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THE ADOPTION OF SELECTED SOIL FERTILITY AND WATER MANAGEMENT TECHNOLOGIES IN SEMI-ARID ZIMBABWE: AN APPLICATION OF THE TOBIT MODEL

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Abstract

Despite the various efforts and vast investments made by non-governmental organizations, government research, and extension departments to develop and promote best bet soil fertility and water management technologies in Zimbabwe, the rates of adoption of these technologies have remained pathetically low. This study was, thus, carried out to discover the factors influencing the decision by farmers to adopt selected best bet soil fertility and water management technologies in Zimbabwe's semi-arid areas. By use of a Tobit regression model, formal education, availability of draught power, access to crop markets, and provision of more permanent land tenure systems were established, as the most important factors influencing adoption. Soil type, perceived rainfall, farm cropping patterns, and availability of labour were also found to have an impact on the beginning of technologies by farmers. It was therefore concluded that an understanding of household socio-economic characteristics is invaluable when designing and targeting technologies for smallholder farmers.

Key Words: Tobit model, technology adoption, soil and water conservation, semi-arid

INTRODUCTION

Soil fertility and rainfall are the two major limiting factors to crop productivity and the attainment of food security in resource poor, smallholder farming systems of Zimbabwe; yet, according to Sims *et al* (2001), technically sound Soil Fertility and Water Management Technologies (SFWMT) have been developed and promoted in the country over the past 50 years. Also baffling are the ever increasing extent of land degradation, due to water erosion, and the worsening food security status of rural households in the semi-arid areas, as a result of low and erratic rainfall and soil infertility.

The semi-arid areas of Zimbabwe are characterized by low rainfall with a high coefficient of variation that, according to Motsi *et al* (2004) is above 20%. The length of the rainy season, according to the rain pentad analysis, is less than 50 days and 90% of the total rainfall is associated with thunderstorm activity, producing falls of short duration and high intensity (Motsi *et al*, 2004). Such kind of rainfall is highly likely to be lost as runoff and to cause water erosion in all but the most sandy of soils. Further, despite the land reform program, the majority of smallholder farmers in the country still largely inhabit areas with low levels of soil fertility. These issues, coupled with the general location of the farmers at lower levels of the income spectrum, and thus, their inability to afford expensive crop productivity enhancing resources, make semi-arid smallholder crop farming in the country a nightmare.

The International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), in conjunction with the Intermediate Technology Development Group (ITDG) and the department of Agricultural Research and Extension (AREX), has been working on various projects to promote the uptake of selected soil fertility and water management technologies in Zimbabwe, particularly in the semi-arid districts of Gwanda, Zimuto, and Zvishavane. Farmer participatory experimentation has been the main strategy used to demonstrate the benefit of these technologies to farmers with the hope to accelerate the rate of adoption of the technologies. Astoundingly, the adoption rates have remained too low to justify the amount of resources (time, money, commitment, etc.) invested. This supports the notion that the development of superior technologies and their promotion to farmers is not a sufficient condition to the attainment of food security if the appropriate pre–conditions for the take up of the technologies by farmers are not known.

This study identifies the farm level factors that influence the adoption of soil fertility and water management technologies by smallholder farmers living in the semi-arid areas of Zimbabwe. The identification of these factors will help a great deal in improving the packaging of soil fertility and water management technologies to suit farmer needs and circumstances. It will also provide an insight on how to target technologies to the appropriate households and on the backup required to improve uptake by farmers.

CONCEPTUAL FRAMEWORK: HYPOTHESES ABOUT FACTORS INFLUENCING ADOPTION

Adoption literature shows that the adoption of agricultural technologies is affected by a host of socio-economic, demographic, institutional, and technical factors; farmers' perception about technology attributes and their attitude towards risk (Feder *et al*, 1985; Shakya & Flinn, 1985; Kebede *et al*, 1990; Adesina & Zinnah, 1993; Nichola, 1994). This section of the paper examines the factors that are hypothesized to be influential in decision making about soil fertility and water management technologies. These variables are later tested in a Tobit regression framework. The choice of the explanatory variables is guided by economic theory and adoption literature.

The first factor is based on the belief that adoption takes place earlier on larger farms than on smaller farms. Feder *et al* (1985) show that, given the uncertainty, the fixed transactions, and information costs associated with innovations, there may be a critical lower limit of farm size, which prevents smaller farms from adopting. This, however, may not apply for some soil and water management technologies that require high labour inputs for their adoption. According to Willey (1978), farm size may also be a surrogate for other factors, such as wealth and access to credit.

Another basic hypothesis is that ownership of land encourages adoption. Several empirical studies support this hypothesis. Land ownership is likely to influence adoption if the investments are tied to the land and the benefits of these investments are long term (Fernandez-Cornejo *et al*, 1994). Tenants are less likely to adopt technologies that require high investments on the land and whose benefits are long term because the benefits of adoption do not necessarily accrue to them.

Labour availability is also another factor hypothesized to influence adoption of innovations. Labour intensive innovations will likely be adopted by households with high access to farm and off-farm labour. Fernandez-Cornejo *et al* (1994) identify another type of farm labour that influences technology adoption, that is, the labour provided by the farm operator him/herself. This kind of labour is often called operator labour and is hypothesized to have a positive impact on the level of adoption of soil and water management technologies because the technologies have a high requirement of the operator's time.

Crop and livestock production variables can be used to find out the impact of growing each major crop on SFWMT adoption. High value crops are likely to induce farmer investment in SFWMT because they offer attractive returns to such investments. The growing of drought tolerant crops is likely to have a negative influence on the adoption of some soil moisture conservation techniques due to the low marginal productivities of such investments. Livestock production activities are assumed to compete with crop production activities and, thus, to have a negative influence on adoption of SFWMT.

Locational factors, such as soil type, fertility levels, and rainfall (either the actual rainfall amount or as perceived by farmers) also affect the adoption of SFWMT. Soil type determines the difficulty of constructing soil and water conservation structures, while at the same time determining soil fertility and the rate and type of soil erosion. The level of inherent soil fertility determines both the rate and extent of adoption of soil fertility, enhancing technologies. Soil type enters the model as a dummy variable with "0" for light soils, including sands, loams, and sandy loams; and "1" for heavy soils, including clays and clay loams.

To improve their productivity, farmers need knowledge and technology options. They also need access to output markets, and perhaps most importantly, they need access to reliable output markets. Access to markets provides both the incentives and the rewards for increasing productivity, and thus adopting SFWMT. Access to reliable markets is, therefore, included in the model as a dummy variable with 0 (implying no reliable markets) and 1 (representing the availability of reliable markets) according to farmer perceptions.

METHODOLOGY

Study Sites

The study was conducted in three semi-arid districts of Zimbabwe, which were the main targets of the promotional efforts of SFWMT in the country. These districts were Gwanda, Zvishavane, and Zimuto. Gwanda lies in the southern parts of the country and is the driest of the three, receiving annual rainfall of less than 250mm. Although the soils are fertile (heavy black clays dominate), crop production is heavily constrained by both low rainfall and shortage of labour. Livestock production and employment in neighbouring South Africa are the chief livelihood strategies.

Zvishavane and Zimuto both lie in the southwestern parts of the country. Zvishavane is partly covered by heavy, red, sialitic soils with some loam soils also dominating in some parts. Annual rainfall is about 450mm to 500mm but is poorly distributed, both spatially and temporally. Livelihoods are largely derived from employment in the nearby mines, illegal gold, and platinum mining, as well as crop farming (dominated by maize and sorghum). Zimuto is the wettest of the 3 districts, receiving around 650mm rainfall annually but agriculture is impaired by the poor sandy to sandy loamy soils that cover most of the district.

Three soil fertility enhancing technologies (fertilizer micro-dosing at 18N per Ha, heaped covered manure, and rotation with legumes) and three soil and water conservation technologies (infiltration pits, tied ridges, and dead level contours) were selected for this study due to their superiority experimentally.

Data Collection

Data used in this study were collected mainly using a structured questionnaire in surveys that were carried out in November 2004. Stratified random sampling was used to select the sample households. The first stage was the selection of three wards from each district. These were considered to be adequately representative of the ten wards in each of the three districts because of the low inter ward variability in characteristics. Then from each ward, simple random sampling was carried out using a sampling frame provided by the department of Agricultural Research and Extension Services. An initial 60 households were targeted for each district to make a total of 180 households, but eventually a total of 175 questionnaires entered data analysis. The other five were either spoilt (2), incomplete (1), or just went missing (2).

Data Analysis: The Tobit model

In the empirical analysis, factors that determine the adoption of SFWMT were examined using a Tobit regression model. The Tobit model is appropriate in cases where the dependant variable has a number of its observations clustered at a limited value, usually zero. It uses all observations, both those at the limit and those above it, to estimate a regression line (McDonald & Moffit, 1980). Moreover as McDonald and Moffit (1980) have shown, in addition to the change in probability of adoption due to a percentage change in the independent variables, the model provides information on the change in independent variables based on intensity of use once the technology is adopted.

The Tobit model was developed in 1958 by James Tobin for censored data to model zero expenditure on consumer durables. A sample is said to be censored if observations on the dependent variable, corresponding to known values of the independent variables, are not observable (Maddala, 1999; Pyndyk & Robinfeld, 1998; Zepeda, 1994). In this study, the dependent variable, “proportion of area under SFWMT”, is censored with a limiting value 0 and values ranging between 0 and 1.

The functional form of the Tobit model, as defined by Maddala (1999) is:

$$Y_i = \beta X_i + \varepsilon, \text{ if } \beta X_i + \varepsilon > 0 \text{ and, } 0 \text{ Otherwise}$$

Where:

$i = 1,2,\ldots,n$

Y_i = a vector of dependant variables

β = a vector of unknown parameters

X_i = a vector of explanatory variables

ε = a vector of residuals (independently and normally distributed with mean zero)

σ^2 = common variance

Zero here is the threshold or censor point. The standard cumulative distribution of the function monotonically translates the values of the attributes, X_i into a probability, which takes values between 0 and 1.

Six regression equations were estimated, one for each of the technologies, with the aid of a computer package called LIMPDEP. Table 1 is a description of each of the variables in the model. Each of the dependant variables (based on proportion of area under each technology) was regressed against a series of explanatory or independent variables.

Table 1: The Empirical Representation of Variables Used in the Tobit Model

Variable	Variable Definition and Description
FMAREA	Dependant variable representing proportion of total arable land with fertilizer.
HCMAREA	Dependant variable representing proportion of total arable land with heaped covered manure
LRAREA	Dependant variable representing proportion of total arable land with legume green manure
IPAREA	Dependant variable representing proportion of total arable land with infiltration pits
TRAREA	Dependant variable representing proportion of total arable land with tied ridges
DLCAREA	Dependant variable representing proportion of total arable land with dead level contours
Age	Age of household head in years
Gender	Gender status of household head = 1 if male and 0 otherwise.
Labour	Total amount of labour available per household per year (people)
Educ	Number of years of formal education
Agtrain	Dummy variable representing whether household head has undergone formal education in agriculture or not = 1 if yes and 0 if no.
Tenure	Dummy variable = 1 if farmer owns any land and 0 otherwise
Farmsize	Size of the total area (Ha) available to the household for farming
Yrsarea	Number of years household has stayed in the area
Inclive	Proportion of income from livestock sales per year.
Soiltyp	Dominant soil type on the farm: 0 if light infertile soils (clays, clay loams and loams) and, 1 if heavy fertile (clays and clay loams)
Percrain	The level of rainfall as perceived by the farmer: 0 if farmer perceives rainfall to be poor and 1 if farmer perceives rainfall to be good.
Draught	Availability of adequate draught power on the farm: 0 if inadequate (less than 2 draught animals and 1 if adequate (2 or more animals)
Market	Dummy variable representing whether farmer has ready access to crop markets or not: 0 if not (distance to market > 10 Km) and 1 if yes (distance to market < 10 Km).
Maize	Dummy variable representing whether farmer produces maize or not = 1 if yes and 0 if no
Cotton	Dummy variable representing whether farmer produces cotton or not = 1 if yes and 0 if no
Sorghum	Dummy variable representing whether farmer produces sorghum or not = 1 if yes and 0 if no
Gnut	Dummy variable representing whether farmer produces groundnuts or not = 1 if yes and 0 if no
Sflower	Dummy variable representing whether farmer produces sunflower or not = 1 if yes and 0 if no

RESULTS: PRESENTATION AND DISCUSSION

The results are presented in the form of four tables (Tables 2 through 5). Table 2 provides the mean values of variables used in the Tobit model for both adopters and non-adopters. For a binary indicator, the mean represents the fraction of sampled households with that attribute. For example, the gender variable shows that 34% of the interviewed households were female-headed, while 66% were male-headed. In comparison, the continuous variables represent the actual mean.

Table 2: Comparison of means of variables used in the Tobit model

Variable	Adopters	Non-adopters
Age of household head (years)	41.23	41.90
Proportion of male headed households	34.20	26.75*
Labour	4.80	3.96*
Number of years of schooling	8.23	8.65
Proportion undergone agriculture training	0.56	0.33*
Proportion owning land	0.64	0.59*
Farm size	2.80	2.03
Number of years farming	14.30	15.02
Proportion of income from livestock	0.21	0.37*
Proportion with heavy clay soils	0.37	0.38
Proportion who perceive rains as good	0.29	0.34
Proportion with adequate draught power	0.79	0.48*
Proportion with good access to markets	0.54	0.46
Proportion growing maize	1.00	1.00
Proportion growing cotton	0.24	0.22
Proportion growing sorghum	0.64	0.53*
Proportion growing groundnut	0.55	0.53
Proportion growing sunflower	0.67	0.66

*Difference significant at 0.01 level of significance

All of the interviewed households indicated that they grow maize. Whether or not a household grows maize is, thus, not a variable and is, therefore, dropped from further analysis. There is a significant difference between adopters and non-adopters on labour availability, land ownership, proportion of income from livestock, and availability of draught power, among other variables. Availability of draught power and proportion of income from livestock seem to be opposing variables. This is probably because those farmers who use their animals for draught power do not sell them, while those who sell to get a bigger proportion of income from livestock do not use their livestock for draught power or are left with inadequate animals for draught power.

Results of the Tobit model are presented in Table 3 for soil fertility improvement technologies (fertilizer micro dosing, heaped covered manure, and rotation with legumes) and in Table 4 for soil and water conservation technologies (infiltration pits, tied ridges, and dead-level contours). The results are presented in a matrix form with the rows representing the coefficients of each explanatory variable in different regression equations and the columns representing each of the regression equations (for each technology). The results are then discussed for each of the regression models.

Table 3: Results of the Tobit model for soil fertility management technologies

Explanatory Variables	Dependant Variables					
	FMAREA		HCMAREA		LRAREA	
	Coefficient	Change in P	Coefficient	Change in P	Coefficient	Change in P
Intercept	-2.21		-2.78		-1.59	
Age	-0.11*	-0.019	0.33	0.051	0.16*	0.023
Gender	1.65	-0.202	-0.87**	-0.048	0.27	0.072
Labour	0.46	0.239	1.28***	0.218	0.21	0.083
Educ	1.07**	0.190	1.15	0.019	1.99***	0.278
Agtrain	1.04***	0.170	0.99***	0.168	0.20***	0.074
Farmsize	0.40***	0.068	-0.72***	0.212	0.10	0.009
Inclive	-1.94***	-0.287	-1.90***	-0.316	-1.30**	-0.221
Soiltyp	-0.78***	-0.015	-1.39***	-0.302	-0.08	-0.011
Percrain	0.17**	0.018	0.12*	0.020	-0.37	0.061
Market	2.64***	0.063	0.32*	0.058	0.08	-0.004
Cotton	0.43***	0.071	0.10*	0.018	0.35***	0.098
Sorghum	0.28	0.023	0.35***	0.233	0.01	0.002
G/nut	-0.05**	-0.008	-0.08*	-0.013	0.32**	0.056

- * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level
- Change in P = Change in probability, that is, the change in the probability of adoption as a result of a 1% change in continuous variables or a switch from 0 to 1 for discrete variables.
- Variables that have been left out of the model do not have a significant influence on the adoption of all 3 soil fertility management technologies.

Table 3 shows results of the Tobit model for soil fertility management technologies. Area under fertilizer application, training in agriculture, farm size, availability of product markets, and cotton growing have a highly significant positive effect on adoption (significant at 1% level). Farmers who have undergone training in agriculture, such as master farmers and farmers in farmer field schools, are more likely to adopt fertilizers than those who are not. Farm size can be taken as a surrogate for wealth and access to credit, in which case the positive effect of farm size on adoption is a reflection of ability to purchase the fertiliser. Markets generally pull technologies through farming systems (Rohbach, 2002). It could be because of this reason that the coefficient for market availability is positive and very significant ($p = 0.001$).

Formal education (in the form of number of years of schooling) also has a positive impact on the adoption of fertilizer. This could be explained in terms of the formal schooling curricular, that generally promote the use of fertilizer. The other explanation could be that educated farmers are more likely to be formally employed somewhere and thus have off farm income, which they can use to purchase fertilizer. Farmer perception on rainfall level has the hypothesized positive influence since risk averse farmers are likely for adopt fertilizers if they perceive good rains. The reason for this is twofold; farmers are not likely to be willing to invest in fertilizer if they think that the crop would fail due to drought and; farmers generally believe that fertilizer “burns” the crop if there are insufficient rains.

Proportion of income from livestock has a negative influence on adoption, as hypothesized, and is also shown in research by Fernandez-Cornejo et al (1994). Also carrying a negative sign is the coefficient for soil type: farmers on heavier, more fertile soils are less likely to bother about applying fertilizer than those on poor, lighter soils. This finding confirms the hypothesis about soil type.

For the dependant variables on “proportion of area under heaped covered manure” and “proportion of area under rotation with legumes”, the number of significant explanatory variables decreases. As can be expected, labour availability has a significant positive influence on proportion of area under heaped covered manure and a positive, but not significant, impact on proportion of area under rotations with legumes. This could be attributable to the fact that the later is less labour intensive than the former. Education and training in agriculture have a positive impact on adoption of legume rotations, a result that can be explained by the dominance of crop rotations in school and farmer training curricular. Cotton production encourages rotations with legumes. This however should not be taken to indicate that farmers are adopting legumes as soil fertility enhancing crops. It might be due to the fact that farmers normally rotate their cotton with other crops to break the build up of cotton pests and diseases. The proportion of income from livestock has the hypothesized negative influence on adoption of both heaped covered manure and legume rotations. Markets were found not to have a significant positive impact on the take-up of both technologies, probably because the technologies are mainly used on subsistence crops.

Table 4 shows the results of the Tobit model for soil and water conservation technologies. Labour and draught power availability emerged as the most influential factors to the adoption of all the soil and water conservation technologies under study (coefficients significant at 1% level). This can easily be attributed to the fact that all of the technologies require considerable amounts of labour and adequate draught power. The variables on education, training in agriculture, and the growing of sorghum also have a positive impact on soil and water conservation technology adoption. Sorghum is the main crop that was used during farmer participatory experiments to promote the use of soil and water conservation technologies. It can, therefore, safely be concluded that farmers developed a habit of using the technologies with sorghum and, thus, the positive influence of sorghum growing on adoption.

The positive impact of land ownership on the adoption of soil and water conservation technologies is consistent with *a priori* expectations. Soil and water conservation technologies require large and more permanent investments on the land, which attract only those who own the land and do not provide enough incentive to those who are temporarily on that land. Tenants or farmers whose land tenure status is not clear are, therefore, less likely to adopt soil and water management technologies.

Farmers with heavier soils are less likely to adopt soil and water conservation technologies as compared to those on lighter soils. There are two possible explanations for this: the first, is that heavier soils are more difficult to work, especially during the construction of the soil and water conservation structures; the second, could be related to better water holding capacities of heavier soils and, thus, their capacity to prolong water availability to crops even without any artificial water conservation structures. This however is in contrast with the higher infiltration rates of lighter soils resulting in their ability to capture even small amounts of rainfall.

Table 4: Results of the Tobit model for soil and water conservation technologies

Explanatory Variables	Dependant Variables					
	IPAREA		TRAREA		DLCAREA	
	Coefficient	Change in P	Coefficient	Change in P	Coefficient	Change in P
Intercept	-3.58		-2.61		-1.02	
Age	0.58**	0.007	-0.22	-0.010	0.29*	0.002
Gender	1.24**	0.174	0.03	0.013	0.94**	0.172
Labour	0.38***	0.051	0.62***	0.098	0.83***	0.381
Educ	0.98*	0.023	1.23**	0.134	0.76*	0.027
Agtrain	0.79**	0.015	1.58***	0.069	1.39**	0.023
Tenure	2.28**	0.069	1.48	-0.202	0.65***	0.04
Farmsize	-0.44*	-0.082	0.87	0.048	-1.93**	-0.152
Inclive	-1.67***	-0.090	-1.03***	-0.290	-1.88***	-0.239
Soiltyp	0.37**	0.014	-0.01	-0.002	1.02**	0.043
Percrain	1.24**	0.119	0.84	0.017	-0.99**	-0.084
Draught	0.33**	0.016	2.76***	0.121	1.47***	0.239
Cotton	0.17	0.003	0.96***	0.102	1.33**	0.140
Sorghum	0.47***	0.007	1.29***	0.201	0.42**	0.013

- * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level
- Change in P = Change in probability, that is, the change in the probability of adoption as a result of a unit change in continuous variables or a switch from 0 to 1 for discrete variables.
- Variables that have been left out of the model do not have a significant influence on the adoption of all 3 soil and water conservation technologies.

In addition to predicting the probability of adoption of technologies (Tables 3 and 4), the Tobit model, as shown by McDonald and Moffit (1980), also provides information on the change in use intensity of the technology in response to changes in explanatory variables for farmers who have already adopted the technology. For continuous variables, such as farm size and the proportion of income from livestock, the values show elasticities of intensity of use to changes in explanatory variables while for dummy variables, the values are changes in the intensity of use of technology in response to a change in the binary variable from zero to one.

Table 5 shows the elasticities (for continuous variables) and the marginal effects (for dummy or discrete variables) at the sample means for both soil fertility management and soil and water conservation technologies for explanatory variables that are significant at least at the 10% level. According to Table 5, a 1% change in farm size is going to result in a 1.67% change in the proportion of area under fertiliser and a shift from tenancy (0) to permanent land ownership (1) is going to increase the area under dead level contours by 0.23% and so on. By comparing Table 5 with Tables 3 and 4, it can be noted that, in all cases, the change in probability of adoption, as a result of changes in explanatory variables, is larger than the change in use intensity.

Table 5: Elasticities and Marginal Effects of Level of Technology use Intensity at Sample Means

Variable	Change in expected level of technology use intensity					
	FMAREA	HCMAREA	LRAREA	IPAREA	TRAREA	DLCAREA
Elasticities						
Educ	0.130		0.148	0.012	0.096	0.129
Farmsize	0.167	0.017		-0.061		-0.045
Inclive	-0.217	-0.215	-0.173	-0.076	-0.261	-0.190
labour				0.031	0.091	0.291
Marginal Effects						
Gender		0.118		0.162		0.145
Agtrain	0.110		0.188	0.016	0.084	0.019
Percrain	0.006			0.099		-0.064
Market	0.044	0.038				
Tenure				0.048		0.023
Soiltyp				0.007		0.033
Draught				0.008	0.091	0.179
Cotton	0.051	0.009	0.068		0.082	
Sorghum		0.123		0.004	0.161	0.007
Gnut	-0.005	-0.006	0.037			

CONCLUSIONS

The study has shown that farmers generally adopt soil fertility enhancing technologies more than they do soil and water conservation technologies. This was found to be due to the fact that the time lag between investment in soil and water conservation and the realization of benefits is larger than for soil fertility enhancing technologies. It, therefore, might be necessary to provide more direct incentives for farmers to adopt soil and water conservation technologies.

Agricultural training and formal education were found to be important in the adoption and intensity of use of both soil fertility management technologies and soil and water conservation technologies. Intensive farmer training in these technologies and the promotion of agricultural education in schools can be considered as important requisites to adoption.

The provision of lucrative markets was found to influence the adoption of soil fertility management technologies more than the adoption of soil and water conservation technologies. This could be as a result of the fact that soil and water conservation technologies are adopted on areas that are too small to produce marketable surpluses that are bulky enough to require proximity to markets. This is opposed to fertility management technologies, which quickly increase crop yields and, thus, produce bulky marketable outputs.

Although land ownership does not significantly influence adoption of soil fertility management technologies, it has a highly significant influence on soil and water conservation technology adoption. Provision of more permanent land tenure systems may, thus, entice farmers to increase their investment in soil and water conservation.

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