The Impact of Sustainable Land Management Practices on Household Welfare and Determinants among Smallholder Maize Farmers in South Africa

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Abstract: This study investigated the impact of Sustainable Land Management Practices (SLMP) on the smallholder maize farmer’s welfare in the Gert Sibande District in the Mpumalanga Province of South Africa. Farmers’ welfare is paramount to agricultural development and rural vitalisation, especially in sub-Saharan Africa. The aim of the study is to identify the factors that influence the adoption of SLMP and to assess its impact on the net farm income. A multivariate-probit (MVP) model was used to analyse the determinants of SLMP adopted and an efficient endogenous switching regression model (ESRM) was used to estimate the impact of SLMP on the net farm income of the smallholder maize farmers. The MVP results show that household socio-economic characteristics and institutional factors statistically influenced the choice of SLMP. Subsequently, the pair-wise correlation matrix of the MVP model revealed complementarities among all SLMP implemented by the farmers. Similarly, the ESRM treatment effect indicated that the average net farm income of farmers who adopted SLMP were significantly higher than that of the group who did not. Consequently, the study recommended support policies on farmers’ demography, farm-based characteristics, and institutional factors to improve the welfare of the farmers and promote rural vitalisation.

Keywords: SLMP; MVP; ESRM; South Africa

1. Introduction

It cannot be refuted that agricultural policies have a substantial effect on land-use patterns. Besides inducing producers to channel their contributions into areas where their products meet the needs of the nation, subsidising the production of certain crops or inputs modifies land-use patterns. The term “land-use pattern” refers to the way in which land is utilised for agricultural purposes. Improved land-use practices can be viewed as sustainable land use or management. Sustainable land management practices (SLMP) are a knowledge-based modus operandi or method that enables the integration of land, water, biodiversity, and environmental management as well as input and output externalities to meet the escalating food and fibre demand and deliver sustainable ecosystem services and livelihoods.

Moreover, SLMP are a necessity if a nation intends to meet the imperative requirements and provide the basic necessities of a growing population. Inappropriate land management results in land degradation and an inevitable drop in the production of food and reduced food security and service functions [1]. Sustainable land management focuses on combatting agricultural or environmental mishaps, the detrimental impact of climate change and especially land degradation [2,3]. This concept is concerned with the utilisation of land resources such as soil, water, animals, and plants with the aim of providing the goods that will meet the ever-changing needs of people, capitalising on the potential inherent in these resources, and maintaining their environmental utilities [4].

Climate change and land degradation threaten the livelihood of millions of people in sub-Saharan Africa (SSA). Soils are affected by climate change in which heavy rainfall,
flooding, and excessive temperatures are likely to increase soil erosion and land degradation unless measures are taken to protect and restore soils to enhance food security and mitigate the effect of climate change [5–7]. SLMP play a vital role in food production and the water cycle in the soil and other ecosystems. Sustainable land management is concerned with how land users look after the land for present and future use. It is defined by [2] as: “the adoption of land-use systems that, through appropriate management practices, enables land users to maximise the economic and social benefits from the land while maintaining or enhancing the ecological support functions of the land resources”.

Considering that the world population is to increase to 9 billion in 2050, it is vital that the agricultural output of cultivated land is intensified [8]. In other words, the growing world population necessitates an increase in food production. Current analyses of farming productivity show that the amount of food farmers grow today will feed only half of the population by 2050 [9]. That is to say, the demand for food will be 60% greater than it is today [10].

Most smallholder farmers in the Mpumalanga Province (see the study area below) still practise subsistence agriculture to the detriment of their livelihood [11]. The options for economic development are directly linked to the quality of the land and its resources. The effects of climate change such as higher temperatures, unpredictable precipitation patterns and water scarcity, cannot be ignored. South Africa has to contend with water shortages. In Mpumalanga, water as it is critical for both agricultural activities and human consumption yet it is insufficient because the region is considered water scarcity [12].

Therefore, SLMP are regarded as a way to enhance farmers’ welfare. Although different measures have been adopted to promote farmers’ welfare, the problems persist [13]. Farmers’ income and sustainable agriculture in the Mpumalanga Province are decreasing gradually, which affect South Africa as a whole [14]. All the symptoms of unsustainability, which include soil erosion and degradation; a decline in water quality; the degradation of biodiversity; pests and disease, are a consequence of inappropriate land management practices [15]. Therefore, the current situation has to be assessed and the available water and land has to be managed more effectively. SLMP have to be investigated to determine whether they have improved farmers’ welfare.

This study examines SLMP and their determinants and explains how they have enhanced smallholder maize farmers’ welfare in the Mpumalanga Province of South Africa. It is in line with South Africa’s national policy of vibrant, sustainable rural communities and improved quality of life; Chapter 6 of the National Development Plan; Vision 2030 (integrated and inclusive rural economy); and the Sustainable Development Goals (goals 1, 2 and 8). This study attempts to provide insight into the policy for national environmental sustainability (sustainable land management practices) and welfare. The objective is to lay a solid basis for bridging the gap and alignment with government’s agricultural blueprint for smallholder farmers. Finally, the study seeks to: (i) identify the existing SLMP, (ii) investigate the factors that influence SLMP, and (iii) assess the impact of SLMP on the net income of smallholder farmers in the Mpumalanga Province.

**Null Hypothesis (H₀): There is no significant relationship between SLMP and farmers’ net income.**

2. Materials and Methods

2.1. Study Area

The study was carried out in the Gert Sibande district in the Mpumalanga Province. The province is situated in the east of the country and borders Eswatini and Mozambique. To the north, it borders the Limpopo Province; to the south, KwaZulu-Natal; to the west, Gauteng; and to the southwest, the Free State Province. The province constitutes about 6.5% of South Africa’s land surface. The Gert Sibande district covers an area of 31,841 km² and comprises seven local municipalities, namely Govan Mbeki, Chief Albert Luthuli, Msukaligwa, Dipaleseng, Mkhondo, Lekwa and Dr Pixley ka Isaka Seme. Figure 1 shows the district and its local municipalities.
Msukaligwa, Dipaleseng, Mkhondo, Lekwa and Dr Pixley ka Isaka Seme. Figure 1 shows the district and its local municipalities.

Figure 1. Map of Gert Sibande District and its Municipalities. Source: https://municipalities.co.za/map/133/nkangala-district-municipality (accessed on 9 March 2019).

2.2. Method of Data Collection

The primary data was collected in 2020. Permission to collect the data was granted and ethical clearance was given. Data was collected from rural farmers during surveys and interviews. Some 250 questionnaires were administered in the study area. The questionnaire served as a data collection tool and consisted of structured questions in English displaying a logical flow. The questions were on land management practices and their adoption, socioeconomics characteristics, and farmers’ income. The questionnaires were pre-tested and validated by local extension officers who knew the farmers and translated the questionnaire into their local language. Face-to-face interviews were conducted in each local municipality. Each session lasted 40 min. The questionnaires were completed anonymously as the respondents’ names, addresses and identity numbers were not required.

2.3. Population, Sampling Procedure, and Sample Size

Data was collected in seven local municipalities. A list of small-scale maize farmers in the municipalities was obtained from the Department of Agriculture, Forestry, and Fisheries (DAFF). The Raosoft sample-size calculator was used to determine the sample size from the population of maize farmers in the study area [16]. This sample-size calculator takes into account the margin of error, confidence level, and response distribution.

The calculation of the sample size $n$ and margin of error $E$ is shown as follows:

$$x = Z^2 \left( \frac{r}{100} \right)^2 \frac{100 - r}{n}$$  \hspace{1cm} (1)
\[
    n = \frac{N x}{(N-1)E^2 + x} 
\]
\[
    E = \text{Sqrt} \left\{ \frac{(N-n)x}{n(N-1)} \right\} 
\]

where \( N \) is the population size, \( r \) is the fraction of responses that you are interested in, and \( Z(c/100) \) is the critical value for the confidence level \( c \).

The stratified random-sampling technique was employed for the study. The farmer population was divided into strata and the random-sampling method was used to select respondents from each stratum. Each stratum represents a local municipality as shown in Table 1. A total of 250 questionnaires were administered across the municipalities.

Table 1. Sample size taken in each municipality (stratum).

| Municipalities     | Frequency | Percent |
|--------------------|-----------|---------|
| Govan Mbeki        | 42        | 16.8    |
| Albert Luthuli     | 33        | 13.2    |
| Mkhondo            | 60        | 24.0    |
| Msukaligwa         | 34        | 13.6    |
| Lekwa              | 32        | 12.8    |
| Pixley Ka Seme     | 19        | 7.6     |
| Dipaleseng         | 30        | 12.0    |
| **Total**          | **250**   | **100.0**|

2.4. Statistical Analysis

The data was statistically analysed using STATA. Descriptive statistics such as frequency, percentages, and mean and standard deviation, were employed to analyse the household demographics and inferential statistics such as endogenous switching regression and multivariate probit, were applied to establish the impact of sustainable land management practices on household welfare (net farm income).

2.5. Empirical Model Specification

Modelling the Adoption of SLMP Determinants

It is assumed that a farmer adopts different practices and combinations of practices for sustainable land management based on the utilities or benefits associated with it. These practices are adopted simultaneously and/or sequentially because they complement each other [17]. Therefore, the combination of the practices and the adoption decision are multivariate [17–19]. To model the adoption of a single practice gives a biased and inefficient estimate and ignores the potential correlation among the unobserved disturbances in the adoption equations [20]. Focusing on the adoption of a single practice disregards the fact that farmers are usually faced with a set of choices. As a result, a binary logit or probit model fails to reflect the possible correlation or interdependence between different SLMP. The different SLMP identified in the study area include Structural and Mechanical Soil Erosion Control (SMSECP); Agronomic Practices (AP); Soil Management Practices (SMP); and Cultivation Practices (CP) [1].

To analyse the factors that influence the adoption of SLMP, the study employed a multivariate probit model (MVP) that takes into account the correlation of the error terms of adoption equations. The model also helps to understand the interdependence between unobserved disturbances of the different SLM practices. Similarly, it can simultaneously estimate the relationships between a set of explanatory variables and adopted adaptation practices by using a binary probit model. The model consists of four binary choices for the equation of SLPM adoption. The MVP model is specified as:

\[
    Y_{im}^* = \beta_m + X_{im} + \varepsilon_{im} 
\]
where \( m = \text{SMSECP}, \text{AP}, \text{SMP}, \text{CP} \).

\( Y^{*}_{im} \) represents a latent dependent variable that captures the unobserved preferences associated with the choice of \( m \).

\( X_{im}, \) and unobserved characteristics captured by the stochastic error term, \( \varepsilon_{im} \) is the error term of SMSECP, AP, SMP, CP.

\( \beta_{im} \) is the vector of parameters to be estimated.

**Endogenous Switching Regression Model (ESRM) for the impact of SLMP on Maize Farmers’ Net Farm Income:**

The study uses the ESRM to estimate the impact of SLMP on the net farm income of maize farmers. Farmers are divided into two categories: a dummy variable of those who adopted SLMP and of those who did not. A farmer was considered an adopter of SLMP if he/she practised at least one of the strategies at the time of interview. Because self-bias selection and unobserved characteristics could create an endogeneity problem, it is imperative to use the ESRM. Failure to account for a possible endogeneity problem will yield a biased and inconsistent estimate. A farmer adopts a technology or strategy if the benefit associated with the technology or strategy is greater than the benefits of not adopting it (\( Q_{Y1} \geq Q_{Y2} \)), where \( Q_{Y1} \) is the net benefit that farmer \( i \) derives from adopting a SLMP and \( Q_{Y2} \) is the net benefit of not adopting it \([21,22]\). The benefits of adopting SLMP were unknown to the researcher and the farmers were observed. Information was obtained during the survey period with \( Y^{*}_{i} \) representing the net benefits derived from SLMP that were not observed but could be expressed as a function of the observed attributes.

\[
Y^{*}_{i} = \beta Z_{i} + \varepsilon_{i} \quad (6)
\]

\( Y_{i} = 1 \) if \( Y^{*}_{i} > 0 \) and 0 if otherwise

where \( Y^{*}_{i} \) is a variable that was not observed (or latent) for adopting the SLMP; \( \beta \) a vector of parameters for estimation and \( Y \) is the observable counterpart (equal to 1 if the farmer adopted it, and 0 if otherwise). This is the first stage of the ESRM. In it, endogeneity owing to self-selection was corrected using a probit selection model (the Heckprobit model).

In the second stage, known as the outcome equations, the impact of SLMP on net farm income was estimated using a net farm income function expressed in Equation (7) as:

\[
Q = f(Y, \beta, Z) + \varepsilon \quad (7)
\]

where \( Q \) is the log form of the net farm income of maize farmers; \( Y \) the adoption of an SLMP; and \( Z \) a set of explanatory variables used in the model.

Regime 1 (adopters): \( Q_{1i} = \lambda_{1} H_{i} + v_{1i} \) \( (8) \)

Regime 2 (non-adopters): \( Q_{2i} = \lambda_{2} H_{i} + v_{2i} \) \( (9) \)

where \( Q_{1i} \) and \( Q_{2i} \) are the logs of the net farm incomes of farmers in regimes 1 and 2 respectively; \( H_{i} \) is a vector of regressors that are, hypothetically, the determinants of maize net farm income; and \( v_{1i} \) and \( v_{2i} \) are the stochastic error terms. The stochastic error terms were assumed to have a trivariate normal distribution with a zero mean and non-singular covariance matrix as expressed in Equation (9):

\[
\text{cov}(\varepsilon, v_{1i}, v_{2i}) = \begin{pmatrix}
\sigma_{1}^{2} & \sigma_{12} & \sigma_{1e} \\
\sigma_{12} & \sigma_{2}^{2} & \sigma_{2e} \\
\sigma_{1e} & \sigma_{2e} & \sigma_{e}^{2}
\end{pmatrix} \quad (10)
\]
where: \( \sigma_1^2 = \text{var}(v_1)\); \( \sigma_2^2 = \text{var}(v_2)\); \( \sigma^2 = \text{var}(\epsilon)\); \( \sigma_{12} = \text{cov}(v_1,v_2)\); \( \sigma_{1\epsilon} = \text{cov}(v_1,\epsilon)\); \( \sigma_{2\epsilon} = \text{cov}(v_2,\epsilon)\); \( \sigma^2 \) represents the variance of the error term in the selection equation; whereas \( \sigma_1^2, \sigma_2^2 \) indicate the variance of the stochastic error term in the generated equation.

The latent characteristics are related to selection bias. The structure of the error might arise because the error term, \( \epsilon_i \), of the selection Equation (7) is correlated with the error terms, \( v_1i \) and \( v_2i \), of the generated Equations (8) and (9), with the expected values of \( v_1i \) and \( v_2i \) on condition that sample selection is non-zero (Maddala, 1983).

\[
E(v_1|Y_i = 1) = E(v_1|\epsilon_i > -Z_i\beta) = \sigma_1 \left[ \frac{\theta(Z_i\beta/\sigma)}{\phi(Z_i\beta/\sigma)} \right] \equiv \beta_1\gamma_1 \tag{11}
\]

\[
> E(v_2|Y_i = 0) = E(v_2|\epsilon_i \leq -Z_i\beta) = \sigma_2 \left[ -\frac{\theta(Z_i\beta/\sigma)}{1 - \phi(Z_i\beta/\sigma)} \right] \equiv \beta_2\gamma_2 \tag{12}
\]

where \( \theta \) and \( \phi \) are the PDF and CDF of the standard normal distribution, respectively. The ratio of \( \theta \) and \( \phi \) was evaluated at \( \beta Z_i \), as represented by \( \gamma_1 \) and \( \gamma_2 \) in Equations (11) and (12). This ratio is the inverse mills ratio (IMR), which indicates the selection bias terms.

The IMR shows the correlation between the adoption of SLMP and the net farm income of maize farmers.

A full information maximum likelihood (FIML) was proposed by [23], which is an efficient method for analysing Endogenous Switching Regression Models. The FIML simultaneously fits the selection equation and the generated equations (Equations (6), (8) and (9)) to yield consistent standard errors. In turn, this gives \( \gamma_1 \) and \( \gamma_2 \) in Equations (11) and (12), respectively, homoscedastic. The log likelihood function of the FIML for the switching regression model employed in this study is as follows:

\[
> \ln Y_i = \sum_{j=1}^{N} (1 - Y_i)_{j_i} \left[ \ln F(Z_i\beta+v_{1j}(Q_{1j} - H_{1j}\lambda/\phi_1)) + \ln f(Q_{1i} - H_{1i}\lambda/\phi_1) + \right] - \ln Y_i \left[ \ln(1-F(Z_i\beta+v_{1j}(Q_{2j} - H_{2j}\lambda/\phi_2)) + \ln f(Q_{2i} - H_{2i}\lambda/\phi_2) \right] \tag{13}
\]

Consequently, the model determines counterfactual effects and the effects of adoption. These effects were estimated as the difference between Equations (8) and (9), which is referred to as the average treatment effects on the treated (ATT):

\[
\text{ATT} = E(Q_{1i} - Q_{2i} | Y_i = 1) = H_i(\lambda_1 - \lambda_2) + (\sigma_{1\epsilon} - \sigma_{2\epsilon})\gamma_1 \tag{14}
\]

3. Results and Discussion

Descriptive statistics and description of the explanatory variables used in the models:

The variables used in the models for the study are explained in Table 2, with the mean values and standard deviation of the two groups (adopters and non-adopters). The average age of the farmers in the study area was 48. In other words, the majority of farmers were middle-aged. The mean years they spent in school was 10 years; their years of farming were the same. The average farm net income was R1,176,812 per month, the mean distance to the market was 39 km, and the household size was six members on average. Furthermore, about 70.8 per cent of the farmers adopted SLMP with a mean value of 0.708 while male-headed household farmers are about 52.4 per cent, having a mean of 0.524. Altogether 82.8 per cent of the farmers had access to extension services and 47.2 per cent had access to credit.

Table 2. Description and summary statistics of variables.

| Variable     | Description and Measurement | Expected Sign | Mean     | Std dev |
|--------------|------------------------------|---------------|----------|---------|
| Gender       | Dummy; 1 if head is a male and 0 if otherwise | ±             | 0.524    | 0.5     |
| Age          | Number of years (Continuous) | +             | 48.384   | 12.388  |
| Marital status | Dummy; 1 if head is married, 0 otherwise | ±             | 0.472    | 0.5     |
Table 2. Cont.

| Variables                                      | Adopters                          | Non-adopters                     |
|------------------------------------------------|-----------------------------------|----------------------------------|
| Gender                                         | Mean (Std dev)                    | Mean (Std dev)                   |
| Age                                            | 49.01 (12.42)                     | 46.62 (12.92)                    |
| Farm size                                      | 136.01 (195.31)                   | 127.25 (195.31)                  |
| Type of Farm                                   | 2.51 (1.40)                       | 1.75 (1.01)                      |
| Who manages farm                               | 2.32 (1.39)                       | 1.40 (0.85)                      |
| Who owns farm                                  | 2.36 (1.25)                       | 1.75 (0.98)                      |
| Land acquired                                  | 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)                      |
| Marital status                                 | 0.46 (0.50)                       | 0.49 (0.50)                      |
Table 2. Cont.

| Variables               | SMSECP  | AP       | SMP       | CP       |
|-------------------------|---------|----------|-----------|----------|
| SMSECP                  | 1       |          |           |          |
| AP                      | 0.396   | 1        |           |          |
| SMP                     | 0.327   | 0.821    | 1         |          |
| CP                      | 0.145   | 0.318    | 0.350     | 1        |

Values in bold are different from 0 with a significance level alpha = 0.05; Source: Field survey, 2020.

Determinants of the adoption of sustainable land management practices:

Table 3 explained the correlation matrix for the choice of sustainable land management adopted by the farmers. There are four different practices as shown in Table 3, which were positively associated with each other and significant ($p < 0.01$) at 1% level of confidence. Table 4 uncovered the same factors stated in Table 5 as the determinants to the individual SLM practices that are jointly adopted by the farmers. Similarly, Table 5 revealed the determining factors that influence the adoption of SLMP among the smallholder maize farmers in the study area which are gender, age, years in school, access to input, who the manage farm and land acquisition.

Table 3. Correlation matrix (Pearson) for the choice of SLMP.

| Variables               | SMSECP  | AP       | SMP       | CP       |
|-------------------------|---------|----------|-----------|----------|
| SMSECP                  | 1       |          |           |          |
| AP                      | 0.396   | 1        |           |          |
| SMP                     | 0.327   | 0.821    | 1         |          |
| CP                      | 0.145   | 0.318    | 0.350     | 1        |

Values in bold are different from 0 with a significance level alpha = 0.05; Source: Field survey, 2020.

Structural and Mechanical Soil Erosion Control Practices (SMSECP): This involves the use of terraces and contour bounds. In Table 4, the number of years spent in school; who manages the farm; land acquisition; water source; access to extension services; and access to cooperatives were positive and significantly influenced the adoption of an SMSECP. The number of years spent in school is an indication of a farmer’s literacy. The result is not surprising since a literate farmer is educated, makes well-informed decisions, and adopts a practice that improves his/her agricultural production and net farm income. The level of education of the person who manages the farm influences his or her adoption of an SMSECP. As reported by [24] that number of years spent in school or educational level of the farmers influence the adoption of SMSEP.

Similarly, access to extension services and a cooperative is a vital tool in a decision to adopt innovation. The study showed that the more access a farmer has to extension services and cooperatives, the higher the probability of adopting SMSECP. This is because information is disseminated by the extension officers as well as a social organisation such as the cooperative group. This result is supported by [25] who reported that farmers with access to extension service tends to adopt agricultural technologies. Social capital has been found to be an important ingredient for effective environmental governance [26].
### Table 4. Determinants of sustainable land management practices.

| Variables            | SMSECP   | Agronomic Practices | Soil Management Practices | Cultivation Practices |
|----------------------|----------|---------------------|---------------------------|-----------------------|
|                      | Coef.    | Std. Err.           | z                         | Coef.                 | Std. Err.           | z     | Coef.    | Std. Err.           | z     |
| Gender               | 0.225    | 0.207               | 1.09                      | 0.326                 | 0.232               | 1.40  | 0.672    | 0.205               | 3.28 ***|
| Age                  | -0.012   | 0.011               | -1.09                     | 0.011                 | 0.011               | 1.04  | 0.024    | 0.011               | 2.23 ** |
| Marital status       | -0.133   | 0.242               | -0.55                     | -0.061                | 0.233               | -0.26 | -0.273   | 0.203               | -1.34  |
| Years in school      | 0.057    | 0.022               | 2.55 ***                  | 0.110                 | 0.028               | 3.97 ***| 0.112    | 0.004               | 4.62 ***|
| Farm size            | -0.001   | 0.000               | -0.85                     | 0.000                 | 0.001               | 1.80 *| -0.000   | 0.000               | -1.39  |
| Farm type            | -0.348   | 0.140               | -2.50 ***                 | -0.086                | 0.117               | -0.73 | 0.014    | 0.109               | 0.13   |
| Manage farm          | 0.251    | 0.113               | 2.23 ***                  | 0.282                 | 0.138               | 2.04 **| 0.308    | 0.119               | 2.59 ***|
| Own farm             | -0.095   | 0.141               | -0.67                     | -0.014                | 0.146               | -0.10 | -0.345   | 0.105               | -3.29 ***|
| Land acquisition     | 0.241    | 0.051               | 4.75 ***                  | 0.177                 | 0.053               | 3.35 ***| 0.141    | 0.047               | 3.01 ***|
| Years of farming     | 0.017    | 0.017               | 0.94                      | -0.013                | 0.017               | -0.75 | -0.012   | 0.017               | -0.95  |
| Water source         | 0.138    | 0.093               | 1.70 *                    | 0.033                 | 0.088               | 0.37  | 0.042    | 0.083               | 0.51   |
| Access to ext. service | 0.989   | 0.350               | 2.83 ***                  | 0.861                 | 0.310               | 2.78 ***| 0.457    | 0.312               | 1.46   |
| Access to coop       | 0.480    | 0.243               | 1.98 ***                  | 0.490                 | 0.333               | 1.47  | 0.357    | 0.295               | 1.40   |
| Access to input      | -0.480   | 0.270               | -1.78 *                   | -0.751                | 0.395               | -1.90 *| -0.382   | 0.305               | -1.26  |
| Access to credit     | -0.939   | 0.270               | -3.48 ***                 | -1.391                | 0.284               | -4.90 ***| -1.024   | 0.242               | -4.23 ***|
| Constant             | -2.670   | 0.756               | -3.53                     | -2.330                | 0.854               | -2.73 | -2.229   | 0.741               | -3.01  |

Likelihood ratio test of rho21 = rho31 = rho41 = rho42 = rho43 = 0: chi2(6) = 143.535 Prob > chi2 = 0.0000; Number of obs = 25; Wald chi2(60) = 188.95; Log likelihood = -336.8407; Prob > chi2 = 0.0000; Note: ***, **, * indicate p < 0.01; p < 0.05 and p < 0.1 probability level of significance respectively. Source: Field survey, 2020.

### Table 5. Full information maximum likelihood (FIML) estimates of the endogenous switching regression model (ESRM).

| Variables            | Adoption of SLMP | Net Farm Income for the Adopters | Net Farm Income for the Non-Adopters |
|----------------------|------------------|----------------------------------|--------------------------------------|
|                      | Coef.    | Std. Err. | z     | Coef. | Std. Err. | z     | Coef. | Std. Err. | z     |
| Gender               | 0.478    | 0.202     | 2.36 **| 0.773 | 0.156     | 4.94 ***| 0.169 | 0.179     | 0.94  |
| Age                  | 0.027    | 0.010     | 2.69 ***| 0.017 | 0.007     | 2.41 **| -0.034 | 0.006     | -5.78 ***|
| Years in school      | 0.128    | 0.023     | 5.59 ***| 0.033 | 0.017     | 1.97 **| -0.091 | 0.017     | -5.37 ***|
Table 5. Cont.

| Variables                | Adoption of SLMP | Net Farm Income for the Adopters | Net Farm Income for the Non-Adopters |
|--------------------------|------------------|----------------------------------|--------------------------------------|
|                          | Coef.            | Std. Err. | z     | Coef.            | Std. Err. | z     | Coef.            | Std. Err. | z     |
| Farm size                | 0.000            | 0.000     | 0.67  | 0.000            | 0.000     | 0.39  | 0.004            | 0.000     | 10.76***|
| Years of farming         | −0.021           | 0.015     | −1.43 | −0.003           | 0.013     | −0.25 | 0.045            | 0.009     | 4.91***|
| Water source             | −0.050           | 0.075     | −0.67 | 0.158            | 0.066     | 2.40**| 0.448            | 0.052     | 8.68***|
| Access to coop           | −0.364           | 0.234     | −1.56 | −0.179           | 0.177     | −1.01 | 1.014            | 0.166     | 6.10***|
| Access to input          | −0.556           | 0.304     | −1.83*| 0.518            | 0.197     | 2.64***| −0.478           | 0.218     | −2.19**|
| Farm type                | 0.035            | 0.093     | 0.37  | 0.397            | 0.111     | 3.58***| 1.014            | 0.166     | 6.10***|
| Manage farm              | 0.397            | 0.111     | 3.58***| 0.518           | 0.197     | 2.64***| −0.478           | 0.218     | −2.19**|
| Land acquired            | 0.079            | 0.046     | 1.72* | 0.368            | 0.267     | 1.38  | 7.725            | 0.290     | 26.60  |
| Access to ext. service   | 0.368            | 0.267     | 1.38  |                  |           |      |                  |           |      |
| Constant                 | −2.525           | 0.748     | −3.38 | 6.083            | 0.479     | 12.70 | 7.725            | 0.290     | 26.60  |
| /lns0                    | −0.879           | 0.131     | −6.71 |                  |           |      |                  |           |      |
| /lns1                    | 0.025            | 0.069     | 0.36  |                  |           |      |                  |           |      |
| /r0                      | −0.703           | 0.360     | −1.95 |                  |           |      |                  |           |      |
| /r1                      | 1.235            | 0.285     | 4.33  |                  |           |      |                  |           |      |
| sigma0                   | 0.415            | 0.054     |      |                  |           |      |                  |           |      |
| sigma1                   | 1.025            | 0.070     |      |                  |           |      |                  |           |      |
| rho0                     | −0.606           | 0.228     |      |                  |           |      |                  |           |      |
| rho1                     | 0.844            | 0.082*    |      |                  |           |      |                  |           |      |

Note: ***, **, * indicate $p < 0.01$; $p < 0.05$ and $p < 0.1$ probability level of significance respectively. LR test of indep. eqns.: $\chi^2(2) = 12.01$; Number of obs = 250; Wald $\chi^2(8) = 505.64$; Log likelihood = $-366.96165$; Prob $> \chi^2 = 0.0000$. 
The source of water on a farm also influences the decision to adopt an SMSECP. An SMSECP deals with soil water control and the effective management of farm land. Similarly, this reported is supported by [27] who reported that land management and water resources are related and inextricably entwined. The means of acquiring land also influences the decision to adopt since most of the farmers used land affair and restitution method of land acquisition. The result is also confirmed by the report of [28,29] who explained that method of land acquisition and access significantly influence the adoption of SMSEP. The farm type and access to agricultural inputs were negative correlated and significantly affected the decision to adopt an SMSECP. The fact that most farms were individual farms suggests that fewer individual farmers opted for an SMSECP because they lacked the structural and mechanical equipment to implement sustainable land practices. The greater the access a farmer has to agricultural inputs, the more he/she values the implementation of an SLMP because farmers regarded the inputs they received as far more important than the management of their soil. Most farmers in the study area did not have second thoughts about managing their land once they were given fertiliser and seed. The result is confirmed by [30,31] who reported that accessed to credit influenced the adoption of sustainable land management.

**Agronomic practices:** This practice focuses on the use of crop rotation, multiple cropping, bush fallow, shifting cultivation, mulching, etc. Similarly, as it was mentioned above in the case of SMSECP, the number of the years spent in school, who manages the farm, land acquisition, access to extension service, access to agricultural input, all followed the same trends in influencing the adoption of agronomic practices as a SLMP. However, the farm size was found to be significant positive correlation—the bigger the farm size, the more the probability and opportunity to adopt agronomic practices, as a farmer can engage in crop rotation, multiple cropping, bush fallowing, and shifting cultivation. Access to credit in the study was reported negative and influenced the adoption of agronomic practices as an SLMP. A better way to explain this scenario could be that low access to agricultural input increases the chance of adopting agronomic practices, as farmers receive little or no credit/loans for SLMP, thus, they try agronomic practices which cost very little, to solve the issue of land management. The result reported by [32,33] explained that access to credit influence the decision to adopt agronomic practices. The study of [34] in Uganda and [35] reported that access to agricultural extension increases the adoption of agronomic practices because they are less costly. The number of years spent in school or educational level of the farmers as reported by [36] influence the decision to adoption of soil management practices. This is confirmed by [37,38] that land acquisition influenced the adoption of agronomic practices.

**Soil management practices:** Soil management involves the use of improved fertiliser, green manure and compost. Following the trend of result and explanation from the above SLMPs, the number of years spent in school, who manages the farm, land acquisition, and access to credit all influenced the decision of adopting soil management practices as an SLMP in the study area. The result is confirmed with [39,40] that access to credit influence the decision to adopt soil management practices. The report of [41] explained that number of years spent in school or educational level of the farmers influence the decision to adoption of soil management practices.

Gender and age were found to be positively significant. The average age of the farmers was 48 years (Table 2), which meant that most farmers were old and had enough experience to make compost and green manure, thus enabling them to adopt soil management practices better. This result is conformed to the report of [24,32,42] who explained that age was statistically significant and influence the adoption of soil management. Similar findings have been reported by [43] that younger farmers are more innovative and better adopters of soil management than older farmers. However, Refs. [44,45] also supported the evidence that older farmers are used to conventional farming method and they are unlikely to change.
At the same time, the variable of who owns the farm, which was mostly dominated by the individual farm owners, has a negative influence on adopting soil management practices as an SLMP, because most individual farmers who own the farm preferred agronomic practices, rather than soil management practices. The result conformed with [46] who reported that patterns of land acquisition significantly influence adoption of soil management practices among smallholder farmers in Kogi State of Nigeria. This was supported by [30,47] who reported that patterns of land acquisition statistically significant and influence the adoption of soil management.

Cultivation practices: The number of years spent in school and access to a cooperative were positively associated with and statistically significant to cultivation practices. This is not surprising as farmers reported that information on cultural practices were shared among the members in a farmers’ group, which they could comprehend better due to their level of educational status. This was conformed to the research of [48] who reported that access to cooperative and social capitals influenced adoption of more environmentally-friendly practices. In the same vein, marital status and years of farming were negatively associated with and statistically significant to cultivation practices. This means that if a farmer has been farming for a long time, the tendency of him/her not choosing the cultivation practices is high. Although this is not expected, farmers with few years of farming embrace cultivation practices, while farmers with more years of farming are not interested in adopting cultivation practices as they are skeptical and not used to the method.

Determinants of farmers’ welfare (Net farm income for both adopters and non-adopters): The net farm income was calculated and used as a proxy for farmers’ household welfare. An ESRM which takes of unobserved characteristics as well as possible self-bias was used to estimate the impact of the SLMP on the net farm income. The result in Table 5 showed the variables that were significant and the correlation coefficients. The correlation coefficients rho_0 and rho_1 of the ESRM were both positive, in which rho_1 was statistically significant for the correlation between adopters and net farm income. This explained that there is self-selection in the adoption of SLMP. This result is similar to [22] who explained that this might not have the same effect on non-adopters, should they choose to adopt. Correspondingly, the findings are substantiated by [21,49]. It is noteworthy to explain that the statistically significance of the likelihood ratio test at 1% for joint independence of the three equations implies that they should not be estimated separately.

The result of the ESRM estimation is presented in Table 5. The table consisted of three equations. The first equation being the probit model of the determinants of SLMP which is similar and has been explained in Table 4. The second and third equation revealed the factors that influence the net farm income of the adopters and non-adopters respectively. Table 5 revealed that gender, age, the number of years spent in school, water source, and access to agricultural input were positively and statistically significant and influenced the net farm income of the adopters of SMLP.

Gender: Farming activities are strongly linked to male farmers because their physical strength to cultivate land and their ability to get access to land surpass that of female farmers, and mean a greater income. This is supported by the findings of [50], who affirms that gender is significant and has a positive effect on the income of maize farmers owing to the ability of male farmers to access production resources and support services.

Number of years spent in school: The number of years spent in school contributes to one’s educational status, which is important to succeed in any business. The result explained that an education of the farmer was statistically significant and positive in explaining the variations in the net farm income of the adopters of SLMP. The more the years spent in school, the better the chance to increase one’s income. This agrees with the findings of [50], who submits that educational status of those who adopt agricultural technologies has a positive effect on farmers’ income. However, the number of years spent in school negatively affects the net farm income of non-adopters. The higher the education, the little or no contribution to the net farm income of the non-adopters. As opined by [22], who found out that educational status of smallholder rice farmers was statistically significant and negative
in explaining the variations in the net farm income of the non-adopters of adaptation strategies to climate change.

Age: Farming experience and a sense of responsibility for his or her household come with age. This result explained that age was statistically significant and positive in explaining the variations in the net farm income of the adopters of SLMP. An older farmer with a wealth of experience who adopt SLMP is likely to generate more income from his/her farming business. On the other hand, age of the farmer was found negatively significant and influenced the net farm income of the non-adopters. The older the farmer who did not adopt SLMP, the lesser the net farm income. However, this result runs counter to the findings of [51], namely that the income of farmers is not influenced by their age.

Access to agricultural input: The results show a positive and statistically significant correlation between access to agricultural input and net farm income. Farmer’s access to agricultural inputs was statistically significant and positive in explaining the variations in the net farm income of the adopters of SLMP. It is obvious that SLMP adopted farmers who have access to agricultural inputs such as seed, fertiliser and agrochemicals, stand a better chance to generate more income. In the same vein, this result was found negative to non-adopters; the farmers have access to agricultural inputs yet lower net farm income. In addition to the above, the farm size; years of farming; and access to a cooperative, were statistically significant and positive in explaining the variations in the net farm income of the non-adopters of SLMP.

Farm size: The farm size was found positive and statistically significant in explaining the variation in net farm income of the non-adopters of SLMP. This suggests that farmers with large farm holding are likely to have more net farm income. The bigger the farm, the greater the income it is expected to generate and vice versa. The farm size and net farm income are directly related. This report is supported by [52–54] which showed that farm net income is positively influenced by farm size.

Years of farming: Farming experience of the maize farmers were positive and statistically significant in explaining the variation in the net farm income of only non-adopters of SLMP. Farmers who have many years of farming have the propensity to increase their net farm income. This reason is not farfetched from the fact that farming activities are presumed to be a vocation and farmers gain knowledge and improve their skills as the number of years in that vocation increases.

Access to cooperative: Access to farmers’ group, membership or agricultural cooperative was found positive and statistically significant in explaining the variation in the net farm income of only non-adopters of SLMP. It is believed that access to cooperatives contributes to the dissemination of information and thus, improve farm income. This result conformed with [15,55] who explained that farmers in cooperative associations share lots of information that can enhance their income.

Impact of sustainable land management practices on farmers’ welfare:
The impact of SLMP on the net farm income is presented in Table 6. The average treatment effect on the treated (ATT) and the t-test indicated that the difference between the average net farm income of adopters of SLMP and that of non-adopters was significant and statistically different from zero. According to Table 6, the difference between the average net farm income of the groups was 0.602, which means that the net farm income of the adopters increased by 60 per cent compared to that of the non-adopters. Also, the mean of the net farm income of the adopters of SLMP (0.799) is higher than that of the non-adopters (0.478). Therefore, adoption of SLMP had a positive impact on the farmers’ net farm income.

Table 6. Impact of adopting SLMP on smallholder maize farmers’ net farm income.

| Variable       | Sample   | Treated | Controls | Difference | S.E.  | T-Stat |
|----------------|----------|---------|----------|------------|-------|--------|
| log_netincome  | Unmatched| 8.819   | 8.753    | 0.066      | 0.154 | 0.43   |
|                | ATT      | 8.766   | 8.164    | 0.602      | 0.315 | 1.91 * |
4. Conclusions and Recommendations

This study analysed the welfare impact of sustainable land management adoption and its determinants on smallholder maize farmers in South Africa. The MVP model was employed to analyse the factors that determine the adoption of SLMP. The model substantiated complementarities or relationship among the different SLMP used by the farmers in the study area. Results of the probit model revealed that gender, age, the number of years spent in school, access to agricultural input, who manages the farm, and land acquisition influenced the choice of adopting sustainable land management practices. Likewise, the net farm income of the adopters was influenced by gender, age, years in school, water source, and access to input whereas age, the number of years spent in school, farm size, years of farming, water source, access to cooperatives, and access to input influenced the net farm income of the non-adopters. Furthermore, the correlation coefficients rho_0 and rho_1 of the ESRM were both positive. Only rho_1 was statistically significant for the correlation between adopters and net farm income. This suggests that if the net farm income generated from the maize yield was estimated without considering the decision to adopt SLMP, the result would have led to a selection bias problem. The treatment effect of the ESRM showed that the average net farm income of adopters was significantly higher than that of non-adopters of SLMP. The study therefore recommends supporting policies concerning farmers’ demography, farm-based characteristics, and institutional factors to improve the welfare of farmers and encourage rural vitalisation. Government must (i) improve the skills of agricultural extension agents so that they are able to disseminate information on SLMP at local level effectively, (ii) promote the formation of social capital groups and (iii) increase the awareness of SLMP among smallholder maize farmers in the study area.

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