err.**	**Z**	$p \leq$ **z**
	Farmers' characteristics			
Constant	0.3029	0.7824	0.39	0.700
Farm size (FS)	0.0038	0.0504	0.07	0.940
Education (EL)	0.2961 **	0.1365	2.17	0.030
Gender (GND)	0.0518	0.2358	0.22	0.826
Age (AGE)	−0.0009	0.0099	−0.09	0.928
Agricultural Experience (AE)	−0.1621 **	0.0072	2.26	0.024
Household size (HS)	−0.0726 **	0.0378	−1.92	0.055
	Vulnerability indicators			
Exposure to climate risks (E)	0.4800	0.3087	1.55	0.120
Sensitivity to climate risks (S)	−0.1833	0.2387	−0.77	0.442
	Factors influencing Willingness to adopt Climate-Smart Agriculture			
Income diversification (ID)	0.2923	0.2363	1.24	0.216
Crop diversification (CD)	0.4276 **	0.2231	1.92	0.055
Access to extension services (AES)	−0.2294	0.2167	−1.06	0.290
Information about CSA (ICSA)	0.5034 **	0.2199	2.29	0.022
Cooperative membership (CM)	−0.1346	0.2602	−0.52	0.605
	Number of observations = 209			
	Log Likelihood −105.66451			
	Likelihood Ratio Chi2 (13) = 55.71			
	Chi square (p) = <0.001 ***			

** and *** denotes the significance levels of 5% and 10%.

Table 8. Second hurdle of the double-hurdle regression model estimated using truncated (Tobit) model.

Parameter.	Coef.	Std. Err.	T	$p > \|t\|$
Farmers' characteristics				
Constant	1.0396	0.6622	1.57	0.118
Farm size (FS)	0.0022	0.0428	0.05	0.959
Educational Level (EL)	0.2816 **	0.1191	2.36	0.019
Gender (GND)	0.0421	0.1956	0.21	0.830
Age (AGE)	0.0004	0.0085	0.06	0.956
Agricultural Experience (AE)	−0.0134 **	0.0061	−2.21	0.029
Household size (HS)	−0.0061 **	0.0309	−1.95	0.052
Vulnerability indicators				
Exposure to climate risks (E)	0.4047	0.2611	1.55	0.123
Sensitivity to climate risks (S)	−0.1463	0.2051	−0.76	0.476
Factors influencing Willingness to adopt Climate-Smart Agriculture				
Income diversification (ID)	0.2630	0.2003	1.31	0.191
Crop diversification (CD)	0.3881 **	0.1866	2.08	0.039
Access to extension services (AES)	−0.1846	0.1806	−1.02	0.308
Information about CSA (ICSA)	0.4355 **	0.1888	2.31	0.022
Number of observations = 209				
Pearson Goodness-of-Fit Test Likelihood Ratio Chi-Square (12)	Chi- Square	Log Likelihood		Sig.
	57.28	−161.172		<0.001 ***

** and *** denotes the significance levels of 5% and 10%.

The first hurdle demonstrates the factors that influence the decision to use climate-smart agriculture (CSA), while the second hurdle illustrates the factors that impact smallholder maize farmers' willingness and intensity of use. According to the findings, the farmers' literacy level and ease of access to new information—which calls for comprehension abilities acquired via formal education—have a significant role in affecting the decision-making process, leading to the adoption of adaptation techniques. The knowledge of CSA (ICSA) $p = 0.5034$, crop diversification (CD) $p = 0.4276$, and smallholder maize farmers' educational level (EL) $p = 0.2961$ were found to have a positive effect on their willingness (choice) to embrace CSA. Conversely, the agricultural experience (AE) of smallholder maize farmers ($p = 0.1621$) and household size (HS) ($p = 0.0726$) had a negative influence on the decision to adopt CSA

3.2.3. Second Hurdle: Probit Regression Model of Results of Sampled Smallholder Maize Farmers in Ga-Makanye, Gabaza, and Giyani (n = 209)

The results of the second hurdle from the double-hurdle regression model (estimated via the Tobit model) are presented in Table 8. The second hurdle estimated the drivers of the adoption of CSA, which uses a maximum likelihood estimator with an efficient and consistent model parameter. The results depicted in Table 8 indicate that smallholder maize farmers' EL $p = 0.2816$, CD $p = 0.3881$, and ICSA $p = 0.4355$ positively influenced the adoption of CSA and the ability to use these practices to address climate change. Maize farmers' HS $p = 0.0061$, and farmers AE $p = 0.0134$ negatively influenced the adoption of CSA to adapt to climate change.

4. Discussion

The coefficients in the first hurdle (estimated via the Probit model) indicate how various factors affect the decision to adopt CSA. The results show that smallholder maize farmers' educational level (EL) is positive and statistically significant at the 5% level. This positive effect implies that one additional year in a farmer's educational level will positively influence the decision to adopt CSA by 29.61%. These results seem to be plausible with the findings of Hitayezu et al. [50] and Roco et al. [54], which showed that farmers educational levels positively influence the adoption of adaptation strategies because educational achievements contribute to providing farmers with the necessary skills and knowledge for implementing desired adaptation strategies. Surprisingly, several writers discovered that the adoption of CSA practices were proportionally influenced by the level of education [55–57]. It follows that farmers with lower levels of education develop fewer comprehension abilities and are less conscious of climate change, which makes them less inclined to react to its impacts.

The coefficient of farmers' agricultural experience (AE) is negative and significant at the 5% level. This inverse relationship between farmers' years in farming and adoption of CSA implies that, for every year that a farmer gains experience, there is a 1.6% likelihood that their decision to adopt CSA will be reduced. These results suggest that farmers with longer farming experience are more aware of the risks posed by climate change, and some are still reluctant due to choosing indigenous knowledge over adopting technologies. Research by Ainembabazi and Mugisha [58] suggests that agricultural experience positively impacts CSA adoption, as farmers with extensive experience appreciate the benefits of implementing CSA principles. However, Abegunde [59] found no significant relationship between farming experience and CSA practice adoption.

Smallholder maize farmers' ability to diversify their crops (CD) was found to be positive and statistically significant at 5%. This positive effect implies that a 1% increase in farmers producing other crops than maize will result in a 42.76% increase in farmers' decisions to adopt CSA. These results are consistent with research by Agbenyo et al. [60] that showed that crop diversification is a key factor in CSA strategies to support resilience towards climate change.

Similarly, the coefficient on information about CSA was found to be positive and significant at the 5% level. This positive effect shows that a 1% increase in information and awareness about CSA will increase smallholder maize farmers' decision to adopt CSA by 50.34%. These results seem plausible with the findings of Kalu and Manacor [61] and Dung [62], who found that knowledge about CSA positively influenced the adoption decisions of these adaptation strategies. However, the coefficient of smallholder maize farmers' household size was found to be negative and significant at the 5% level. This negative effect shows the inverse relationship between farmers' household size and their decision to adopt CSA. This implies that one additional member living with the farmer will decrease the likelihood of adopting CSA by 7.26%. These results are consistent with the findings of Malila et al. [63], who found an inverse influence between household size and adoption decisions among farmers.

The empirical results indicate that, in the second hurdle, farmers' educational level (EL) is positive and significant at the 5% level. This positive effect indicates that education positively influences the intensity and adoption rate of CSA among smallholder farmers. This implies that an additional year of farmers acquiring education will likely influence the adoption rate of CSA by 28.16%. These findings are consistent with the first hurdle results, which indicate that smallholder maize farmers' willingness to adopt CSA is positively influenced by their level of education. This indicates that, because farmers can readily understand the information, knowledge, and skills required, education plays a critical role in influencing their desire to embrace improved agricultural techniques such as CSA practices and techniques.

Smallholder maize farmers' farming experience (AE) was found to be negative and statistically significant at the 5% level. However, this negative relationship implies that there is an inverse influence, or not much influence, of farmers' adoption rates towards CSA. This implies that an additional year of farming experience in the production of maize will likely reduce the adoption rate by 13.4%. The implication is that farmers who have more experience in farming have identified various adaptation strategies to reduce their vulnerability to the risks posed by climate change. These results seem to be in line with the study of Makamane et al. [35], which found that experience in farming lowers the adoption rate of various adaptation strategies, including CSA.

The empirical results indicate that farmers' household size (HS) is negatively influencing the adoption of CSA among smallholder maize farmers and is significant at the 5% level. The inverse relationship between household size and CSA adoption implies that the variable HS will not influence the adoption of CSA, as there is abundant labor and more people living with the farmer who may assist with farming activities. These findings align with the conclusions of Malila et al. [63], showing that household size does not exert a statistically significant impact on the adoption level of CSA practices. The findings imply that one additional member living with the farmer will decrease the willingness to adopt the CSA practices by 0.61%. This is because smallholder farmers rely on family labor for production, so if farmers have more hands required for their produce, they are less likely to adopt the practices.

Moreover, information about CSA was found to be positive and statistically significant at the 5% level. This positive effect implies that a 1% increase in CSA information accessibility will increase the adoption of these adaptation strategies by 43.55%. The implication is that farmers become aware of CSAs by accessing information relating to them. Furthermore, crop diversification (CD) as a CSA practice was found to be positively influencing the willingness to adopt CSA among smallholder maize farmers, and it is significant at the 5% level. This positive relationship implies that, when farmers do not solely produce maize but rather produce other crops, they are likely to adopt CSA practices to mitigate the risks imposed by climate change. The implication is that a 1% increase in farmers diversifying their production will increase the adoption rate and use of CSA by 38.8%. These results concur with the findings of Awiti [64], who noted that crop diversification positively influences the labor cost share, implying that more labor is required in a diversified farming system, hence crop diversification's effects on production cost. The results do not necessarily imply CSA but show that crop diversification can be used as an improved farming technique to mitigate the risks of climate change.

5. Conclusions and Recommendations

The study aimed to analyze the socioeconomic factors influencing smallholder maize farmers' willingness to adopt climate-smart agriculture (CSA). Subsequently, the double-hurdle model was used to examine those factors, which influence smallholder maize farmers' willingness to adopt CSA. The factors considered include farm size, educational level, gender, age, and household size of farmers, exposure to climate risks, sensitivity to climate risks, income and crop diversification, accessibility to extension services, and information about CSA. Results showed that educational level, crop diversification, and information about CSA positively influenced farmers' willingness to adopt CSA, while agricultural experience and household size negatively influenced it. The null hypothesis of this study stating that there are no factors that influence the willingness to adopt CSA is rejected, as there is sufficient evidence that there are factors that influence the will to adopt CSA and, consequently, the capacity of the smallholder farmers to adapt to climate-related challenges. Farmers must have access to knowledge that guides them to new resource-conserving and climate-resilient production systems (i.e., CSA). This will require the generation and dissemination of new knowledge, as well as iterative research with early adopters and policy support. Farmers cannot adopt the CSA practices unconsciously; rather, they need proper guidance on how to adopt, decide which effective strategy will work best, and what resources are needed for the adoption. The Department of Agriculture, Land Reform, and Rural Development should provide CSA workshops and educational programs to farmers, enhancing their knowledge and decision-making processes, and fostering relationships for future assistance.

Considering the vulnerability of the farmers in the study areas to climate change effects and the prospects of CSA, to address those climate-related challenges, the CSA program is necessary. The adoption of a CSA program among smallholder maize farmers should be included and implemented at the lower level, taking into consideration their educational levels. The program can include workshops on climate change action stakeholders or interventions that will address CSA within lower levels. According to the Mnkeni report [9], which stated that CSA is knowledge intensive, those guides should be viewed as progress towards academic and experiential knowledge. This includes bi-weekly workshops for different groups based on how old and knowledgeable the farmer is, as it may be helpful in some instances not to integrate educated, modernized farmers with older farmers who use indigenous knowledge. Whilst these farmers may learn from one another, in some instances, mixing the two groups may not have an effective teaching and learning process, as older people require patience and more time to comprehend all the information provided. CSA workshops that show observations can be implemented at each farmer's farms through inviting other farmers, thus rotating the visitation so that it becomes easier when farmers learn about CSA through active engagement. This is supported by the theories of Piaget and Vygotsky, who believed that the teaching−learning process becomes effective when there is active engagement, motivation, and hands-on activities. This is essential for farmers who do not have adequate formal educational skills [65].

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