African Crop Science Journal, Vol. 30, No. 3, pp. 375 - 389
Printed in Uganda.

ISSN 1021-9730/2022 $4.00

DOI: https://dx.doi.org/10.4314/acsj.v30i3.8

ASSESSMENT OF ALLOCATIVE EFFICIENCY OF SMALLHOLDER TEA FARMERS IN SOUTH-WESTERN UGANDA

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(*Received 8 June 2022; accepted 22 July 2022*)

ABSTRACT

Tea ranks third after coffee and fish in terms of export value in Uganda's crop sector. Smallholder productivity and efficiency in Uganda remains a paradox, especially in perennial crops, with past research presenting mixed results on allocative efficiency. The objective of this study was to determine allocative efficiency and its influencing factors among smallholder tea farmers in western-Uganda. A cross-sectional survey dataset was collected from a random sample of 170 tea farmers from Kabale and Kanungu districts in south-western Uganda. The study employed a Stochastic Frontier Approach and the Value of Marginal Product Approach in determining the input elasticities and allocative efficiency levels respectively. Results showed that average allocative efficiency scorers for land, fertiliser, labour and herbicides were 11.17, 1.68, 3.08 and 4.43, respectively; indicating under-utilisation of the inputs. Ordinary Least Squares estimates indicated that allocative efficiency score of fertiliser was positively related to farm size, herbicide type and extension visits. The allocative efficiency score for herbicides was positively influenced by extension access and herbicide type. Similarly, the allocative efficiency score for land was positively influenced by extension access while that of labour was positively influenced by farm size. The results indicate that increasing the scale of tea production in the region is likely to improve productivity and profitability since the average allocative efficiency scores were greater than unity.

Key Words: Stochastic Frontier Approach, Value of Marginal Product Approach

RÉSUMÉ

Le thé se classe au troisième rang après le café et le poisson en termes de valeur d'exportation dans le secteur des cultures ougandaises. La productivité et l'efficacité des petits exploitants en Ouganda restent un paradoxe, en particulier dans les cultures pérennes, les recherches antérieures présentant des résultats mitigés sur l'efficacité allocative. L'objectif de cette étude était de déterminer l'efficacité allocative et ses facteurs d'influence chez les petits producteurs de thé de l'Ouest de l'Ouganda. Un ensemble de données d'enquête transversale a été recueilli auprès d'un échantillon aléatoire de 170 producteurs de thé des districts de Kabale et de Kanungu dans le Sud-Ouest de l'Ouganda. L'étude a utilisé une Approche de Frontière Stochastique et l'Approche de la Valeur du Produit Marginal pour déterminer respectivement les élasticités des intrants et les niveaux d'efficacité allocative. Les résultats ont montré que les scores moyens d'efficacité allocative pour la terre, les engrais, la main-d'œuvre et les herbicides étaient de 11,17, 1,68, 3,08 et 4,43, respectivement ; indiquant une sous-utilisation des intrants. Les estimations des moindres carrés ordinaires ont indiqué que le score d'efficacité allocative des engrais était positivement lié à la taille de l'exploitation, au type d'herbicide et aux visites de vulgarisation. Le score d'efficacité allocative pour les herbicides a été positivement influencé par l'accès à la vulgarisation et le type d'herbicide. De même, l'efficacité allocative de la terre était positivement influencée par l'accès à la vulgarisation tandis que celle de la main-d'œuvre était positivement influencée par la taille de l'exploitation. Les résultats indiquent que l'augmentation de l'échelle de la production de thé dans la région est susceptible d'améliorer la productivité et la rentabilité puisque les scores moyens d'efficacité allocative étaient supérieurs à l'unité.

Mots Clés : Approche de frontière stochastique, approche de la valeur du produit marginal

INTRODUCTION

Tea ranks third after coffee and fish in terms of export value in Uganda's crop sector (UBoS, 2020). Tea exports in Uganda increased from 53,458 metric tonnes in 2015 to 59,278 tonnes in 2017, earning the country 70,317 and 79,713 million US dollars, respectively (UBoS, 2018). This was partly due to expansion in area under tea production from 20,570 hectares in 2000 to approximately 28,000 ha by the year 2015; and availability of tea processing factories (MAAIF, 2016).

Uganda's tea productivity stands at 1.65 metric tonnes per hectare (t ha^{-1}), which is low compared to the cases of Malawi (2.4 t ha^{-1}) and Kenya (2.2 t ha^{-1}) (FAO, 2014; NPA, 2020). A key driver to increasing tea production and productivity is resource use efficiency, which is less emphasised in literature in the Ugandan setting (Kamau, 2008). In order to address productivity and profitability issues, resource use efficiency is considered important in agricultural production particularly in developing countries where majority of the producers are resource constrained (Hong and Yabe, 2015; Okello *et al.,*2019). Coelli *et al.* (2005) and Tijani *et al.* (2010) aver that optimal resource use efficiency is positively associated with increased production, productivity and consequently, with profitability. Decisions on the resource use levels are influenced by their relative prices, prices of output and the level of technology used (Simar and Wilson, 2020).

A number of papers have estimated cost efficiency as proposed by Färe *et al.* (1985); while a few studies have estimated revenue and profit efficiency based on availability of input and out prices (Simar and Wilson, 2020). The cost efficiency measure gives the fraction by which the cost of producing given quantities of output, could be reduced when faced with a given level of input prices; and achieving this reduction might require altering the mix of inputs used to produce that output.

Most studies have investigated the extent to which farms achieve cost efficiency; and rarely investigate the reduction and increases in resources necessary to achieve the efficiency. The objective of this study was to determine allocative efficiency of key inputs and factors affecting resource allocation among smallholder tea farmers in south-western Uganda.

METHODOLOGY

Study area. The study was conducted in the highlands of Kabale and Kanungu districts in south-western highlands agro-ecological zone of Uganda. The two districts were purposively selected because they were predominantly tea areas in the region and had benefitted from the Tea Expansion Strategy by Ministry of Agriculture, Animal Industry and Fisheries.

Sampling procedure. A list of sub-counties was generated in a reconnaissance field survey carried out prior to the study, in collaboration with the district production offices from each district; and tea extension officers attached to tea processing companies located in the areas. The sub-counties were considered as the primary sampling units because it was discovered from the pretesting exercise that a reasonable number of farmers owned tea gardens that extend beyond parish borders. In this case, the tea dominant growing sub-counties were sampled and used for selection of respondents. The main focus was put on the tea growing household as an independent and rational decision maker in tea production and marketing processes. For the case of Kabale district where tea growing started within this decade, most farmers that were initially included in the sample were dropped because they had not started harvesting.

From each district, five dominant tea growing sub-counties were sampled out of the 35 sub-counties. This was followed by simple random sampling to get the respondents for interviews. Disproportionate random sampling was used to select sub-counties due to variations in population of tea farmers within the different sub-counties (tea dominant sub-counties were chosen).

A sample of 385 respondents was determined using the sampling formula as in Equation 1, considering the precision level of ±5% (Israel, 2003; Singh and Masuku, 2014).

$$n = \frac{z^2 p(1-p)}{e^2} \quad \text{...................... Equation 1}$$

Where:

n = sample size, *e is the desired level of precision (margin of error), p is the estimated proportion of an attribute that is present in the population* and z = z-value for a 95 per cent confidence interval.

For the purpose of this study a margin of error of five per cent was chosen. The level of maximum variability (P=0.5) is often used in the calculation of the sample size for the proportion because it generally produces a larger sample size than is the case by the sample size of the mean (Israel, 2003). Besides, a "good" estimate of the population variance necessary for the calculation of the sample size based on the mean, is often not available. Therefore the sample was calculated as:

$$n = \frac{1.96^2\,(0.5(0.5)}{0.5^2} = 385 \text{ households}$$

The sample size was revised to 285 to accommodate the cost implications of data collection. The sample was shared disproportionately between Kanungu and Kabale districts as 185 and 100, respectively, based on households growing tea. However, the actual number used in the analysis reduced to a total of 170 households, 151 for Kanungu and 19 for Kabale district. The shrinkage of the sample was a result of lack of harvest data, at the time of the survey, among many households particularly those from Kabale district. This reduction in sample size could have had an effect on the confidence intervals and a risk on statistical errors. However, considering the precision level of ±10%, the sample used in the analysis is well above 100 households required for achieving the true population values with a probability of 10% precision.

Data collection. Data were collected with a pretested semi-structured questionnaire. Pretesting was done on a few individual tea farmers in Kabale district, with guidance from one of the district agriculture extension staff. The responses obtained from the questionnaire were validated with information from key informant interviews. During data collection, the household head and/or spouse; or a mature child well versed with the family routine of tea growing activities and socioeconomic variables, acted as respondents.

The data collected were cleaned while still in the field by filling in the missing data, for example on prices and wages; and converting local measuring units for particular variables into their standard forms (for example acres into hectares). The variables were coded for better management in STRATA statistical software. Missing data were replaced using averages computed from the farms located in the same subcounty.

Analytical framework. This study employed a Stochastic Frontier Production function model (Aigner *et al.,* 1977). First, we estimated the Cobb Douglas and Translog production models, and using the Log Likelihood Estimator, and compared the robustness of the two models. The results indicated that the flexible Translog model was more robust than the Cobb Douglas model. From the Translog model, individual input elasticities were generated. The elasticities were used to compute the value of marginal products (VMPs) of the selected inputs. Finally, the allocative efficiencies for each of the inputs were determined from ratios of VMPs to input prices. These systematic processes are elaborated in Equations 2 - 10.

Data analysis

Estimation of stochastic frontier production function. In order to determine allocative efficiency, a two-step procedure was adopted. First, the production function was specified, from which the input elasticities were estimated using a parametric stochastic frontier approach, with the Translog production function represented by Equation 2.

$$Y = f(X) \quad \text{.................................. Equation 2}$$

Where:

Y = quantity of tea output harvested in kilograms; X is a vector of inputs (acreage, labour, fertiliser and herbicide); and *f(.)* is a suitable function that could be as simple as the Cobb-Douglas (Equation 3) or complex but of flexible form such as the Translog (Equation 4). Acreage was measured in hectares (ha), labour in man days, and fertiliser in kilogramme; while herbicide was quantified in litres.The Translog production function written in its logarithmic form was adopted for this study. The function has been widely used in literature as it does not place apriori restrictions on the value of output elasticities, returns to scale and elasticities of substitution (Tzouvelekas, 2000).

$$\text{In}Y = \text{In}\beta_0 + \beta_1\text{In}X_1 + \beta_2\text{In}X_2 + \beta_3\text{In}X_3 + \beta_4\text{In}X_4 + \varepsilon \quad \text{................................ Equation 3}$$

$$\text{In}Y = \text{In}\theta_0 + \theta_1\text{In}X_1 + \theta_2\text{In}X_2 + \theta_3\text{In}X_3 + \theta_4\text{In}X_4 + \frac{1}{2}\{\propto_1 [\text{In}X_1]^2 + \propto_2 [\text{In}X_2]^2 + \propto_3 [InX_3]^2 + \propto_4 [InX_4]^2\} + \delta_1\text{In}X_1\text{In}X_2 + \delta_2\text{In}X_1\text{In}X_3 + \delta_3\text{In}X_1\text{In}X_4 + \delta_4\text{In}X_2\text{In}X_3 + \delta_5 InX_2InX_4 + \delta_6 InX_3InX_4 + \varepsilon \quad \text{.. Equation 4}$$

Where:

Y_i is quantity of fresh green tea in kg ha^{-1} of i^{th} farm; β_0, θ_0, β_j, θ_j, α_i and δ are parameters to be estimated; x_i are variable inputs and e_i = error term representing unobserved factors.

The parameters β_1, β_2, β_3 and β_4 of the Cobb-Douglas function represent elasticities of production for inputs X_1, X_2, X_3 and and X_4. It is expected that parameters β_1, β_2, β_3 and β_4 are positive because an increase in any of the variable inputs, X_1, X_2, X_3 and and X_4, would correspondingly lead to an increases in tea output. The elasticities of output with respect to inputs for the Translog function are estimated as:

$$e_i = \frac{\partial lnY}{\partial lnX_i} = \theta_i + 2 * \frac{1}{2} * \alpha_i X_i + \delta_j X_j = \theta_i + \alpha_i X_i + \delta_j X_j \quad \text{..................... Equation 5}$$

Where:

j is subscript referring to the jth input 1 to 4.

Tea farmers were majorly growing two clones, one with narrow leaves (303/577) and the other with broad leaves (6/8). Age of the tea garden was included to capture the effect age of tea trees on output; output was expected to increase with age of trees. The dummy on tea variety was included in the model as a form of production technology. Battese dummies were included for fertiliser and herbicide to accommodate zero values for farmers who were not used to these inputs. The elasticities were computed based on the Translog stochastic frontier production function (Equation 4).

Elasticity of land

$$\frac{\partial \ln \text{Output}}{\partial \ln \text{acreage}}];\ \varepsilon_1 = \theta_1 + \alpha_1 \overline{\ln \text{land}} + \delta_1 \overline{\ln \text{labour}} + \delta_2 \overline{\ln \text{fertiliser}} + \delta_3 \overline{\ln \text{herbicide}} \quad \text{.. Equation 6}$$

Elasticity of labour

$$\frac{\partial \ln \text{Output}}{\partial \ln \text{labour}}];\ \varepsilon_2 = \theta_2 + \alpha_2 \overline{\ln \text{labour}} + \delta_1 \overline{\ln \text{acreage}} + \delta_4 \overline{\ln \text{fertiliser}} + \delta_5 \overline{\ln \text{herbicide}} \quad \text{.. Equation 7}$$

Elasticity of fertiliser

$$\frac{\partial \ln \text{Output}}{\partial \ln \text{fertiliser}}];\ \varepsilon_3 = \theta_3 + \alpha_3 \overline{\ln \text{fertiliser}} + \delta_2 \overline{\ln \text{acreage}} + \delta_4 \overline{\ln \text{labour}} + \delta_6 \overline{\ln \text{herbicide}} \quad \text{.. Equation 8}$$

Elasticity of herbicide

$$\frac{\partial \ln \text{Output}}{\partial \ln \text{herbicide}}];\ \varepsilon_4 = \theta_4 + \alpha_4 \overline{\ln \text{herbicide}} + \delta_3 \overline{\ln \text{acreage}} + \delta_5 \overline{\ln \text{labour}} + \delta_6 \overline{\ln \text{fertiliser}} \quad \text{.. Equation 9}$$

The final elasticities obtained for each of the inputs were then used to determine Marginal Physical Products (MPPs) and, consequently the Marginal Value Products (MVPs).

Estimation of allocative efficiencies. Allocative efficiency is achieved when farmers employ inputs such that their MVPs are equal to their input prices. The elasticities of production, with respect to each of the inputs, were then used to obtain the value marginal products (Equation 10).

$$MPP_i = \frac{\partial Y}{\partial X_i} = e_i * \frac{Y}{X_i} \quad \text{.......... Equation 10}$$

Where:

Y is output; X_i is quantity of input i, and e_i is the elasticity of output for input i estimated from the Translog stochastic frontier production function.

The value marginal product for each input was computed using Equation 11.

$MVP_i = P_y * MPP_i$ .... Equation 11

Where:

MVP_i is the value marginal product for input *i* and P_y is the price of output Y.

The VMPs were then divided with the respective marginal factor costs, to obtain allocative efficiency (AE) indices for each input *i* (Helali and Kalai, 2015; Awunyo-Vitor *et al.,* 2016) as in Equation 12. Farmers are price takers in the input market; therefore, the marginal cost of input approximates the price of input *i* (P_i).

$$AE\ index = \frac{VMP_i}{P_i} \text{ .... Equation 12}$$

The allocative efficiency index (AE) that is equal to one, implies that the farm is allocatively efficient in the use of the particular input; while an index that is less than one implies that the farm is allocatively inefficient in the use of the input. The latter case shows that VMP < MFC and thus the input is over utilised. The farmer is better off reducing the level of use of the particular input since marginal benefit is lower than the marginal cost. The AE index that is greater than one implies that farm is allocatively inefficient in the sense that it allocates less than the level of input that is required to maximise profit (Rudra, 1973). The farm would be better off increasing the level of input use since additional units bring in a higher benefit compared to the additional cost.

Factors affecting resource allocation. The analytical framework used for the analysis of factors affecting resource allocation is specified in Equation 13.

$$\ln AE = \varphi_o + \sum_{j=1}^{m} \varphi_j z_j + e \text{ ....Equation 13}$$

Where:

ln AE is the natural logarithm of the allocative efficiency score for a given input; φ_o and φ_j are parameters to be estimated; while z_j is a vector of m exogenous variables included in the model to explain the variation in the level of input used across farms.

The model was estimated using Ordinary Least Squares for the four inputs: acreage, labour, fertiliser and herbicide (Equation 13). A positive effect of z implies that increasing the level of z increases the level of the marginal value of product of the given input relative to its marginal fact cost. The behavioural effect is for the farmer to utilise the input at below optimal level since the input opportunity cost perceived by the farmer is well above the input market price. In contrast, the negative effect of z is to increase the level of utilisation of the input as the farmer perceives a lower marginal value product relative to the market price of the input. The z vector comprised of farm characteristics and institutional variables hypothesized to influence household deviation from the optimal level of input use.

In Zimbabwe, results by Matshe and Young (2004) demonstrated the importance of individual characteristics (such as gender and education) and household farm characteristics (such as farm size and remittance) in influencing labour market decisions of rural households. Farm size is included as a proxy for wealth or fixed capital. Therefore, farmers with larger farm sizes are expected to relax the capital constraint and be able to increase the level of resources utilised. In contrast, smaller farmers are expected to use resources at below optimal level. Obare *et al.* (2010) found plot size to have the largest elasticity of production, suggesting that productivity would be higher when more land is brought into production. According to Khaldi (1975), larger farmers are able to take advantage of rapid technological changes; and taken together with rising education, larger farmers are able to achieve higher scale efficiency in the use of information.

Being a member to farmer group is expected to increase the social capital of the farmer and relax the labour and credit market constraints. Improvement in social networks is likely to improve framers' access to information and, consequently improvement in resource allocation efficiency. In a study of allocative efficiency for Irish potato by farmers in Kenya, Obare *et al.* (2010) found membership to farmer association to be positively associated with allocative efficiency. They attributed this to the possibility that farmers who belong to an organisation benefit from better access to inputs and to information. Presence of social networks is likely to improve access to new information related to improved production practices as new adopters may learn from each other, especially if they are located in similar environment (Obare *et al.*, 2010).

Access to extension is expected to improve information access on prices and technical aspects. The positive effect of extension on price information is likely to relax the market constraints and, hence improve resource allocation efficiency. Similarly, knowledge gained from contacts with extension agents could influence adoption of new technologies and improve productive efficiency (Obare *et al.*, 2010). Similar results are expected for education, as improved access to information from higher institutions of learning is likely to improve resource allocation efficiency (Khaldi, 1975). Education enables actors to analyse and draw valid conclusions from available information leading to optimal resource allocation (Abdulai and Huffman, 2000).

Participation in nonfarm work reduces financial constraints for resource poor farmers; and thus enables them to buy productivity enhancing inputs (Abdulai and Huffman, 2000). Amare and Shiferaw (2017) found that nonfarm income has a positive impact on farm hired labour and improved seed intensity, and a negative effect on onfarm labour use. Pfeiffer *et al.* (2009) obtained similar results for Mexico, where they found that off-farm income has a negative effect on agricultural out and the use of family labour, but the effect on purchased inputs was positive. Similarly, access to credit improves farmers' allocative efficiency by enabling the farmers to overcome the financial constraints for the purchase of productivity enhancing inputs such as fertiliser and high yielding seeds, and facilitates acquisition of information needed to increase productivity (Wozniak, 1993).

Distance to markets is positively correlated with allocative inefficacy due its likely positive effect on information access and reduction in transaction and transport costs (Abdulai and Huffman, 2000). According to Abdulai and Huffman (2000), farmers with poor access to markets for consumer goods tend to be less interested in profit maximising activities compared to those with sufficient supply of consumer goods. On the other hand, staying next to the market centres might provide farming households with options of nonfarm activities that reduces their effective farming labour and reduce their overall efficiency (Okello *et al.*, 2019).

Age of household head and age squared are often included in models analysing resource allocation to capture the effects of general experience and nonlinear life cycle effects. Farming experience, which is positively correlated with knowledge accumulation and capital, is expected to lead to better managerial skills acquired over time (Bozoglu and Ceyhan, 2007). Hence, middle aged farmers are expected to have more knowledge about farming practices accumulated over time; while older farmers are expected to have depleted their savings over time. The positive effect of experience implies that allocative efficiency increases with number of years. Hence, more experienced farmers are more likely to apply inputs in an optimal manner as farmers are able to better assess the importance and complexities of good farming decision making including the efficient use of inputs (Obare *et al.*, 2010). The variables included in the resource allocation analysis are defined and summarised in Table 1.

TABLE 1. Definition of variables and summary characteristics

Variable	Definition	Mean	SD	Expected impact
Farmsize	Land available to household (ha)	7.773	10.601	+
Membership	1 = Household head is a member of farmer group and 0 otherwise	0.324	0.469	+
Timesextension	Number of times visited by extension agent in six months	1.188	1.9246	+/-
School	Years spent in school (years)	6.388	5.022	+/-
Nonfarm	1 = farmer participates in nonfarmincome activities and 0 otherwise	0.312	0.465	+/-
Marital	1 = farmer is married and 0 otherwise	0.818	0.787	+
Agehh	Age of household head in years	50.482	13.088	+
Agesquared	Age squared in years	2718.753	1396.675	-
Hhsize	Size of household	7.406	5.509	+/-
Fertilizer_npk	1 = farmer uses NPK fertiliser and 0 otherwise	0.818		ND
Herbicide_roundup	1 = farmer uses roundup herbicide and 0 otherwise	0.347		ND

RESULTS AND DISCUSSION

The results of the Translog stochastic frontier production function are presented in Table 2. The coefficients of acreage, labour, fertiliser and herbicide plus the square terms and cross terms were used in the computation of input elasticities presented in Table 2. The tea clone variable was included to capture the differences in productivity due differences in clone attributes. The clone being 303/577 had a positive and statistically significant effect (P=0.05) on output, implying that farmers who grew the narrow leaved (303/577) tea clone obtained higher outputs compared to their counterparts who grew the broad leaved (6/8) clone. This result is in agreement with the study by Nyabundi *et al.* (2016) on genotype and environment interactions, and yield components of tea cultivars in Kenya. The result reflecting the positive effect of 303/577 clone compared to 6/8 clone is consistent with Government of Uganda's massive promotion of the clone through the National Agricultural Advisory Services and/or Operation Wealth Creation program (MAAIF, 2016).

The effect of plantation age on tea output was not statistically significant. The Battese dummies were included in the function to allow for inclusion zero values for fertiliser and herbicide in the log-linearised Translog function (Battese, 1997).

The coefficients of the inputs and their square and cross terms were used to compute the input elasticities presented in Table 3. The sum of all the elasticities of fertiliser, herbicide, labour and land was well above unity, which is indicative of increasing returns to scale. This result implies that farmers in south-western Uganda would gain from improving scale of tea production. The result is indicative of underutilised management factor, particularly in areas of Kabale where tea production was in its infancy stage. This observation is consistent with the elasticities computed for each input (Table 3). The elasticities were below unity and above zero, with the exception of acreage, implying that farmers were

TABLE 2. Tea production function estimates based on the stochastic frontier Translog function

Variables	Coef.	Std. Err.
lnacreage	2.145**	1.072
lnlabour	-0.620	1.099
lnfertiliser	-1.072*	0.622
lnherbicide	-0.251	0.407
0.5*lnacreage squared	-1.283**	0.559
0.5*lnlabour squared	0.050	0.308
0.5* lnfertiliser squared	0.217*	0.127
0.5*lnherbicide squared	-0.059	0.059
lnacreage* lnfertiliser	-0.101	0.089
lnherbicide* lnfertiliser	-0.066***	0.026
lnlabour* lnfertiliser	0.124	0.087
lnacreage*lnherbicide	0.427**	0.149
lnlabour*lnherbicide	0.099	0.121
lnland*lnlabour	-0.118	0.323
Fertiliser Battese Dummy	1.390	1.329
Herbicide Battese Dummy	0.183	0.253
Tea clone grown dummy	0.381**	0.161
Ln Plantation age	0.002	0.004
Constant	8.418***	2.186

Asterisks *, ** and *** respectively represent 10 percent, 5 percent and 1 percent significance level

TABLE 3. Elasticities and returns to scale computed from the Translog stochastic frontier production function

Input	Elasticity
Acreage	1.109
Labour	0.206
Fertiliser	0.125
Herbicide	0.045
Returns to scale	1.485

operating in stage two of the production function for these inputs; implying that farmers were rational in the use of these inputs. The elasticity of production with respect to acreage was above unity, which indicates that with respect to acreage, farmers were operating in stage one of the production function. Thus farmers could make significant gains in efficiency by increasing the amount of land allocated to tea production. The result could be indicative of serious constraints in the land market within the region; and output can only be increased by improving productivity of available resources. The results could also imply that farmers are still hesitant to switching from traditional food crops, in which they have vast experience, to tea production that is relatively new in the region.

The results of marginal value products and allocative efficiency score are presented in Table 4. The marginal value products for labour, fertiliser and herbicide were below the average value products, which is indicative of farmers operating in the rational second stage of the production function. The marginal value product was above the average value product for acreage, which is indicative of farmers operating in the first stage of the production function with respect to acreage. This is indicative of increasing marginal returns to land and possibly is the primary reason why farmers are experiencing increasing returns to scale.

The allocative efficiency scores are presented in the last four rows of Table 4. The AE scores are all above unity, implying that farmers are operating below optimal level with respect to all the inputs. The highest score was obtained for acreage and the lowest score was of fertiliser. The test for the null hypothesis of allocative efficiency that the constant and slope are, respectively, zero and one in the regression between marginal value product against input price was rejected for acreage, labour and herbicide based on the magnitude of F-values (Table 5). The test, however, was not rejected for fertiliser; implying that farmers' allocation of the input was tending to optimal levels on the average. The rejection of the allocative efficiency test for acreage, labour and herbicide is indicative of rigidities in the markets for these inputs.

TABLE 4. Average value products, marginal value products and allocative efficiency scores for acreage, labour, fertilizer and herbicide

Variable	Obs	Mean	Std. Dev.	Minimum	Maximum
Output price	170	330.1	24.1	165.0	480.0
AVP acreage	170	1,552,161.0	4,169,247.0	45,000.0	33,200,000.0
AVP Labour	170	71,458.1	136,859.9	1,730.8	1,031,250.0
AVP Fertilizer	142	44,774.8	279,038.5	1,320.0	3,300,000.0
AVP Herbicide	145	466,984.0	594,949.7	466.7	2,904,000.0
MVP acreage	170	1,721,922.0	4,625,241.0	49,921.7	36,800,000.0
MVP Labour	170	14,740.7	28,232.1	357.0	212,731.1
MVP Fertilizer	142	5,585.6	34,809.5	164.7	411,668.0
MVP Herbicide	145	77,868.2	99,206.2	77.8	484,233.6
Input prices					
Rent per ha	170.00	268,000.0	283,746.3	10,000.0	3,000,000.0
Wage per day	170.00	5,433.8	4,887.4	1,111.1	53,361.1
Price of fertilizer	142.00	2,549.4	1,160.3	2,500.0	3,500.0
Price of Herbicide	145.00	15,008.8	6,441.9	13,000.0	20,000.0
AE acreage	170.00	11.2	33.5	0.1	366.1
AE Labour	170.00	3.1	5.7	0.1	47.7
AE Fertilizer	142.00	1.7	9.9	0.1	117.6
AE Herbicide	145.00	4.4	5.7	0.0	27.9

TABLE 5. Test for allocative efficiency

Variable	Constant		Slope		R2	Adj.R2	F-test*	
	Coeff.	Std. Err.	Coeff.	Std. Err.			F-value	Prob.
Acreage	1960380	489357.9	-0.890	1.256	0.003	-0.03	9.51	0.000
Labour	13765	3251.3	0.180	0.445	0.001	-0.005	10.89	0.000
Fertilizer	-70782.5	33869.3	24.9**	11.1	0.035	0.028	2.71	0.070
Herbicide	35816.2	86768.5	2.390	4.909	0.002	-0.005	26.66	0.000

*Joint test for allocative efficiency that constant = 0 and Slope =1

Several studies conducted in sub-Saharan Africa indicated presence of imperfections in the rural labour markets (Biesbroeck, 2011; Dumas, 2013; Barrett and Dillon, 2017; Bagamba *et al.*, 2022). The allocative inefficiencies observed for labour and herbicide could be linked to failures in the labour market, since the two inputs are close substitutes. The higher marginal value products relative to wage rates are indicative of a higher dependence on hired labour in tea production in the region.

The results of the estimates of factors affecting resource allocation are presented in Tables 6 and 7. Table 6 presents results on factors affecting labour and acreage in tea production. Four factors were found to have a positive and statistically significant effect on allocative efficiency scores for labour, implying that the factors are positively correlated with under allocation of labour since on average, the allocative efficiency score was well above unity. Farm size was the only variable, of the

TABLE 6. OLS estimates for the factors that influence lnAE (Land and Labour) for the smallholder tea farmers in South-Western Uganda

	lnAE_Labour		lnAE_acreage	
	Coef.	Std. Err.	Coef.	Std. Err.
Distance from Factory	0.011*	0.006	0.001	0.007
Farm size	0.022***	0.008	-0.007	0.007
Belonging in a group	0.358*	0.186	-0.067	0.205
Age of HH	0.053	0.050	0.158***	0.058
Age squared HH	-0.001	0.001	-0.002***	0.001
Have Nonfarm income	-0.012	0.195	-0.141	0.223
Size of HH	0.005	0.010	0.020	0.014
Times visited by extension	-0.044	0.183	0.350*	0.191
Herbice_Roundup	-0.279	0.191	-0.202	0.216
Fertilizer_NPK	0.440*	0.245	0.700**	0.316
Credit Access	0.130	0.186	-0.130	0.213
Experience HH	0.008	0.006	0.010	0.006
Constant	-1.595	1.313	-3.033*	1.562
Obs	170		170	
F(12, 157)	2.520		2.590	
Prob > F	0.005		0.004	
R-squared	0.130		0.128	

Asterisks represent * 10 per cent, ** 5per cent ***, 1 per cent, respectively

four, that was statistically significant (P<0.01). The result implies that larger farmers are more likely to under employ labour in tea production, which further confirms rigidities in the labour market and reliance more on hired labour by larger farmers. Imperfections in the labour market probably caused by shirking and high search and supervision costs constrain farmers from employing labour to optimal level (Key *et al.*, 2000).

The effect of age was positively correlated with allocative efficiency score for acreage, being statistically significant at 1% level, implying that the amount of land allocated to tea decreases with age. The quadratic term of age was negatively correlated with acreage allocative efficiency score, implying that beyond prime age, the effect of age is to increase land allocated to tea production. The two results imply that farmers of prime age tend to allocate land below optimal level; while young and aged farmers tend to move from under allocation to optimal level. The results are inconsistent with the hypothesis that allocative inefficiency should reduce with age as farmers are better able to assess farming complexities and improve resource allocation efficiency (Obare *et al.*, 2010). The result of the quadratic term is inconsistent with the life cycle hypothesis that naturally beyond prime age, individual productivity and efficiency should diminish (Abdulai and Huffman, 2000). However, there is a possibility that household heads of prime age are engaged in a number of other activities that divert their attention from tea production. Government programmes for supporting the youth could have involved more youth in tea production in the region; while the aged could still be holding on their land. The experience accumulated by the aged

TABLE 7. OLS estimates for the factors that influence allocation of herbicide and fertilizer inputs

Variable	lnAE_Herbicide		lnAE_Fertiliser	
	Coef.	Std. Err.	Coef.	Std. Err.
Distance from Factory	-0.011*	0.007	-0.007	0.008
Farm size	-0.009	0.008	0.014*	0.008
Belonging in a group	0.036	0.242	0.199	0.216
Age of HH	-0.040	0.057	0.035	0.054
Age squared	0.000	0.000	-0.000	0.001
Nonfarm income	-0.002	0.240	0.311	0.257
Size of HH	0.033**	0.015	-0.009	0.011
Times visited by extension	0.097**	0.041	0.058**	0.026
Roundup	-0.477**	0.224	-0.350*	0.207
NPK	0.572	0.473	0.874	0.600
Credit Access	0.138	0.251	0.227	0.208
Experience HH	0.011	0.008	-0.011**	0.006
Constant	0.965	1.647	-2.827*	1.453
Obs	145		142	
F(12, 132)	3.350		2.900	
Prob > F	0.000		0.001	
R-squared	0.153		0.117	

overtime most likely enables them to acquire better managerial skills and to improve input efficiency (Bozoglu and Ceyhan, 2007)

The results of herbicide and fertiliser explaining the factors influencing use levels are presented in Table 7. The second and third column contain coefficients and the standard errors for the factors that influence the level of herbicide use, respectively. Two variables (household size and extension) were found to be significantly and positively correlated with allocative efficiency score. Being exposed to Roundup as the trade mark for herbicide had a negative effect on the allocative efficiency score, implying that farmers that used Roundup used lower levels of herbicide. The positive correlation of household size implies farms with large households used less herbicide probably in favour of family labour since the two inputs are close substitutes. The agricultural extension variable was positively correlated with allocatively inefficiency, in the sense that farmers that had been visited by extension service providers more frequently used lower levels of herbicide than optimal. Without more information, this result cannot be interpreted as it contradicts the hypothesis of a higher correlation between extension access and input allocative efficiency (Obare *et al.*, 2010). Most likely, extension information was more oriented to technical efficiency such that overall productive efficiency was likely to be high, but farmers remained allocatively inefficient because of lack of access to information on market prices.

Extension visits had a similarly significant effect on fertiliser where the visits were positively correlated with allocative efficiency scores. Farm size was also positively collated with lower use of fertiliser, but at 10% statistical significance level. One variable that came out as a booster of allocative efficiency in fertiliser use was experience in tea production, whereby the correlation being statistically significant at 5%. This result suggests that farmers with a long experience in tea production acquired adequate information, which enables experience higher profit efficiency (Abdulai and Huffman, 2000).

CONCLUSION

The study of allocative efficiency in tea production in south-western Uganda has shown that productivity increased with scale of production, implying that farmers could benefit from increasing the scale of tea production. Farmers in the region operated in the second stage of the production function for herbicides, fertilisers and labour inputs, which is rational. In contrast, farmers operated in the first stage of the production function with respect to land, implying that they can gain from productive efficiency by increasing the size of operation (i.e. increasing farm size without necessarily increasing the levels of other inputs). Of the four inputs, only fertiliser was found to be allocated at optimal levels on average.

Farm size was found to affect negatively the allocative efficiency of labour, which is indicative of rural market imperfections. The results of age and its quadratic term on acreage were inconsistent with the hypothesis that experienced farmers are more likely to allocate resources in an optimal manner; while, beyond prime age, older farmers are expected to deplete their savings over time. In contrast, prime aged farmers were found to allocate lower acreage than optimal compared to the aged and young counterparts. Extension visits were positively associated with allocative inefficiency of herbicide and fertiliser application contrasting the hypothesis of a higher correlation between extension access and input allocative efficiency. Most likely extension efforts were directed at boosting technical at the expense of price information.

Market information needs to be integrated in the extension information packages to enable farmers improve overall profit efficiency.

ACKNOWLEDGMENT

The study was funded by the National Agricultural Research Organisation (NARO), Kachwekano Zonal Agricultural Research and Development Institute (KAZARD)

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