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Impact of adoption of sustainable land management practices on food security of smallholder farmers in Mpumalanga province of South Africa

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Abstract This study was carried out to investigate the impact of the adoption of sustainable land management practices (SLMP) on food security among smallholder farmers in Mpumalanga Province, South Africa. A cross-sectional survey was conducted, where 250 maize farmers in the study area were interviewed. A household expenditure survey was used to measure the food security status and equally an efficient endogenous switching probit was employed to estimate the impact of SLMP on food security. The results show that 71% of the sampled respondents adopted SLMP, while 68% of the farmers were food secured. Furthermore, the results from the endogenous switching regression revealed that marital status, household size and membership in a social organization influence food security status. Similarly, the estimate of the average treatment effect on the treated indicated that maize farmers who adopted SLMP had a mean difference of 20 percentage or about 80% higher probability of being food secured compared to farmers who did not adopt. By implications, the study recommends that policies to improve SLMP should be introduced in the study area.

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Introduction

The agricultural sector plays a crucial role in African economies, particularly in sub-Saharan African (SSA) countries, where more than three-fourths of the population relies on rain-fed agriculture for their livelihoods (Abeje et al., 2019). Tun et al. (2015) highlights that land degradation can lead to a decline in crop production potential and the implications are dire particularly for rural people who rely on agriculture for their livelihoods. The degradation, which is further enhanced by the negative impacts of climate change results in reduced agricultural productivity and jeopardises food security and increases poverty (Liniger et al., 2011). According to Abera et al. (2020), land degradation continues to be a challenge, partly due to lower adoption rates and the discontinuities in the usage of sustainable land management practices (SLMP). Moreover, the expected growth in population in Africa is expected to adversely impact natural resources, agriculture, future food security, investments and public policy

(Warinda et al., 2020) and this calls for urgent attention.

For a country such as South Africa which is battling with the triple challenge of poverty, income inequality and unemployment, agriculture is strategically positioned as a sector that can make strides in uplifting the conditions of the poor and improve food security. However, as indicated by Food and Agriculture Organization—FAO (2009), South Africa's agricultural natural resources are diverse, complex and vulnerable to degradation thereby requiring concerted efforts in achieving sustainable land use and management. Sustainable land management (SLM) is key in dealing with the adverse impacts of land degradation and reduced agricultural productivity (Abeje et al., 2019). The SLM includes a range of practices such as minimum tillage (MT), commercial fertilisers (CFs), building terraces, soil/stones bunds (level/graded), tree planting, compost, farmyard manure (FYM) and enclosures, (Schmidt and Tadesse, 2009; Kassie et al., 2010; Adimassu et al., 2016).

The interconnectedness between numerous UN Sustainable Development Goals (SDGs) such as SDG1 (eradicate poverty), SDG2 (end hunger, achieve food security and improved nutrition, and promote sustainable agriculture) and SDG 13 (climate action) and possibly a number of many other goals necessitates urgent attention into looking at how the challenges of food insecurity and land degradation can be simultaneously tackled. Since there are numerous traditional and modern SLMPs that are already in existence, it becomes paramount to understand the drivers behind the adoption of such technologies among smallholder farmers.

Even though a majority of such studies (including Abeje et al., 2019; Kassie et al., 2010; Sileshi et al., 2019) have been done in other countries such as Ethiopia, fairly limited studies, if any, have been carried out in South Africa. Moreover, different regions are affected differently due to their local context in terms of socio-economic factors. Since such studies in Mpumalanga are limited, this study is expected to reveal new knowledge and improve policy in terms of food security. Moreover, most of the existing studies focuses on other welfare outcomes such as productivity, production and income; and rarely on food security. However, it is important to understand the factors that influence the adoption of farming practices and technologies and the effects that the adoption of such practices has on food security. This study aims to fill that gap by addressing the following three specific objectives: (1) to measure the food security status of the households (2) to investigate the factors that influence farmers‘ decision to adopt SLMP, and (3) to assess the impact of SLMP adoption on household food security status.

The remainder of the paper is organised as follows. Section two gives the review of the literature pertaining to SLMP. The methodology is presented in section three. The empirical results are presented and discussed in section four. The paper ends with some conclusion and policy recommendations in section five.

Literature review

Drivers of SLMP adoption

The adoption of more efficient and sustainable farming practices and technologies is a key for achieving economic growth, food security and poverty alleviation (Birungi & Hassan, 2007).

Empirical studies on technology adoption have reported numerous factors that affect the probability of a farmer adopting a certain technology. As highlighted by Giger et al. (2018), the farmers‘ decisions to adopt SMLP are influenced by a number of socio-economic and cultural factors rather than just the monetary costs and benefits involved. Hence, when undertaking an adoption study, a broad range of factors are considered.

For instance, Sileshi et al. (2019) analysed the impact of soil and water conservation (SWC) on household vulnerability to food insecurity in Ethiopia. The results showed that socio-economic and farm specific characteristics such as household head‘s gender and level of education, irrigation and fertilizer usage, source of information, and cultivated land were the factors influencing the farmers‘ decision to adopt SWC practices. Tufa et al. (2019) assessed the productivity and income effects of adopting improved soybean varieties and agronomic practices (ISVAPs) among soybean growers in Malawi. The authors found that age and education of household head, the size of land under cultivation, participation in a seed market, access to an agricultural extension service and membership in a farmers' organization positively and significantly influenced the adoption of ISVAPs.

In another study, Mango et al. (2017) investigated the factors that influence the farmers' awareness and adoption of land, soil and water conservation practices in the Chinyanja Triangle, Southern Africa. The findings showed that a range of farmers' socio-economic characteristics including the household head's age, level of education, agricultural advice reception, membership in farmer group, pieces of land owned or used in production and land-to-man ratio influenced the farmers' decision to adopt the land, soil and water conservation practices. The reviewed literature shows that various factors influence the decision to adopt or not to adopt a technology amongst smallholder farmers. However, these factors cannot be generalized across all farmers as there are a number of other factors that can come into play.

Impact of SLMP adoption on welfare outcomes

The concept of SLMP has been widely studied in some countries in sub-Saharan Africa. This section focuses on the impact of adoption of SLMP on food security. However, due to the general scarcity of studies focusing specifically on food security, studies that focuses on other outcome variables such as income, production, productivity and livelihoods are also reviewed. The impact of SLMP on agricultural production, productivity and other welfare parameters such as income and food security in developing countries from empirical studies are quite mixed.

For instance, in Ethiopia, Sileshi et al. (2019) found that SWC adoption significantly enhanced the per capita food consumption and net value crop; and improved the current food security status and reduced future vulnerability to food insecurity (in the presence of shocks) of households in Ethiopia. In another study, Kassie et al. (2010) studied the impact of minimum tillage (MT) and commercial fertilisers (CFs) in low and high agricultural potential areas in the Ethiopian highlands. The results showed that MT has a positive and significant impact on agricultural productivity in low agricultural potential areas. The results further revealed that CFs have a significant and positive impact on crop productivity in the high agricultural potential region while MT showed no significant impact.

In Malawi, Tufa et al. (2019) reported that the adoption of ISVAPs significantly increased soybean yield and net crop income among soybean farmers. Moreover, Schwilch et al. (2014) also found that SLM adoption enhanced production and better management of water and soil degradation; and improved people's livelihoods and prevented further outmigration from the dryland areas. In another study, Zikhali (2008) reported that contour ridges positively and significantly influence land productivity in Zimbabwe.

However, contrasting results were reported in a study by Schmidt and Tadesse (2019) to study the impact of sustainable land management on household crop production in the Blue Nile Basin of Ethiopia. Their results revealed that the adoption of SLMP had no significant effect on household level value of total crop production in comparison with control households. Similarly, a study by Nyangena and Köhlin (2009) in Kenya also showed that plots under SWC technologies generated lower crop yields as compared to those without in Kenya. As indicated by Kassie et al. (2010), the mixed results reported in the literature on the impact of SLMP adoption suggest the need for careful, location-specific studies, rather than generalizing. This, therefore, necessitates the carrying out of the current study to understand how SLMP affects food security in South Africa.

Study area

The study was conducted in Gert Sibande District Municipality in Mpumalanga Province of the Republic of South Africa as shown in Fig. 1. The district is a Category C municipality and is the largest of the three districts in the province with an area of 31 841 km^2 which covers almost half (40%) of its geographical area (Mpumalanga Province's total land mass of 76 495 km^2). The district consists of seven local municipalities, namely Govan Mbeki, Chief Albert Luthuli, Msukaligwa, Dipaleseng, Mkhondo, Lekwa and Dr Pixley ka Isaka Seme. The major towns are: Amersfoort, Amsterdam, Balfour, Bethal, Breyten, Carolina, Charl Cilliers, Chrissiesmeer, Davel, Ekulindeni, Embalenhle, Empuluzi, Ermelo, Evander, Greylingstad, Grootvlei, Kinross, Leandra, Lothair, Morgenzon, Perdekop, Secunda, Standerton,

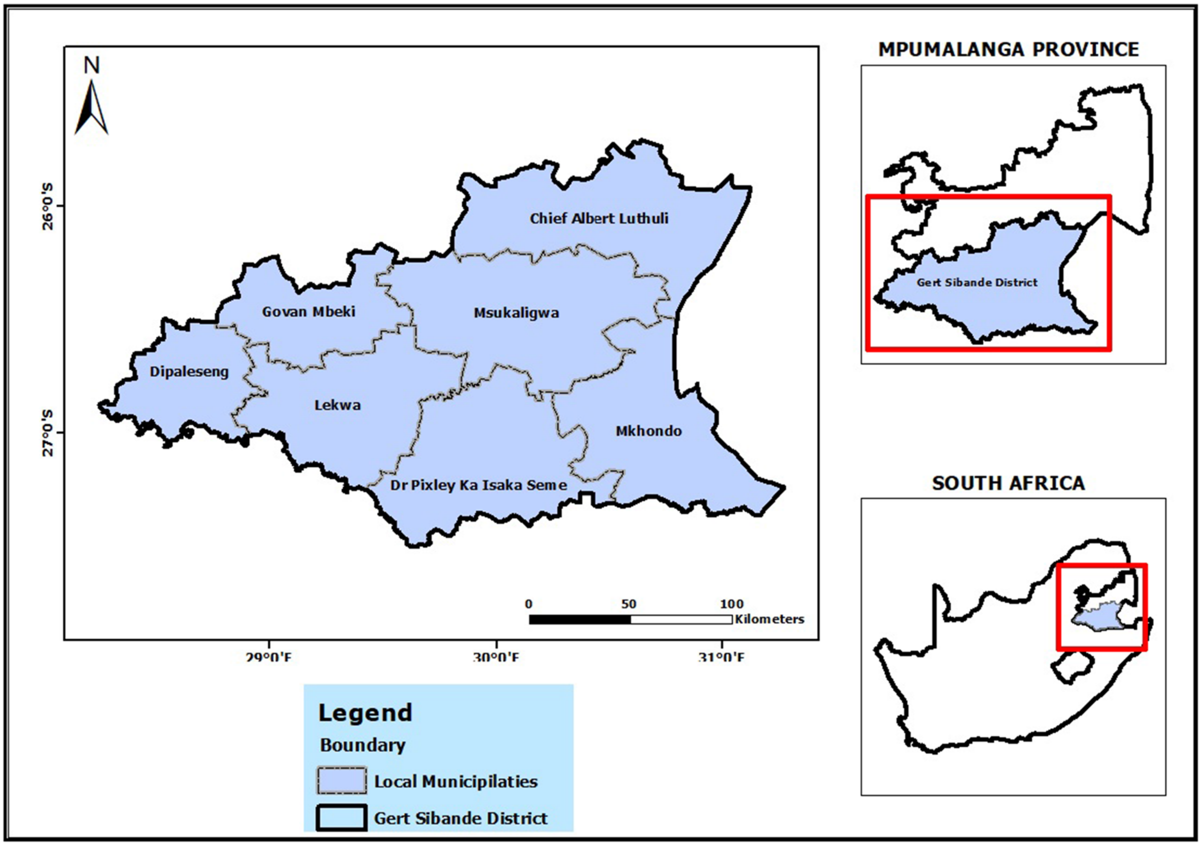

Fig. 1 Map of Gert Sibande District municipality, Mpumalanga Province. *Source*: https://municipalities.co.za/map/132/gert-sibande-district-municipality (2020)

Trichardt, Volksrust, Wakkerstroom, eManzana, eMkhondo (Piet Retief).

The Mpumalanga province itself, is situated in the east of the country and is bounded by Eswatini and Mozambique. It is bordered by the Limpopo province, far to the north, KwaZulu-Natal to the south, Gauteng to the west and the Free State province to the southwest. As at 2019, the population of the district was projected at 1 122 590 in 2019, with an average grown rate of 1.1% per annum between 2009 and 2019. This makes the district the smallest amongst the three in terms of population size. The district is known for a large agricultural sector in the country with a diversified economy with a largest undermining complex in world and is home to major industrial complexes associated with the petro-chemical industry.

The main economy sector is mining and manufacturing followed by agricultural activities. The area between Carolina, Bethal and Ermelo produces the most sheep and wool in South Africa which indicate the significant of agriculture in South Africa. It is expected that Gert Sibande District Municipality will grow at an average annual rate of 1.75% from 2018 to 2023, which is comparable to the average annual growth rate of Mpumalanga Province and South Africa, expected to grow at 1.40% and 1.50%, respectively (Profile Gert Sibande District, 2020). In 2018, Gert Sibande district contributed a meagre of 2.06% to the GDP of South Africa, 27.68% to the Mpumalanga Province's total GDP of R 363 billion which ranked the district the lowest relative to all the regional economies in the Mpumalanga Province.

Methodological approach

Population, sampling procedure, and sample size

The representative sample size was determined using Slovin's formula, as given in Eq. (1), after which a total number of 250 questionnaires were administered to the maize farmers in the district using a proportionate random sampling technique. This was achieved by adopting a quantitative model as presented below:

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

where n is the sample size,

N = total population of maize farmers in the 7 local municipalities across the district,

e = maximum variability or margin of error (MoE). This is estimated at 5% (0.05),

1=probability of the event occurring,

250 = the number of respondents sampled or sample size.

Data collection

Data was collected through face-to-face interviews using a semi-structured survey questionnaire which was validated by two agricultural economists' expert. The questionnaire contained closed questions aimed at capturing numeric data and open-ended questions which captured qualitative data or open responses. The questionnaire was subdivided into sections based on the objective of the study. A reliability test was done on the research instrument to ascertain the use.

Data analysis

Data was analysed using both descriptive and inferential statistics. Descriptive statistics such as percentages, mean values, and standard deviation were used to describe farmers' socioeconomics and household food security status (HFSS). Consequently, a switching regression model was adopted to determine the impact of SLM on food security status. Table 1 shows the variables used in the model, and their measurement.

Household food security status (HFSS) calculation

Following Oduniyi and Tekana (2019), the study used a Household Expenditure Survey (HES), to determine household food security. The HES is referred to the expense a household spend on food per month. This was achieved by calculating the per capita food expenditure of i-th household, divided by 2/3 mean per capita food expenditure of all households, over a period of a month. The obtained value represents the food security status index, which is a threshold. An individual above the threshold values is regarded as the food secured, and otherwise, food insecure. In other words, any household with a per capita monthly food expenditure above or equal to two-thirds of the mean per capita food expenditure is considered to be food secure, while otherwise is considered to be food insecure.

The calculation can be mathematically written as:

$$\mathrm{F_i} = \frac{\text{per capita food expenditure for the ith household}}{2/3 \text{ mean per capita food expenditure of all household}} \quad (2)$$

where $\mathrm{F_i}$ is the household food security index.

$Fi \geq 1$ =the i-th household is food secure.

$Fi < 1$ =the i-th household is food insecure.

Econometric model

Individual decision to adopt sustainable land management practices is attributed to constrained optimisation whereby a farmer chooses practices that are available, affordable and beneficial to his/her farming business. The benefit is tied and determined by a set of variables that are observables and unobservable. The aforementioned factors may affect farmers' decision to adopt SLMP, thus, the adoption becomes a potential endogenous. As a result of this, there is a self-bias problem, where failure to address the selection bias issue associated with the adoption of SLMP will produce a biased estimate. Following a study by (Ma et al., 2018; Oduniyi & Tekana, 2021) an adopter is regarded as a farmer who has adopted at least one SLMP. Several models such as the propensity score matching approaches have been widely used in an attempt to estimate a binary treatment variable on various outcome variables to evaluate policy interventions (see; Martey et al., 2019;

Table 1 Descriptive statistics *Source*: Author's computation (2020)

Variables	Description and variable measurement	Expected sign
Adoption of SLMP	Dummy, 1 if yes, 0 if otherwise	
Food secured	Dummy, 1 if yes, 0 if otherwise	
Gender	Dummy; 1 if household head is a male and 0 if otherwise	+
Age	Number of years (Continuous)	−
Years spent in school	Number of years (Continuous)	+
Farm size	Size in hectares (Continuous)	+
Type of farm	Categorical variables (1=Individual, 2=Family, 3=Community, 4=Cooperation, 5=Tribal, 6=Lease)	+
Farm manager	Categorical variables (1=Individual, 2=Family, 3=Community, 4=Cooperation, 5=Tribal)	+
Owner of the farm	Categorical variables (1=Individual, 2=Family, 3=Community, 4=Cooperation, 5=Tribal)	+
Land acquisition	Categorical variables (1=own finance, 2=bond, 3=LRAD, 4=PLAS, 5=Restitution, 6=Inheritance, 7 =Land affairs, 8=Land hiring, 9=Tribal chief)	−
Years of farming	Number of years (Continuous)	+
Access to ext ser	Dummy, 1 if yes, 0 if otherwise	+
Social organization	Categorical variables (1=farmers' group, 2=religious based group, 3=gender-based group, 4= community-based group, 5=age group, 6=none)	+
Monthly income (R)	Monthly farm income in ZAR ((Continuous)	+
Marital status	Dummy; 1 if household head is married, 0 otherwise	−
Household size	Number of Members (Continuous)	−
Member in soc org	Dummy, 1 if yes, 0 if otherwise	+
Access to agri-input	Dummy, 1 if yes, 0 if otherwise	+
Agri-subsidy	Dummy, 1 if yes, 0 if otherwise	+

Rubhara et al., 2020), however, this approach addresses selection bias by controlling only the observable variables (Ma et al., 2018). Thus, to establish causation, endogenous switching probit was employed to control for the selection bias and unobserved heterogeneity.

Endogenous switching probit

An endogenous switching probit (ESP) is a two-stage estimation technique, which addresses the selection bias stemming from both observed and unobserved heterogeneities (Li et al., 2020) and can also estimate two outcome equations. In the first stage, the SLMP adoption function was modelled by analysing the factors that affect farmers' decisions to adopt SLMP. The second stage estimate both the household food security and insecurity status.

Let the decision to adopt SLMP be represented by the following latent response model:

$$S_1^* = \mathrm{Z_i a} + \mu_i \tag{3}$$

$$\mathrm{S_1} = \begin{cases} 1 & if\ S_1^* > 0 \\ 0 & if\ otherwise \end{cases} \tag{4}$$

where S_1^* represent a continuous latent variable, α is a parameter to be estimated and μ_i is an error term. The binary response y_i is also defined as follows:

$$y_1^* = \mathrm{x_i}\beta + \mathrm{S_i} \tag{5}$$

$$y_1 = \begin{cases} 1, & if\ y_1^* > 0 \\ 0, & if\ otherwise \end{cases} \tag{6}$$

where y_i is the main outcome variable and y_1^* represents a continuous latent variable, β represents a vector of parameters to be estimated, r is the coefficient of the endogenous treatment dummy, and μ_i is a residual term.

Inverse-probability-weighted regression adjustment: IPWRA

Similarly, the study explores the use of IPWRA to estimate the impact of the adoption of sustainable land management practices on maize yield between adopters and non-adopters. This is decisive since crop yields are closely related to food security and livelihoods of the majority of South Africa smallholder farmers. The IPWRA is a treatment-effects estimator which is used to estimate the causal effect of a treatment on an outcome based on observational data. This estimator is also considered as a trustworthy remedy for potentially biased estimates (ATT). The IPWRA estimator has the double-robust property, which means that the estimates of the effects will be consistent if either the treatment model or the outcome model but not both are mis specified (Woolridge, 2003).

The IPWRA combines the features of both the regression adjustment (RA) and Inverse probability weighting (IPW). RA estimators model the outcome to account for the non-random treatment assignment. IPW estimators model the treatment to account for the non-random treatment assignment. IPWRA estimator model both the outcome and the treatment to account for the non-random treatment assignment. IPWRA uses IPW weights to estimate corrected regression coefficients that are subsequently used to perform regression adjustment.

For the regression adjustment (RA) model, the ATT can be expressed as;

$$ATT_{RA} = n_A^{-1} \sum T_i [r_A(x, \delta_A) - r_N(x, \delta_N)] \tag{7}$$

where n_A is the adoption of SLPM sub-sample, r_A is the regression model for adopters of SLMP (A) and r_N is the regression model for non-adopters of SLMP (N) regressed on observed characteristics x_i and parameter estimates $\delta_i = (\alpha_i, \beta_i)$. The regression adjustment averages the predicted outcomes to calculate the effects.

The inverse weights for the treated group is equal to 1 while that for the control group can be defined as

$$\frac{\hat{p}(x)}{1 - p(x)} \tag{8}$$

Since the IPWRA blend both the RA and IPW, thus, it can be written mathematically as

$$ATT_{IPWRA} = n_A^{-1} \sum_{i=1}^{n} T_i [r_A^*(x, \delta_A^*) - r_N(x, \delta_N^*)] \tag{9}$$

where $\delta_A^* = (\alpha_A^*, \beta_A^*)$ is developed from a weighted regression process;

$$\min_{\alpha_A^*, \beta_A^*} \sum_{i=i}^{N} T_i (Y_i - \alpha_A^* - X\beta_A^*) / \hat{p}(X, \hat{\gamma}) \tag{10}$$

and $\delta_N^* = (\alpha_N^*, \beta_N^*)$ is gotten from the weighted regression process;

$$\min_{\alpha_N^*, \beta_N^*} \sum_{i=i}^{N} (1 - T_i)(Y_i - \alpha_N^* - X\beta_N^*)^2 / (1 - \hat{p})(X, \hat{\gamma}) \tag{11}$$

Comparing ATT based on RA, ATT obtained from IPWRA is similar, except that different weighted estimates are used for the regression parameters (Wooldridge 2010).

Empirical results and discussion

This section presents and discusses the important findings of the study. Firstly, the descriptive results are presented, followed by the inferential results.

Descriptive results

Table 2 presents a summary of the data (disaggregating adopters and non-adopters), focusing on the variables that are used for further analysis. The mean age for SLMP adopters was 49.01 while the non-adopters had a mean age of 46.62. This implies that the adopters were relatively older as compared to non-adopters.

The results further show that all the farmers were generally experienced in farming with the mean number of years for adopters at 10 years and 12 years

Table 2 Descriptive Statistics *Source*: Author's computation (2020)

Variables	Mean (std dev)	
	Adopters	Non-adopters
Gender	0.58 (0.49)	0.38 (0.49)
Age	49.01 (12.42)	46.62 (12.92)
Years spent in school	3.01 (0.82)	3.01 (0.82)
Farm Size	136.01 (195.31)	127.25 (195.31)
Type of Farm	2.51 (1.40)	1.75 (1.01)
Farm manager	2.32 (1.39)	1.40 (0.85)
Owner of the farm	2.36 (1.25)	1.75 (0.98)
Land Acquisition	4.80 (1.90)	4.30 (2.89)
Years of Farming	10.34 (6.55)	12.00 (7.21)
Access to Ext Ser	0.88 (0.32)	0.70 (0.46)
Social Organization	2.98 (2.22)	2.73 (2.24)
Monthly income (R)	17,220.86 (19,980.72)	16,215.07 (14,392.33)
Food Security	0.66 (0.47)	0.71 (0.46)
Marital status	0.46 (0.50)	0.49 (0.50)
Household size	6.85 (2.53)	5.52 (3.07)
Member in Soc Org	0.68 (0.47)	0.68 (0.47)
Access to Agri-input	0.75 (0.44)	0.95 (0.23)
Agri-subsidy	0.11 (0.31)	0.23 (0.43)

for non-adopters. In terms of monthly income, the adopters had a higher mean of R17220.86 as compared to non-adopters with R16215.07. With regard to household size, adopters had a higher mean of 6.85 as compared to non-adopters with a mean of 5.52.

Distribution of farmers by adoption status

The sampled farmers were grouped according to their adoption status of the sustainable land management practices. As mentioned earlier on in the methodology section, an adopter is someone who is using at least one of the methods for sustainable land management. Table 3 shows that the majority of the farmers, approximately 71%, adopted at least one method of SLM, while 29% did not adopt any. Even though these statistics do not reveal the intensity of adoption, they at least give a general idea of the adoption status among the sampled farmers. Table 4 presents a frequency analysis for sustainable land management practices. Minimum soil disturbance or zero tillage was the most adopted strategy with a frequency of 71%, followed by mixed cropping or intercropping at 63%. The least adopted strategy was the agroforestry with a frequency of 20%.

Distribution of farmers by food security status

The respondents were further grouped according to their food security status. The household food

Table 3 Adoption of SLM *Source*: Author's computation (2020)

Adoption of SLM		Frequency	Percent
	No	73	29.2
	Yes	177	70.8
	Total	250	100.0

Table 4 Frequency of SLMP used in the study area Source: Author's computations (2021)

SLMP	Frequency (%)	Ranking
Mulching/Surface cover	58	5th
Fallowing	40	10th
Crop rotation	52	6th
Mixed-cropping / Inter-cropping	63	2nd
Cover crops	51	8th
Improved fertiliser	55	3rd
Soil erosion control	56	7th
Agroforestry	20	11th
Land enclosure	45	9th
Minimum soil disturbance/Zero tillage	71	1st
Integrated soil fertility management	60	4th

security status was determined using the household expenditure survey (HES) described in the methodology section. The results in Table 5 show that the majority, approximately 68%, of the farmers were food secure while 32% were classified as food insecure. This implies that generally the households in the study area are food secure. The result was supported by Ahmed et al. (2017) who found out that 77.6% of the households in rural area of Pakistan were food secured. Consequently, Oduniyi and Tekana (2020) reported a similar report that 54.3% of the rural household farmers in Northwest province of South Africa were food secured.

Impact of smallholder farmers' adoption of SLMP on food security

In this sub-section, the results of the endogenous switching regression model are presented and discussed. The model is a two-stage estimation procedure and as such the results are presented in the same logic. Table 6 shows the results generated from the two stages. The results shows that the decision to adopt the SLMP was influenced by a number of socio-economic and plot level characteristics of the farmers such as: gender of household head, age of household head, who managed the farm, how the land was acquired, years of farming experience and access to extension services.

With regard to the gender of household head, the results show gender positively and significantly influenced SLMP adoption. In this particular study, this means that men have a higher propensity to adopt as compared to their female counterparts. The results are in agreement with Manda et al. (2016) who reported that the likelihood of adopting sustainable agricultural practices (SAPs) is lower among female-headed households. Furthermore, Sileshi et al. (2019) also found that gender of household significantly influenced the adoption of soil and water conservation practices among farmers in Ethiopia.

Age was also found to be an important factor and had a positive and significant influence on the adoption of SLMP. This result implies that the older the farmer gets, the more they adopt SLMP. The results of a study by Mango et al. (2017) also reported

Table 5 Food security status *Source*: Author's computation (2020)

Food Security Status	Frequency	Percent
No	81	32.4
Yes	169	67.6
Total	250	100.0

Table 6 Impact of SLMP adoption on food security *Source*: Author's computation (2020)

Variables	Coef	Std. Err	z	P>|z|
SLM adoption				
Gender	0.593	0.189	3.14	0.002***
Age	0.017	0.010	1.76	0.078*
Education	0.103	0.104	0.99	0.324
Farm Size	− 0.000	0.000	− 0.31	0.759
Farm Type	− 0.027	0.091	− 0.30	0.767
Farm manager	0.403	0.116	3.48	0.001***
Owner of the farm	− 0.020	0.103	− 0.19	0.848
Land Acquire	0.092	0.038	2.39	0.017**
Farming Years	− 0.050	0.0183	− 2.75	0.006**
Income	5.40e−06	6.55e−06	0.82	0.410
Extension Service	0.555	0.239	2.33	0.020**
Social Organization	0.059	0.046	1.27	0.203
Constants	− 2.100	0.687	− 3.06	0.002***
Food secure				
Age	− 0.005	0.010	− 0.51	0.613
Marital Status	0.460	0.230	2.00	0.045*
Household Size	− 0.342	0.050	− 6.89	0.000***
Education	− 0.014	0.124	− 0.11	0.911
Farm Size	0.000	0.000	0.44	0.661
Member of Social Org	− 0.272	0.284	− 0.96	0.338
Income	9.95e−06	6.20e−06	1.60	0.109
Extension Service	0.193	0.320	0.60	0.547
Gender	− 0.104	0.093	− 1.12	0.264
Agricultural Input	0.096	0.275	0.35	0.727
Agricultural Subsidy	0.068	0.186	0.37	0.715
Constant	3.075	0.821	3.75	0.000***
Food insecure				
Age	0.019	0.030	0.64	0.519
Marital Status	− 0.173	0.414	− 0.42	0.676
Household Size	− 0.368	0.192	− 1.92	0.055*
Education	− 0.113	0.343	− 0.33	0.742
Farm Size	− 0.000	0.002	− 0.33	0.740
Member of Social Org	− 1.111	0.414	− 2.68	0.007**
Income	0.000	0.000	1.59	0.111
Extension Service	0.887	0.743	1.19	0.233
Gender	0.067	0.375	0.18	0.859
Agricultural Input	− 0.182	0.495	− 0.37	0.713
Agricultural Subsidy	0.238	0.384	0.62	0.535
Constant	2.350	1.453	1.62	0.106
/athrho1	− 16.104	5005.356		
/athrho0	9.962	417.306		

Table 6 continued

Variables	Coef	Std. Err	z	P>|z|
rho1	− 1	2.04e−10		
rho0	1	3.71e−06		
LR test of indep. eqns. (rho1=rho0=0): chi2(2)=10.11 Prob>chi2=0.0064				

Number of obs=250

Wald chi2(12)=49.05

Log likelihood=− 220.78368

Prob>chi2=0.0000

*, ** and ***Indicate significance levels at 10%, 5% and 1% respectively

that the household head's age played a positive and significant role in influencing the farmers' decision to adopt the land, soil and water conservation practices in Chinyanja Triangle, Southern Africa. Kassie et al. (2013) also found that the adoption of sustainable agricultural practices (SAPs) was positively influenced by the age of farmers. The authors attributed this to the fact that as farmers get older, they tend to have accumulated more experience in agricultural technologies and assets. However, other authors such as Tufa et al. (2019) reported contrasting results where they reported that younger farmers had a higher likelihood of adopting improved soybean varieties and agronomic practices (ISVAPs) in Malawi.

The results further showed that how the land is managed (i.e., whether it is managed by an individual, family members, farmers group, corporation/company farm or trust) is also an important factor influencing the adoption of SLMP. As well, how the land was acquired had a positive and significant effect on the adoption of SLMP.

The number of years engaging in farming had a significant and negative effect on SLMP adoption. This implies that the higher the number of farming years, the less likely it is for the farmers to adopt SLMP. This result is supported by Ullah et al. (2018) who found that farming experience significantly influenced the adoption of improved cultivars of peach in among Pakistan farmers. Finally, the results revealed that access to extension services positively and significantly influenced the farmers' decision to adopt SLMP. Similarly, Tufa et al. (2019) found that access to extension services increased the propensity to adopt ISVAPs among soybean growers in Malawi. Also, Abdoulaye and Sanders (2005); Ng'ang'a et al. (2019); Abdulai & Huffman (2018) reported that institutional factors such as extension contact significantly influence the adoption of agricultural technologies.

Table 6 further shows the results of the food security status equation in the regime where farmers adopted SLMP and these are reported in the "food secure" section. The food security equation in the regime where farmers did not adopt SLMP is also reported in the "food insecure" section. These results constitute the second stage of the estimation procedure. Table 5 shows that the household head's marital status and household size are important factors influencing the SLMP adopters to be food secure. For the food insecure regime, the results show that household size and membership to the social organization are important factors contributing to non-adopters being food insecure.

The household size was found statistically significant with a negative coefficient for both the adopters and non-adopters of SLMP. This suggests that increase in household size is more likely to decrease the probability of achieving the food security status of the adopters of SLMP. A one unit increase in the household size decreases the probability of a household achieving food secure. This simply explains that increase in the household size put the extra burden to the household head which could lessen the available resource, thus, affect the food security status (Oduniyi, 2018). This result is confirmed by Gebre (2012) and Ahmed et al. (2017) who reported that a negative association between an increase in household size and food security status.

The marital status of the maize farmers was found positive and statistically significant in explaining the variation of the food security status of the adopters of SLMP. The result explains that a married household head who adopted SLMP has a probability of being food secure. The marital status of the household head is a significant predictor of food security in such a way that a married head has a tendency to be more responsible and provide food for every member of the family. However, this finding refutes Sekhampu (2013) who found out that the marital status of household head was negatively associated and have a higher probability of being food insecure.

Social organization membership was found negative and statistically significant in explaining the variation of the food security status of the adopters of SLMP. This suggests that the membership status of maize farmers who did not adopt SLMP negatively influenced food security status. Despite being a member, these households did not adopt SLMP or make use of the information shared, thus, no positive significance but low food security status below the threshold. This explained that member of social organization plays a significant role to food security as information on SLMP are shared and help are being received. Nosratabadi et al. (2020) substantiated the result that social capital had a significant influence on food security status.

Impact of farmers‘ adoption of SLMP on the food security status

The last part of the estimation is presented in Table 7 which shows the average treatment effect on the treated. The table explains the effect or impact of SLMP adoption on food security by interpreting SLMP as a treatment. Smallholder maize farmers who adopted SLMP had a mean difference of 19.8 percentage point or about 80% higher probability of being food secured compared with the counterfactual scenario of smallholder maize farmers who do not adopt or non-adopters of SLMP. Adoption of SLMP enhanced food security status among the adopters.

The findings of this study are in agreement with Sileshi et al. (2019) who reported that the adoption of SWC improved food security status and reduced future vulnerability to food insecurity (in the presence of shocks) of households in Ethiopia.

The reason is not farfetched from the fact that the adopters had a better monthly income whereby they can buy and have food available for the households. This is not surprising because using a household expenditure survey to measure food security status uses per capita food expenditure which is focused on the monthly income earned. Thus, more income earned in a month could means that there is a probability of being food secured. This result is supported by Branca et al. (2013) who found that the adoption of sustainable land management practices positively influenced food security.

Impact of SLMP on maize yield

This section focuses on the impact of SLMP adoption on maize yield. In reference to Table 8, the potential outcome (PO) means section of the output displays the POMs for the two treatment groups. The mean maize yield for the farmers who adopted SLMP was 11.99 tons while the non-adopters of SLMP was found to be 8.531 tons. The average treatment effect (ATE) is now calculated to be $11.99 - 8.531 = 3.462$. This suggest that farmers who adopted SLMP had more yield compare to the farmers who did not adopt SLMP, with an average mean yield of 3.462 tons. This finding is in agreement with Kassie et al. (2010) who reported that minimum tillage, which is a form of sustainable land management approach, had a positive and significant impact on agricultural productivity in low agricultural potential areas in rural Tanzania.

Similarly, the impact of SLMP on maize yield was found positive and the result of the mean difference

Table 7 Treatment effect on the treated *Source*: Author’s computation (2020)

Variable	Obs	Mean	Std. Dev
Treatment effect	177	− 0.198	0.246

Table 8 Impact of SLMP on maize yield using IPWRA *Source*: Author's computation (2021)

Crop yield	Coef	Robust Std. Err	z	$P>\|z\|$
Potential outcome means				
Non-adopters of SLMP	8.531	0.982	8.69***	0.000
Adopters of SLMP	11.99	1.066	11.26***	0.000
ATE				
Adopters' vs Non-adopters of SLMP	3.462	1.154	3.00***	0.003

Iteration 0: EE criterion=3.275e-19

Iteration 1: EE criterion=7.536e-30

Treatment-effects estimation

Number of obs=250

Estimator: IPW regression adjustment

Outcome model: linear

Treatment model: probit

***, ** and *means significant at 1%, 5% and 10% significance levels, respectively

was statistically significant ($p<0.01$) and increase the maize yield by 346%.

Conclusion and policy recommendations

Smallholder farmers are faced with several challenges including poor cultivation land management practices which translates to low agricultural productivity. The main consequence of this is food insecurity. This study assessed the impact of the adoption of sustainable land management practices on the food security status of farmers in Mpumalanga Province of South Africa. To determine the food security status of the farmers, the household expenditure survey (HES) was employed. Thereafter, the endogenous switching probit model, a two-stage estimation technique, was used to i) determine the factors influencing the probability of adopting methods of sustainable land management; and ii) assess the impacts of the adoption of SLMP on food security. The study further employed the inverse-probability-weighted regression adjustment (IPWRA) to estimate the impact of the adoption of sustainable land management practices on maize yield between adopters and non-adopters.

The results showed that a number of socio-economic and farm level characteristics play an important role in influencing the farmers' decision to adopt SLMPs. The results further revealed that gender of household head, age of household head, farm manager, how the land was acquired and access to extension services increased the probability of adopting SLMP amongst the smallholder farmers. Given these results, there is a need to ensure gendered equitable access to agricultural technologies so that women are also at the forefront in adopting these technologies. Moreover, improved access to extension services among smallholder farmers can also stimulate the adoption of technology adoption.

With regard to the impact of SLMP adoption on food security, the estimation on the average treatment effect on the treated showed that adoption of SLMP significantly enhanced food security status as well as maize yield among smallholder maize farmers in the study area. Given these positive outcomes, the promotion of adoption of these SLMPs among smallholders becomes paramount in order to ensure food security and increased maize yield among all the farmers in the area. This can be done by minimising the barriers to adoption amongst all farmers and improve access to resources, for instance, extension services and land ownership.

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Declarations

Conflict of interest The authors of manuscript declare no conflict of interest.

Ethical statements I hereby declare that: (1) This material is the authors' own original work, which has not been previously published elsewhere. (2) The paper is not currently being considered for publication elsewhere. (3) The paper reflects the authors' own research and analysis in a truthful and complete manner. (4) The paper properly credits the meaningful contributions of co-authors and co-researchers. (5) The results are appropriately placed in the context of prior and existing research. (6) All sources used are properly disclosed (correct citation). Literally copying of text must be indicated as such by using quotation marks and giving proper reference. (7) All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

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