Vol. 14(3), pp. 60-78, July-September 2022
DOI: 10.5897/JDAE2022.1330
Article Number: 981E93169386
ISSN 2006-9774

http://www.academicjournals.org/JDAE

Journal of Development and Agricultural Economics

Full Length Research Paper

Impacts of cassava whitefly pests on the productivity of East and Central African smallholder farmers

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Received 19 January, 2022; Accepted 15 June,2022

A key constraint to smallholder cassava production systems in Africa is the cassava whitefly pest species. These pests are a group of several cryptic species within *Bemisia tabaci* that cause direct damage to cassava and vector viruses that cause disease. We employ a farm-level stochastic production frontier (SPF) model to determine the impacts of the cassava whitefly pests on the productivity and technical efficiency (TE) of smallholder cassava farmers in Malawi, Tanzania, and Uganda. Primary data were collected from a sample of cassava farmers using a structured survey questionnaire. A total of 1200 farmers were selected from Malawi (400), Tanzania (350) and Uganda (450), and interviewed using a multi-stage sampling technique. Cassava output was significantly correlated with land area, the quantity of cuttings used to propagate the crop, and total labor used. We found that whitefly infestations as well as several socio-economic factors significantly affected the technical inefficiency of cassava farmers. Whitefly and disease infestations contributed to higher levels of technical inefficiency of cassava farmers. The mean TE score was significantly lower (50%) for cassava farms with whitefly infestation compared to those without any infestation (80%). These findings underscore the need for policies to ensure that cassava farmers have better access to improved inputs, especially clean planting materials, and the knowledge to integrate this technology into their farming system effectively.

Key words: Cassava, productivity, smallholder, whitefly pest.

INTRODUCTION

Cassava is an important food security crop in many African farming systems and provides more than half of the dietary calories for over 700 million people in Africa (Szyniszewska, 2020). Africa is the world's largest

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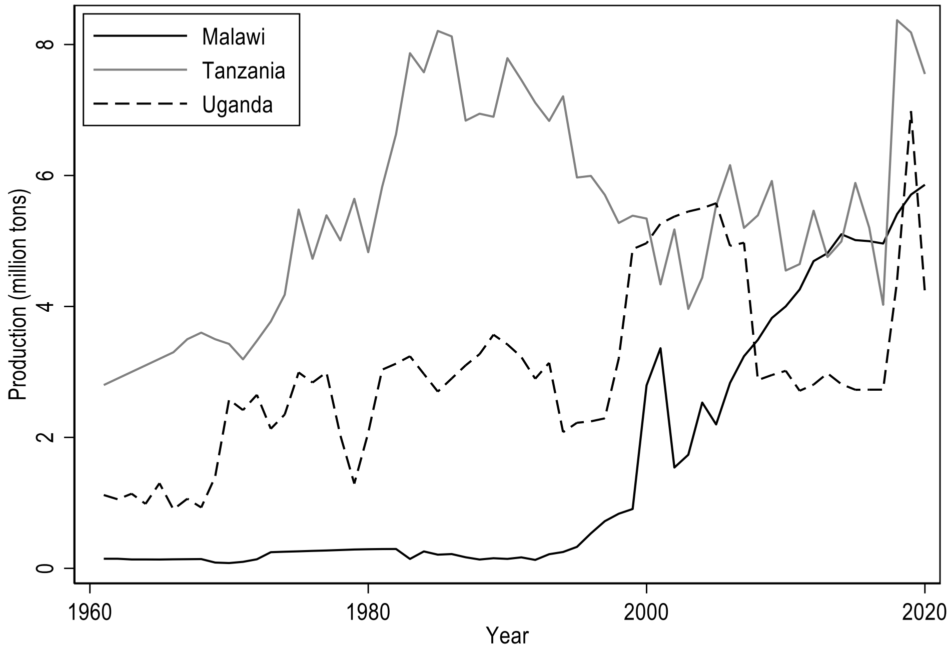

Figure 1. Cassava production in Malawi, Uganda, and Tanzania (1961–2020).
Source: FAOSTAT (2022).

cassava-producing region and accounts for nearly 55% of global cassava output (FAO, 2022). Cassava is produced mainly by smallholder farmers whose average cultivated area is less than one hectare (Ha). Most of the production is used for household consumption or sold as a food crop to domestic markets. It is mainly grown under intercropping systems with other crops such as maize, legumes, and bananas. Cassava production in Malawi, Tanzania, and Uganda has increased over the years but is interspersed with periods of decline (Figure 1). Cassava's relevance as a food security crop relates to being tolerant of poor soils and seasonal droughts, its ability to survive in marginal lands with minimal inputs and the possibility of harvesting throughout the year (Reincke et al., 2018). Both roots and leaves can be consumed, and cassava roots are cheaper than grains such as maize and rice and so can be a vital reserve crop during periods of conflicts (Bennett, 2015).[1]

In terms of productivity, Uganda ranks highest in East Africa with an average of 13 metric tons per hectare (Mt/Ha), while in Tanzania and Malawi, the yields are much less than 6 Mt/Ha. However, cassava productivity in Africa is the lowest globally, with an average of 10 Mt/Ha compared to 26 Mt/Ha in Asia (FAO, 2021). Fermont et al. (2009) estimated that cassava productivity in East Africa could reach 20 Mt/ha using existing technologies and best practices. Yield potential in a well-controlled research setting with irrigation and fertilisation is 45 Mt/Ha or higher (Tian et al., 2009).

In Uganda, cassava productivity ranges 40-50 Mt/Ha at the research level. If translated to farmer level, it would increase cassava production, improve food security, and incomes among cassava farmers. To reduce research-farmer yield gaps which is currently over 50% (FAOSTAT, 2022), a better understanding of the factors contributing to low cassava yields is needed to help to design and prioritise interventions in the context of limited resources. Several factors such as pests and viral diseases, lack of access to improved seeds and inputs, soil fertility, weeds, poor crop management and high labour requirements contribute to the yield gap for cassava production systems in Africa (Fermont et al., 2009; Kintché et al., 2017). Cassava production is currently constrained by two significant viral diseases, cassava mosaic disease (CMD) and cassava brown streak disease (CBSD), which have threatened cassava production systems across East and Central Africa over the past 15 to 20 years (Legg et al., 2006, 2011; Vurro et al., 2010; Patil et al., 2015; Chikoti et al., 2019). The viruses that cause these diseases are vectored by at least three cryptic species in the whitefly *Bemisia tabaci* group (Mugerwa et al., 2018) and they can also be spread through the movement of infected cassava cuttings (Boykin et al., 2018; Macfadyen et al., 2018).

This paper uses the common name "cassava whitefly" to refer to multiple species in the *B. tabaci* pest species complex. It has only recently become clear that this singular species and genus name is a complex of

[1] Cassava also has some disadvantages. The tubers are very low in protein which can be a problem for proper nutrition of young children, and some varieties can contain high levels of cyanide (Parmar et al., 2017).

morphologically identical but very different whitefly species (Mugerwa et al., 2018). In Uganda, there is a molecular evidence that the *B. tabaci* Sub-Saharan Africa 1 (*B. tabaci* SSA1) species is common in cassava fields (Kalyebi et al., 2021; Macfadyen et al., 2021), but it is not the only species present in fields across Malawi, Tanzania and Uganda. We know that smallholder cassava production systems in East Africa are incredibly diverse in crop types grown over space and time (Kalyebi et al., 2021; Macfadyen et al., 2021).

Farmers in these landscapes need to have the knowledge and resources to manage various pest challenges to maintain food security for their households and production at the country level.

Yet there has been relatively little focussed research support to identify intervention options that can be integrated into these particular farming systems (Alene et al., 2013, 2018). Many studies show that cassava is important for income and food security in many African countries (Alene et al., 2013, 2018; Avit, 2020; Fermont et al., 2010; Roothaert and Magado, 2011).

Most research to date, however, has focused on developing new cassava varieties with resistance or tolerance to diseases, while there has been little work on the impacts of whitefly pests and associated diseases on smallholder production systems (Alene et al., 2013). Furthermore, research investment in understanding the scale of the problem associated with the cassava whitefly pests and the limitations on cassava productivity have been piecemeal (Macfadyen et al., 2018). Fermont et al. (2009) suggested that pests and diseases were relatively unimportant production constraints. However, there have been high cassava whitefly populations in East and Central Africa over time, causing yield losses of about 40% per year (Macfadyen et al., 2018). In the 1990s, a devastating CMD pandemic occurred in the region, originating in Uganda and progressed through East and Central Africa (Legg and Fauquet, 2004).

CMD continues to threaten cassava production in the Lake Victoria region, reducing yields by up to 80-90% (Vurro et al., 2010). Each year it is estimated that about 30% of the cassava harvest in Africa is lost to CMD, equivalent to $1.25 billion worth of production (Legg et al., 2006). Meanwhile, CBSD was listed amongst the seven most dangerous plant diseases globally because of the food security impacts in Africa (Pennisi, 2010).

The total economic losses to CBSD are estimated to be US$100 million annually (Pennisi, 2010). However, few studies have examined the impacts of cassava whitefly pests and diseases on productivity of smallholder production systems (Alene et al., 2013).

This study aims to fill this gap in the literature and provide a firm socio-economic basis against which to assess the impact of interventions to reduce the damage caused by whitefly and whitefly-vectored diseases. Furthermore, this study provides an up-to-date socio-economic assessment against which to measure the impacts of current and future investments in cassava research.

Against this background, we conducted a comprehensive socio-economic study to determine the status of cassava productivity in Malawi, Tanzania, and Uganda with the following research questions: (1) What is the status of cassava production and productivity in the study areas in Malawi, Tanzania, and Uganda? These are key baseline data against which any improvements in cassava productivity can be measured. (2) What is the impact of the cassava whitefly and diseases on smallholder farmers' productivity? A key objective of this paper was to document the impact of the cassava whitefly, as damage from direct feeding (and the production of sooty mould) can be as problematic as the viruses they vector. The data to show which of these is more impactful (cassava whitefly or the viruses they vector, or a combination of both) is not available. Farmers who use cassava varieties that are tolerant to diseases (so virus impacts are assumed to be low) still see losses from cassava whitefly feeding damage. Throughout our study, the data we collected includes impacts of both the cassava whitefly and disease, as this is what farmers observe. (3) What is the current adoption rate of improved cassava varieties in the study countries? These are also key baseline data required for future intervention evaluations in smallholder cassava production systems. There are significant changes throughout the three countries to the way cassava is grown (e.g. two seasonal plantings per year in Uganda versus one in Malawi, and the degree and type of intercropping changes) and its role in the farming system and farm household.

Few studies have examined the impacts of the cassava whitefly pests and diseases on the productivity of smallholder farmers (Alene et al., 2013). The impact of whitefly pests to smallholder production systems (that is, the trade-offs in the use of labour and inputs for cassava and other crops grown) is also not well understood. We address this issue by employing a farm-level stochastic production frontier (SPF) model, which incorporates "environmental factors" such as pests and diseases and socio-economic factors (Sherlund et al., 2002). Our paper offers two contributions relative to the existing literature. Firstly, it estimates the impacts of the cassava whitefly pests and diseases on the productivity of smallholder farmers. We illustrate these impacts by focusing on smallholder farmers' productivity and technical efficiency (TE). TE is a component of economic efficiency and reflects the ability of a farmer to maximize output from a given level of inputs (that is, output orientation). We recognize that there are gains in output that could be achieved in the short run by also improving allocative efficiency, but this was not the focus of the current study. Secondly, we provide preliminary estimates of the adoption of improved cassava varieties in Malawi, Tanzania, and Uganda. Our results can help design extension strategies and evaluate the effectiveness of potential interventions to control whitefly pests and diseases in East and Central Africa. The results will inform policymakers on how to increase efficiency by determining the extent of technical inefficiency prevailing in smallholder cassava systems and the potential sources of inefficiency to target interventions more appropriately. The results will also help ensure the long-term sustainability of scarce resources such as land and other inputs by identifying efficient use of resources committed to production of cassava in an optimal manner.

METHODOLOGY

This study is based on 2015/2016 cross-sectional data collected from a sample of smallholder cassava farmers in Malawi, Tanzania, and Uganda. A combination of methods was used to gather data for the study. These include household surveys, field observations, workshops, and literature reviews. The socio-economic data collected were analyzed using descriptive statistics such as means, standard deviation and frequency. The profitability of cassava production was determined using a gross margin (GM) analysis to gain insights into whether it influences the adoption of improved varieties. GM were calculated as the difference between the gross value of output and variable costs, using the prevailing input and output prices in the study countries. The impact of the cassava whitefly pests and diseases on the productivity of smallholder cassava farmers was analysed by using an SPF model. This section provides details of the methods and data used in the study.

Stochastic production frontier model

Given the influence of weather, pests, diseases, other exogenous factors and measurement errors on resource use efficiency in agriculture, a common approach for estimating TE involves the use of the stochastic production frontier (SPF) model. We employed the SPF model to examine the impacts of the cassava whitefly pests and diseases on productivity in smallholder production systems. SPF models have been widely used to study TE of farming systems in several African countries (Sherlund et al., 2002; Tchale and Sauer, 2007; Liu and Myers, 2009; Eze and Nwibo, 2014; Debebe et al., 2015; Ainembabazi et al., 2017; Baffoe-Bonnie and Kostandini, 2019; Missiame et al., 2021; Taffesse et al., 2021). However, with the exception of Sherlund et al. (2002), Baffoe-Bonnie and Kostandini (2019), many of the studies cited above neglect the influence of environmental factors such as pest and disease infestation, which may result in biased estimates of the production frontier. This is important because most farming systems in Africa are rain fed and production decisions are influenced by environmental and ecological factors (Sherlund et al., 2002). We employed a model that incorporates environmental factors such as pests and diseases and socio-economic factors in both the production frontier and the inefficiency functions. We specified the SPF model for cross-sectional data as follows (Kumbhakar et al., 2015):

$$ln y_i = f(x_i;\beta) + \varepsilon_i \tag{1}$$

$$\varepsilon_i = v_i - u_i \tag{2}$$

where: y_i represents cassava output of a single farm *i*, x_i is a vector (in logs) of input variables, β is a vector of parameters to be estimated, the composed error term (ε_i) is the sum or difference of a normally distributed disturbance (v_i), representing measurement and specification error, and a one-sided disturbance (u_i), representing production inefficiency. The v_i is assumed to be independently and identically distributed across observations as $v_i \sim N(0, \sigma_v^2)$. Several different distributional assumptions have been proposed for the u_i, the most common being a normal distribution truncated at zero (Aigner et al., 1977) and a half-normal distribution truncated at zero (Jondrow et al., 1982). Following Aigner et al. (1977), we assume that the inefficiency effects are independently distributed and u_i arises by truncation (at zero) of the normal distribution, with mean u_i and variance σ^2 ($u_i \sim N^+(\mu, \sigma_\mu^2)$).

Following Jondrow et al. (1982), the TE of an individual cassava farm was defined in terms of the observed output (y_i) to the corresponding frontier output (y_i^*). The y_i^* is the maximum output attainable given the existing production technology and assuming 100% efficiency.

$$TE_i = \frac{y_i}{y_i^*} = \frac{f(x_i;\beta).exp(v_i - u_i)}{f(x_i;\beta).exp(v_i)} = exp(-u_i) \tag{3}$$

Because $u_i \geq 0$, the ratio is bounded between 0 and 1, with $u_i = 1$ implying that the farmer is fully efficient technically. The value of $exp(-u_i) \times 100\%$ is the percentage of the maximum output that is produced by the individual cassava farm *i* (Battese and Coelli, 1988).

Translog stochastic frontier production function

The functional form employed in the empirical analysis is the translog stochastic frontier production function. We specified a flexible, functional form to account for non-linearity and interactive substitution and complementarity effects among the production factors. An alternative specification for production frontier is the Cobb-Douglas function which is nested within the translog function (Taylor and Shonkwiller, 1986). We tested empirically for the correct functional form of the model. We assumed separability of country functions and estimated separate SPF models for each country to account for differences in resource availability, technology, weather, pest and disease pressures, and socio-economic conditions across the various cassava systems in the study countries (Sherlund et al., 2002). The translog SPF model was specified as follows:

$$ln y_i = \beta_0 + \sum_{j=1}^{3} \beta_j ln x_i + \frac{1}{2} \sum_{j=1}^{3} \sum_{k=1}^{3} \beta_{j,k} ln x_{ij} ln x_{ik} + \tau_i + v_i - u_i \tag{4}$$

where: *i* subscript denoting the *i*[th] farm in each country. Three inputs were employed in the production frontier: land (acres) under cassava (x_1), number of bags of cassava cuttings (x_2), and total labor (x_3, measured in person-days) obtained by summing family and hired labour. Battese and Coeli (1992) suggested that family and hired labor are both productive. We tested this assumption empirically and accepted it in this study. Alene et al. (2006) also used total family labor, exchange labor and hired labor in person-days. Thus, only total labor days were included in the final model. Other inputs such as fertiliser and chemicals were dropped from the analysis because there was low usage across the smallholder cassava production systems in the study countries. We recognise that farmers make decisions on these inputs, and thus there might be an endogeneity variable problem. While there have been renewed efforts in addressing endogeneity in stochastic production functions (Amsler et al., 2016; Karakaplan, 2017), this topic is worthy of a separate investigation. We include district fixed effects dummy variables (τ_i) to account for the influence of agro-climatic factors (e.g., rainfall and temperature), and changes in the farming systems across the districts included in the study countries (Sherlund et al., 2002; Baffoe-Bonnie and Kostandini, 2019). Since these fixed effects dummy variables are common to all farms in a district, they capture region-specific unobserved heterogeneity across cassava production systems in the study countries. β_0 is a constant while β_i are coefficients to be estimated. We used robust standard errors clustered at the district level to account for heteroscedasticity in the model.

To assess the factors influencing inefficiency, we defined technical inefficiency as a function of farm-specific factors. The technical inefficiency function, comprising the vector of variables Z, was incorporated into the SPF model, assuming that they may indirectly influence efficiency. We assume that the mean of the truncated normal is data-dependent and a linear combination of our Z variables, as given in Equation 5. We followed the earlier studies which recommended jointly estimating both Equations 4 and 5 in a single-stage maximum likelihood estimation procedure (Battese and Coelli, 1995; Belotti et al., 2013; Koirala et al., 2016). We implemented the estimation procedure in Belotti et al. (2013) using the statistical software Stata version 16.The model was specified as:

$$u_i = \delta_0 + \delta_1 Z_1 + \delta_2 Z_2 + \delta_3 Z_3 + \delta_4 Z_4 + \delta_5 Z_5 + \delta_6 Z_6 + \delta_7 Z_7 + \delta_8 Z_8 + \delta_9 Z_9 + \delta_{10} Z_{10} + \delta_{11} Z_{11} + \delta_{12} Z_{12} + \delta_{13} Z_{13} + \delta_{14} Z_{14} + \delta_{15} Z_{15} \quad (5)$$

Where the Z's are socio-economic variables including:

(i) Z_1 is the gender of the household head (a dummy variable with the value of 1 if yes and zero if otherwise),
(ii) Z_2 is the education level of the farmer in years,
(iii) Z_3 is farming experience in years,
(iv) Z_4 is household size,
(v) Z_5 is farm size in acres,
(vi) Z_6 is land tenure measured using categorical variables. We divided tenure into four categories: freehold, leasehold, customary and other forms such as squatters,
(vii) Z_7 is membership in a farmers' group (a dummy variable, with the value of 1 if yes and zero if otherwise),
(viii) Z_8 is access to credit (a dummy variable, with the value of 1 if yes and zero if otherwise),
(ix) Z_9 is access to extension services (dummy variable, with the value of 1 if yes and zero if otherwise),
(x) Z_{10} is a dummy variable for intercropping systems to test their effects on the output of cassava farmers.
(xi) Z_{11} is a dummy variable for improved cassava varieties which is included to test whether or not they directly affect productivity (Sherlund et al., 2002),
(xii) Z_{12} is the distance (km) to the nearest market,
(xiii) Z_{13} is the distance (km) to the district headquarters,
(xiv) Z_{14} is the plot altitude (meters above sea level),
(xv) Z_{15} represents the cassava whitefly pest and disease infestation. We used farmer estimated yield losses as our proxy measure of productivity impacts (Sherlund et al., 2002),
(xvi) δ_0–δ_{16} are parameters to be estimated.

Since the dependent variable is technical inefficiency as opposed to TE, we expect the parameters δ_1 δ_{11} to have negative signs while δ_{12} δ_{15} to have positive signs. Several hypotheses were tested using a generalised likelihood ratio test. The first null hypothesis tested whether technical inefficiency effects are absent ($\sigma_u^2 = 0$) and was specified as $H_0{:}\,\gamma = 0$, where $\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$ and its value ranged between 0 and 1 (Kumbhakar et al., 2015). This test was conducted against the full SPF model. The second null hypothesis was whether the correct functional form of the SPF model in Equation (4) was a Cobb-Douglas function. The third null hypothesis was whether the explanatory variables influence the inefficiency function in Equation 5. Given the assumption that the inefficiency effects are distributed as a truncated normal, the null hypothesis was that the matrix of parameters is zero ($H_0{:}\,\delta_1 = \delta_2 = \cdots = \delta_{10} = 0$).

Finally, we followed other studies and evaluated the elasticity of output with respect to the k[th] input variable (ε_k) at the mean values of the data points as follows (Hong et al., 2019):

$$\varepsilon_k = \frac{\partial lny}{\partial lnx_k} = \beta_k + 2\beta_{kk}\, ln\bar{x}_k + \sum \beta_{kj}\, ln\bar{x}_{ji} \quad (6)$$

where: $\bar{x}$ are the means of input variables used in the production frontier. The elasticity (ε_k) measures the responsiveness of output to a 1% change in the *k*th input. Returns to scale (RTS) measure the sum of all production elasticities for all the inputs or the proportionate change in output if all the inputs were changed simultaneously by 1% (Coelli et al., 2005). The various forms of RTS are increasing ($\varepsilon_p > 1$), constant ($\varepsilon_p = 1$), and decreasing ($\varepsilon_p < 1$). By restricting the sum of output elasticities of all inputs to be equal to 1, we can test the assumption of constant returns to scale.

Study areas

The study was conducted in Malawi, Tanzania, and Uganda, and it focused on areas with high cassava whitefly populations and districts most affected by disease (CMD and CBSD) outbreaks. We targeted areas with similar biophysical and socio-economic characteristics to identify a clear causal influence and effects on households. The study involved the design and development of survey tools, training of enumerators, workshops and pre-testing of survey tools and questionnaires in the study countries. In Uganda, the study specifically targeted the major cassava-producing districts in the north (Apac), central (Nakasongola and Kiryandongo), and eastern regions (Serere, Tororo, and Kamuli). Apac district is located within the northeastern savanna grassland agro-ecological zone while Kamuli, Serere and Tororo are situated within the Kyoga plains agro-ecological zone. Both zones are characterized by lowland rainfed conditions with annual rains averaging 1215-1328 mm (usually two seasons per year) and temperature ranges of 15-32.5°C. Altitude ranges from 914-1800 m.a.s.l. Nakasongola and Kiryandongo on the other hand are situated within the pastoral rangeland agro-ecological zone and receive relatively less average annual rainfall of about 915-1021 mm which also comes in two seasons per year with temperature ranges of 12.5-30°C and an altitude range of 129-1524 m.a.s.l. In Tanzania, the survey covered the districts of Geita, Musoma rural, Rorya, and Ukerewe. These districts are around Lake Victoria, experiencing bimodal rainfall with annual of 1,200 mm during long rains and 415 mm on short rains, with annual mean tpreture range of 28 to 15.8°C. The topography is generally undulating with the soils varying from the red friable clays north of Geita town to the more dominant brown, the yellow red loamy sands and sands in Ukerewe island. In Malawi, the study targeted the main growing areas in the northern belt along the lakeshore (Karonga, Nkhata Bay, and Nkhotakota) and the central belt (Lilongwe). Malawi is classified into three agro-ecological zones based on soil factors, altitude, the amount, duration, and variability of rainfall, and temperature regimes: the Lower Shire valley; the lakeshore plains and Upper Shire valley; and the mid-altitude plateau, with the highlands sometimes counted as a fourth. There are two distinct seasons: a wet, warm season from October to April,

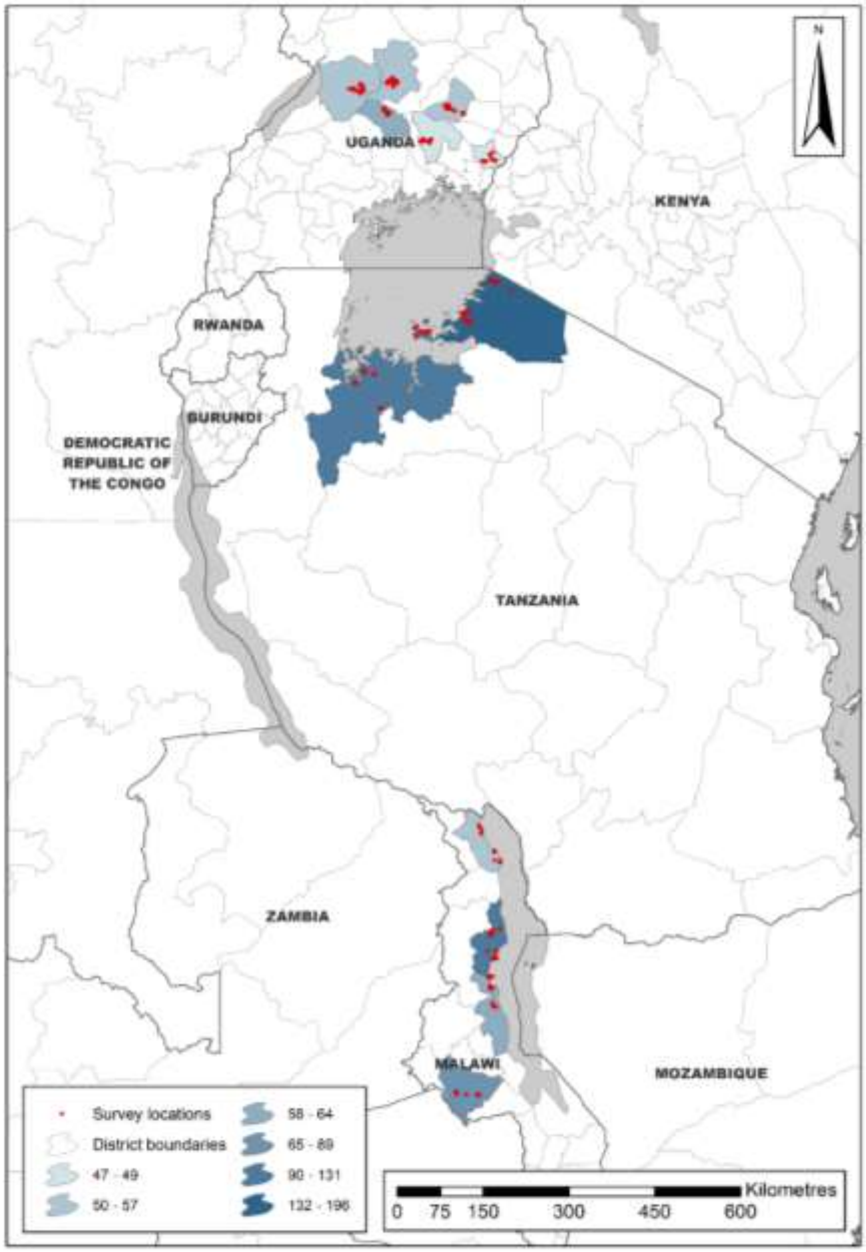

Figure 2. Number of sample households (per 3 km × 3 km grid) in Malawi, Tanzania, and UgandaData
sources: Farmer surveys, 2015/2016.

and a dry, cool season from May to September. Figure 2 shows the distribution of sample households across selected cassava production regions.

Sampling procedure and data collection

We obtained data and information from primary and secondary sources. The primary data were collected from a sample of 1,200 cassava farmers across Malawi, Tanzania, and Uganda. A multi-stage sampling procedure was used to select respondents. In the first stage of the sampling procedure, six districts in each country were purposively selected based on their cassava production statistics in past years. Each district was assigned an equal number of sample households. The second stage was the random selection of 4–6 villages within the selected districts and finally, the random selection of 50 cassava households per village. This gave a total of 1200 households: 450 in Uganda, 400 in Malawi, and 350 in Tanzania. The sampling strategy ensured an unbiased and representative sample of the population of cassava farmers in the study areas. We generated the sampling frame from which farmers were selected randomly from a list of farmers obtained from the district agricultural officers in each country. Figure 2 shows the distribution of households across districts in each country. It was desirable to have a sample representative of all cassava farmers in the country for generalisation. We used sampling weights specified as the inverse of the probability of inclusion of the observations to fit the regressions (Cameron and Trivedi, 2010).

Data were collected using a pre-tested structured questionnaire completed during face-to-face interviews by trained enumerators and extension staff with individual farmers.[2] Respondents were interviewed by appointment, made through the district extension workers and contact farmers. Pre-testing was conducted on 20 farmers in each country to assess the suitability of the questionnaire. Data collected included socio-economic characteristics of respondents such as age, gender, education levels, household income, and quantities of inputs used in cassava production, such as cassava acreage, output, labor, prices, cassava variety, and impacts of whitefly pests and diseases. The respondents were provided with additional information, including color pictures of the cassava whitefly pests and diseases with associated symptoms to minimise potential bias from farmers self-assessment. Field observations supplemented information obtained from interviews. The final surveys were conducted during October 7-31, 2015 in Uganda and Malawi and August 15-21, 2016 in Tanzania. The survey questionnaire took on the average, 2–3 hours to be completed by a respondent. It was reviewed and approved by the CSIRO Ethics Committee before its release in 2015 and 2016.

RESULTS AND DISCUSSION

Descriptive statistics of the survey sample

Table 1 presents the descriptive statistics of the sample. In terms of farming systems characteristics, the average farm size was significantly higher ($P < 0.05$) in Uganda (9.84 acres) and Tanzania (4.26 acres) than in Malawi (2.70 acres). On average, cassava occupied 2 acres (or 51%) of the total farm size in the study countries, but the proportion of land under cassava was much lower in Uganda (22%). Cassava output was also higher in Uganda than in Tanzania and Malawi, and a greater proportion was sold at markets (54%). On average, improved cassava varieties are profitable across the study countries. The average cassava farmer in this sample used approximately 6 bags of planting material per acre and employed about 112 person-days of family labor per acre, and 47 person-days of hired labor per acre from outside the household (Table 1). These figures indicate that labor remains a key constraint for smallholder cassava production systems in the three study countries.[3] Daniels et al. (2011) found labor to be a costly input in their study of the cassava value chain in Niger. Another study by Fermont et al. (2010) reported labor to be a costly input in their study of cassava production in Kenya and Uganda. Improved cassava varieties were widely adopted by farmers in Uganda (70%) and Malawi (51%), compared to Tanzania (11%). More than one-third of the sample practised legume intercropping system. However, there was little usage of chemical fertiliser and pesticides (Table 1). Nweke (1996) reported that less than 10% of cassava farmers used inorganic fertilisers in Africa. In general, non-labour inputs are undersupplied to cassava farmers. The reasons for the undersupply include uncoordinated distribution networks for inputs, limited private sector involvement in fertiliser supply, and high distribution costs to remote farmers (Daniels et al., 2011). High input costs are also a major barrier for smallholder farmers. Furthermore, little information is currently available regarding cassava's yield response to fertiliser in East Africa (Fermont et al., 2008). However, a study by Biratu et al. (2018) reported that cassava productivity can be improved through the integrated use of NPK and manure in Zambia. In Brazil, a study also showed that cassava varieties are responsive to fertilisation (Jala et al., 2019).

Most survey respondents (75%) were aware of whitefly pests and diseases before this survey. The respondents reported a high incidence (>80%) of cassava whitefly and diseases in their cassava fields consistent with other studies (Chipeta et al., 2016). These impacts were asymmetrically distributed, with higher mean impacts reported in Uganda and Tanzania compared to Malawi (Table 1). We recognise that farmers' self-assessment of the impacts may be biased, and the severity of pests and disease symptoms in plants is not always correlated with the degree of yield loss (Hillocks et al., 2016). However, our results match field surveys reported by other studies and highlight the magnitude of the whitefly problem. For example, Legg and Fauquet (2004) estimated that cassava whiteflies caused 30-40% cassava yield losses. In Tanzania, a similar field trial conducted by Hillocks et al. (2001) showed that CBSD could decrease root weight in the most sensitive cultivars by 70%. In Uganda, a recent trial protected cassava plots of clean cuttings from whitefly infestation using insecticides. The root and stem yield losses of greater than 60% were recorded in the unprotected control plots. This loss was primarily due to the direct impacts of the whitefly (as disease pressure was low) (Omongo et al., 2022). Therefore, as estimated by farmers (Table 1), our survey results fall near the range of experimental and published estimates. The patterns in several socio-economic factors were consistent across the three countries (Table 1).

Male cassava farmers headed more than 65% of the sample households. This statistic is consistent with national figures in the study countries. For instance, only three in ten households in Malawi were headed by women in 2015/2016 (National Statistical Office (NSO), 2017). Furthermore, we argue that the proportion of female cassava farmers was low in this study because the land ownership systems in these countries favor men and household decision-making on land use is dominated by men (Kassie et al., 2013, 2015). The average age of

[2] The survey was conducted by the CSIRO in collaboration with the respective countries National Agricultural Research Institutions. These included the National Root Crops and Resources Research Institute in Uganda, Mikocheni Agricultural Research Institute and Agricultural Research Institute Ukiriguru in Tanzania, and the Department of Agricultural Research Services in Malawi.

[3] A caveat is noted here. A reviewer observed that since family labor may be residents on the farm and since they are unpaid, they may not be performing any significant economic function on the farm. However, most smallholder farmers depend on family labor for their farm operations (Alene et al., 2006). The implication is that family labor is likely to be overestimated in the study. We thank the reviewer for pointing out this limitation.

Table 1. Descriptive statistics of the sample.

Variable	Malawi (n=400)	Tanzania (n=350)	Uganda (n=450)	Pooled (n=1200)
Farm characteristics				
Cassava yield (kg/acre)	2,929 (1,907)	6,290 (1,268)	9,381 (3,057)	6,200 (4,194)
Farm size (acres)	2.69 (1.97)	4.26 (3.54)*	9.84 (20.10)***	5.60 (8.54)
Cassava acreage (acres)	1.44 (2.19)	2.46 (1.83)	2.21 (3.30)	2.04 (2.44)
Share of land under cassava (%)	53	58	22	44
Proportion of cassava sold (%)	9.14 (16.76)	34.86 (20.18)	53.88 (38.46)	32.63 (25.13)
Net income ($/acre)	70.40	149.42	84.80	101.54
Benefit/cost ratio (BCR)	3.00	7.4	5.00	4.50
Cassava cuttings (bags/acre)	5.88 (1.49)	6.57 (6.33)	6.15 (2.10)	6.20 (3.31)
Family labor (person-days/acre)	106.32 (113.20)	116.9075 (111.0875)	70.95 (96.29)	112.25 (168.96)
Hired labor (person-days/acre)	12.73 (26.29)	15.96 (33.31)	34.03 (78.73)	47.19 (53.20)
Total labor (person-days/acre)	119.48 (113.00)	126.34 (113.84)	104.79 (128.85)	116.87 (118.56)
Improved cassava variety (1/0)	0.51 (0.50)	0.11 (0.31)	0.70 (0.57)	0.44 (0.43)
Intercropping system (1/0)	0.36 (0.47)	0.71 (0.45)	0.30 (0.46)	0.46 (0.46)
Inorganic fertiliser (%)	3.0	0.0	0.0	1.0
Pesticide use (%)	2.0	2.0	1.0	1.7
Pest and disease variables				
Whitefly infestation (1/0)	0.62 (0.48)	0.98 (0.14)	0.64 (0.48)	0.75 (0.37)
CMD incidence (1/0)	0.67 (0.47)	0.95 (0.22)	0.78 (0.42)	0.80 (0.37)
CBSD incidence (1/0)	0.57 (0.49)	0.98 (0.13)	0.84 (0.37)	0.80 (0.33)
CMD impacts on yield (%)	17.28 (12.68)	43.55 (23.23)	38.42 (23.73)	33.08 (19.88)
CBSD impacts on yield (%)	18.39 (13.56)	54.03 (22.72)	49.43 (30.25)	40.62 (22.18)
Altitude (m)	654.48 (260.42)	1221.61 (104.88)	1073.60 (100.13)	983.23 (155.14)
Socio-economic characteristics				
Age of HHH (yrs.)	47.41 (15.16)	51.07 (13.49)	46.06 (14.65)	48.18 (14.43)
Age of spouse (yrs.)	38.29 (13.37)	42.17 (11.64)	38.28 (13.52)	39.58 (12.84)
Farming experience (yrs.)	19.35 (13.18)	27.73 (14.04)	18.13 (12.54)	21.74 (13.25)
Male household head (%)	65	80	76	73.67
Education of HHH (yrs)	5.88 (3.38)	8.72 (5.94)	8.13 (4.13)	7.58 (4.48)
Education of spouse (yrs.)	5.15 (3.25)	8.72 (5.95)	5.97 (3.69)	6.61 (4.30)
Household size (number)	6.32 (2.65)	7.52 (3.75)	8.56 (3.91)	7.47 (3.44)
Adult females (number)	1.83 (1.11)	1.99 (1.23)	2.16 (1.66)	1.99 (1.33)
Adult males (number)	1.59 (1.12)	2.07 (1.28)	2.21 (1.85)	1.96 (1.42)
Children<15 yrs (number)	2.92 (1.69)	4.40 (2.47)	4.24 (2.37)	3.85 (2.18)
Institutional characteristics				
Access to credit (%)	16	22	33	23.67
Member of organization (%)	34	43	47	41.33
Access to extension services (%)	45	31	28	34.67
Extension visits (number)	5.39 (3.03)	3.48 (4.24)	2.62 (2.03)	3.83 (3.10)
Distance to market (km)	4.86 (25.39)	4.56 (12.19)	4.66 (5.73)	4.69 (4.44)
Walking time to market (hours)	1.85 (6.62)	-	1.47 (3.13)	1.68 (5.29)
Land tenure				
Freehold (dummy)	0.09 (0.29)	0.38 (0.49)	0.28 (0.45)	0.25 (0.41)
Leasehold (dummy)	0.01 (0.10)	0.01 (0.09)	0.04 (0.19)	0.02 (0.13)
Customary (dummy)	0.87 (0.34)	0.59 (0.49)	0.62 (0.49)	0.59 (0.43)
Others (dummy)	0.03 (0.17)	0.03 (0.16)	0.06 (0.23)	0.04 (0.20)
Livestock ownership (%)	85	90	97	90.67

Significance levels: * p<0.05; ** p<0.01; *** p<0.001. HHH= Household Head; CMD is Cassava Mosaic Disease; CBSD is Cassava Brown Streak Disease.
Source: Field surveys, 2015/16. Figures in brackets are standard deviations.

Table 2. Hypotheses tests for the stochastic frontier and technical inefficiency function.

Null hypothesis	Likelihood ratio stat	Critical value (5%)	Decision
Malawi			
1. No stochastic frontier ($\gamma = 0$)	587.00	5.138	Reject
2. Cobb-Douglas frontier ($\beta_4 = \beta_5 = \cdots = \beta_9 = 0$)	31.47	12.592	Reject
3. No technical inefficiency functn. ($\delta_1 = \delta_2 = \ldots = \delta_{15} = 0$)	7.05	3.84	Reject
Tanzania			
1. No stochastic frontier ($\gamma = 0$)	430.41	5.138	Reject
2. Cobb-Douglas frontier ($\beta_4 = \beta_5 = \cdots = \beta_9 = 0$)	35.70	12.592	Reject
3. No technical inefficiency functn. ($\delta_1 = \delta_2 = \ldots = \delta_{15} = 0$)	7.44	3.84	Reject
Uganda			
1. No stochastic frontier ($\gamma = 0$)	418.89	5.138	Reject
2. Cobb-Douglas frontier ($\beta_4 = \beta_5 = \cdots = \beta_9 = 0$)	39.63	12.592	Reject
3. No technical inefficiency functn. ($\delta_1 = \delta_2 = \ldots = \delta_{15} = 0$)	7.57	3.84	Reject
Pooled			
1. No stochastic frontier ($\gamma = 0$)	275.13	5.138	Reject
2. Cobb-Douglas frontier ($\beta_4 = \beta_5 = \cdots = \beta_9 = 0$)	21.03	12.592	Reject
3. No technical inefficiency functn. ($\delta_1 = \delta_2 = \ldots = \delta_{15} = 0$)	8.077	3.84	Reject

The critical values for the test statistics are from a mixed chi-squared distribution and were drawn from Table 1 of Kodde and Palm (1986).
Source: Farmer surveys, 2015/2016

cassava farmers in the sample was about 48 years. The average educational attainment of cassava farmers was approximately 8 years across the three countries. Similarly, the average household size was seven persons across the sample. It should be noted that larger household sizes have advantages in providing labor for cassava production. Overall, these statistics suggest that the sample was representative of the general profile of farmers in the study countries. For example, comparison with national statistics for Malawi (NSO, 2017), Tanzania (National Bureau of Statistics (NBS), 2018) and Uganda (Uganda Bureau of Statistics (UBOS), 2017) indicates that the sample age, education, and household size were not significantly different to that of the general population. In terms of institutional factors, there was variation across the study countries, but most cassava farmers lacked access to credit, and only 41% were members of a farmers' group. A related issue here is market access, which can affect transaction costs for cassava farmers in accessing information, planting materials, technologies, and support institutions. The average "walking distance" to the nearest market (a proxy for market access) was about 5 km and the average "walking time" to the nearest market 1.8 h. The implication is that cassava farmers are missing access to enable them to exploit gains that may come with such support services.

Stochastic production frontier models

The hypotheses about the SPF model were tested using generalized likelihood ratio tests, as summarized in Table 2. The tests were used to confirm the correct functional form of the model. The model was initially specified as a translog production frontier in all cases. The hypothesis that the correct functional form of the model is Cobb-Douglas was imposed by testing the squared and cross-product terms from the translog production function ($H_0: \beta_{i,k} = 0$). The results showed that at the 5% level of significance, (1) the SPF model is appropriate (H_0: $\gamma = 0$ is rejected); (2) the Cobb-Douglas functional form is rejected for all the models and (3) the technical inefficiency function depended on the vector of explanatory variables (H_0: $\delta 1 = \delta 2 = \ldots = \delta 15 = 0$ is rejected). To examine the effects of omitting environmental factors, we estimated the production frontier with and without the environmental variables (Sherlund et al., 2002). Tables 3 and 4 reports parameter estimates of the translog SPF models without and with environmental factors, respectively. The SPF models were all statistically significant and appropriate, based on the Wald chi-square statistics ($P < 0.05$). The variance ratios (gamma, γ) is significantly different from zero across all the models, suggesting that the variations in

Table 3. Stochastic production frontier estimates for cassava farms in Malawi, Tanzania, and Uganda (without environmental factors).

Variable	Malawi	Tanzania	Uganda	Pooled
ln (Land)	0.21 (0.16)**	0.25 (1.21)*	0.75 (1.15)***	0.82 (1.03)**
ln (Cuttings)	0.34 (0.28)*	0.80 (0.96)*	0.54 (0.51)*	0.59 (0.27)*
ln (Total labor)	0.93 (0.28)***	0.10 (0.29)*	0.90 (0.52)*	0.11 (0.54)*
ln $(\text{Land})^2$	-0.01 (0.74)	-0.14 (0.34)*	-0.45 (0.23)*	-0.44 (0.09)***
ln $(\text{Cuttings})^2$	0.03 (0.04)*	0.10 (0.14)*	0.03 (0.02)*	0.01 (0.01)*
ln $(\text{Total labor})^2$	-0.12 (0.04)**	-0.10 (0.03)**	-0.04 (0.03)*	-0.04 (0.03)
ln (Land) x ln (Cuttings)	-0.34 (0.13)**	-0.18 (0.44)*	-0.22 (0.14)*	-0.09 (0.08)*
ln (Land) x ln (Total labor)	-0.30 (0.28)*	0.10 (0.18)*	-0.34 (0.13)**	0.05 (0.20)*
ln (Cuttings) x ln (Total labor)	0.02 (0.10)*	0.40 (0.21)*	0.040 (0.08)*	0.08 (0.05)*
Constant	5.37 (1.01)***	7.36 (1.69)***	1.10 (2.07)	6.77 (1.90)***
Diagnostic statistics				
Sigma-u (σ_u)	0.39 (0.07)***	0.62 (0.10)***	1.66 (0.14)***	0.84 (0.07)***
Sigma_v (σ_v)	7.72 (2.42)***	35.61 (3.01)***	57.94 (8.35)***	6.38 (1.33)***
Gamma (γ)	0.05 (0.03)***	0.02 (0.03)***	0.03 (0.02)**	0.13 (0.05)***
Log-likelihood	-676.12	-245.73	-639.44	-1404.16
Wald chi^2	460.74	941.02	137.40	208.45
AIC	1384.23	525.46	1312.88	2836.32
BIC	1446.94	578.47	1375.21	2899.23
Obs.	400	350	450	1200

Legend: * $p<0.05$; ** $p<0.01$; *** $p<0.001$.
Source: Farmer surveys, 2015/2016

cassava output are not a result of randomness and unobserved heterogeneities, but due to farmers' inefficiencies in resource use. The gamma (γ) values suggest that approximately 20-73% of the sample variation in inefficiency was explained by the set of exogenous factors in the full specification model (Table 4).

Since the initial focus here is model comparison, we limit the presentation of estimates in Table 4 to the key variables of interest. For model selection, we used the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) statistics.[4] The statistical superiority of the full model specification is apparent based on the AIC/BIC statistics. We found differences in AIC/BIC metrics across the models with and without environmental factors to be definitive in all cases. We found that the full specification performs better across all models considered (Tables 3 to 4) with large AIC/BIC differences. The full specification model clearly demonstrates a better overall fit. This suggests likely omitted variable bias in the estimates without environmental factors (Sherlund et al., 2002). Thus, going forward we focus on the full specification model in Table 4.The results of the full SPF model estimation indicate that cassava output is significantly correlated with land area, the number of cuttings used, and total labor used (Table 4). The output elasticities are positive and statistically significant which is consistent with the production regularity condition of monotonicity (Sauer et al., 2006; Moreira and Bravo-Ureta, 2010). This implies that a 1% increase in the quantity of one input, *ceteris paribus*, will increase output by the magnitude of the output elasticity. For example, the elasticity of output to cassava stem cuttings is 0.50 in the pooled model, and is the second largest contributor to cassava output. Thus, a 1% increase in the current level of cuttings increases cassava output by 0.50%. Land is the largest contributor to cassava output in the pooled model, with an elasticity of 0.67.

This implies that a 1% increase in the current level of land employed by farmers results in an increase of about 0.67% in cassava output. These findings are consistent with existing studies of cassava production systems in Africa, which show that land, cuttings, and labor are important determinants of cassava output (Eze and Nwibo, 2014; Dogba et al., 2021; Missiame et al., 2021; Tafesse et al., 2021). Tafesse et al. (2021) found that land size, urea fertiliser application and cassava planting

[4] Burnham and Anderson (2004) provide a rule of thumb for interpreting the difference between the minimum AIC value (AIC_{min}) and any alternative model *i* (AIC_i) defined as $\Delta_i = AIC_i - AIC_{min}$. The best model has Δ_i=0, and all other models have Δ_i>0. The larger the Δ_i for any model, the less plausible it is. Burnham and Anderson propose that (1) if Δ_i<=2, there is substantial support for model *i*; (2) if 4<=Δ_i<=7, then there is less support; and (3) if Δ_i>10, then there is no support. Concerning the BIC, Raftery (1995) argues that a BIC difference of 10 clearly indicates a less preferred model.

Table 4. Stochastic production frontier estimates for cassava farms in Malawi, Tanzania, and Uganda (with environmental factors).

Variable	Malawi	Tanzania	Uganda	Pooled
ln (Land)	0.64 (0.08)**	0.56 (0.02)***	0.47 (0.55)***	0.67 (0.16)**
ln (Cuttings)	0.18 (0.47)*	0.07 (0.06)**	0.52 (0.69)*	0.50 (0.23)*
ln (Total labor)	0.19 (0.98)*	0.15 (0.02)**	0.29 (0.57)*	0.10 (0.41)*
ln $(\text{Land})^2$	-0.16 (0.22)	-0.03 (0.01)*	-0.28 (0.77)**	-0.17 (0.45)*
ln $(\text{Cuttings})^2$	0.08 (0.02)**	0.05 (0.01)*	0.02 (0.03)*	0.10 (0.02)*
ln $(\text{Total labor})^2$	-0.23 (0.21)	-0.21(0.01)*	-0.02 (0.03)	-0.02 (0.03)*
ln (Land) x ln (Cuttings)	-0.82 (0.71)**	-0.64 (0.01)**	-0.46 (0.20)*	-0.10 (0.08)*
ln (Land) x ln (Total labor)	-0.28 (0.66)*	0.04 (0.01)***	-0.39 (0.16)*	-0.01 (0.16)*
ln (Cuttings) x ln (Total labor)	0.33 (0.10)**	0.39 (0.01)***	0.24 (0.12)*	0.05 (0.04)*
Constant	8.42 (2.13)*	14.79 (3.48)***	10.79 (2.43)*	5.08 (1.38)**
Districts		-	-	
Lilongwe	-0.93 (0.24)***	-	-	-
Nkhata Bay	-0.21 (0.20)***	-	-	-
Nkhotakota	-1.16 (0.25)***	-	-	-
Butiama	-	-1.99 (0.43)***	-	-
Musoma	-	-1.22 (0.25)***	-	-
Rorya	-	-0.82 (0.28)**	-	-
Ukerewe	-	-1.30 (0.27)***	-	-
Apac	-	-	1.31 (0.55)*	-
Kamuli	-	-	2.79 (0.85)***	-
Kiryandongo	-	-	0.04 (0.19)	-
Nakasongola	-	-	1.75 (0.64)**	-
Serere	-	-	0.84 (0.49)	-
Diagnostic statistics				
Sigma-u (σ_u)	0.55 (0.26)**	0.20 (0.27)***	0.39 (0.68)**	0.66 (0.13)***
Sigma_v (σ_v)	0.76 (0.12) ***	0.39 (0.01)***	1.44 (0.10)***	2.87 (0.37)***
Gamma (γ)	0.73 (0.34) ***	0.52 (0.27)***	0.27 (0.71)**	0.23 (0.20)***
Log-likelihood	-120.04	-249.24	-258.33	-533.06
Wald chi^2	587.00	430.41	300.38	298.32
AIC	222.67	183.08	618.66	1130.12
BIC	309.22	298.98	770.47	1247.00
Obs.	400	350	450	1200

Variable definitions are given in the text. standard errors in parentheses. Significance levels: * p<0.05; ** p<0.01; *** p<0.001. Country fixed effects included in the pooled model.
Source: Farmer surveys(2015/2016).

material all had a positive and significant effect on cassava production in Southern Ethiopia. The finding on land, labor and cuttings are also consistent with those of Eze and Nwibo (2014) from Nigeria. Land and labor appear to be substitute inputs, as indicated by their statistically significant negative second-order effect in the pooled model. By contrast, the quantity of cuttings and labor are complementary inputs, as indicated by their statistically significant positive second-order effects across the study countries.

The second-order terms (interaction terms) represent the second-order derivatives of the translog production function. A positive coefficient suggests incremental changes in the marginal physical product (MPP) with every 1% increase in factor levels and vice versa, *ceteris paribus*. The squared term of land and labor were negative and statistically significant ($p < 0.01$) in the pooled model (Table 4). The negative coefficients of land and labour suggest that the MPP will fall with every additional unit they employ, thereby having negative effects on total cassava output. This suggests that cassava farmers are overusing land and labour. The squared term of cuttings was positive and statistically significant ($p < 0.01$) in the pooled model. The implication is that the current level of cuttings employed by cassava farmers is sub-optimal. In production theory, cassava farmers would be said to be operating in stage I, where the MPP of cuttings is still rising. Therefore, it is recommended for cassava farmers to increase the units of cuttings they employ, *ceteris paribus*.

We included a set of dummy variables for each district in the model for each country. The districts with the largest number of observations were selected to be the omitted reference group for consistency. The coefficients of the district dummy variables were significant indicating substantial differences in cassava output amongst the districts included in the study (Table 4). In Malawi, cassava farmers in Lilongwe, Nkhata Bay and Nkhotakota produced significantly less output than those in Karonga district. Similarly, in Tanzania, cassava farmers in Butiama, Musoma, Rorya and Ukerewe districts had significantly less output than those in the Geita district. In Uganda, cassava output was significantly higher among farmers located in the districts of Apac, Kamuli and Nakasongola than in Tororo district. This result is consistent with national statistics which shows that these districts dominate production, contributing about two thirds of total cassava production in Uganda (UBOS, 2021). These results may be explained by the differences in agro-climatic factors such as rainfall and temperatures and cassava production systems in those districts.

In Table 5, we report the elasticity of production with respect to input variables. The estimated values of output elasticities for all inputs are positive, suggesting that the estimated translog production frontier model is a well-behaved production technology.

Additionally, all elasticity estimates were statistically significantly different from zero ($p < 0.05$). We found that total labor and land have the highest output elasticity across the three countries. The sum of production elasticities with respect to input variables was 1.9, 1.1, and 1.1 for Malawi, Tanzania, and Uganda, respectively. This result implies that cassava farms are operating in the increasing RTS region of the production frontier, suggesting they are in the "irrational" production stage. In this stage, cassava farmers tend to be inefficient in using resources.

Technical efficiency estimates

To compare the efficiency level across the three countries, we computed the distribution of TE scores of cassava farms (Figure 3). Table 6 shows summary statistics for TE by country. The mean TE of cassava farms was highest in Uganda (0.77), followed by Malawi (0.58) and Tanzania (0.53). This finding implies significant room for improvement and that efficiency levels could be increased through better use of available technologies and the same level of inputs. We examined the effects of omitting environmental variables on the estimates of TE. We found a large increase in the estimated mean and median TE under the full specification model (Table 6). This shows that the omission of environmental factors leads to a substantial downward bias in estimates of TE. This finding is in agreement with those of Sherlund et al. (2002) and Baffoe-Bonnie and Kostandini (2019) who demonstrated that accounting for environmental factors has a significant impact on farmers TE scores.

Our results indicate that accounting for environmental factors reduces inefficiencies that otherwise may be attributed to the characteristics of smallholder farmers. We argue that it may be more cost-effective to improve efficiency than to introduce new technologies if farmers are not optimizing the use of existing ones. The finding is consistent with other studies of cassava production systems. A survey byBravo-Ureta and Evenson (1994) estimated an average economic efficiency of 52% for smallholder cassava farmers in Paraguay, showing considerable room for productivity gains through better use of available resources and the given technology. We constructed confidence intervals around the mean scores using the approach of Horrace and Schmidt (1996), which showed significant variation in TE scores among cassava farms that may arise from their characteristics and existing technologies (Table 6).

To further explore the impacts of the cassava whitefly pests and diseases, we disaggregated the mean TE scores by infestation status of the cassava farms. Figure 4 is a plot of mean TE by the cassava whitefly, CMD and CBSD infestation status. This plot shows that the mean TE score was significantly lower (0.50) for cassava farms with whitefly (0.58), CMD (0.55) and CBSD (0.52) infestation than those without infestation (0.80 on average). The difference is especially large for CBSD/CMD in Malawi and Malawi (Figure 4). In other words, the TE scores were worse when cassava whitefly pests and diseases came into the smallholder cassava production systems. These results underscore the need for policies to ensure that cassava farmers have better access to improved inputs, especially clean planting materials.

Determinants of technical inefficiency

We return to the estimated technical inefficiency function in Table 7, where a negative sign indicates a decrease in technical inefficiency or an increase in TE. Focusing on the primary variable of interest, the coefficients of the cassava whitefly pest and disease infestation were positive and statistically significant in explaining farmers' inefficiency across all three countries.

This indicates that the whitefly and disease infestations contributed to higher levels of technical inefficiency of cassava farmers. This finding contradicts Fermont et al. (2009), who suggested that pests and diseases were relatively unimportant as production constraints for cassava farmers in Uganda. On the contrary, the use of

Table 5. Output elasticities for cassava production in the study countries.

	Malawi	Tanzania	Uganda
Land	0.70 (0.22)***	0.46 (0.18)**	0.26 (0.32)***
Cuttings	0.80 (0.32)**	0.15 (0.20)*	0.38 (0.36) *
Total labour	0.46 (0.93)*	0.51 (1.07)**	0.48 (0.62)**
Returns to scale (RTS)	1.96	1.12	1.12

Notes: Figures in brackets are standard errors.
Source: Farmer surveys (2015/2016).

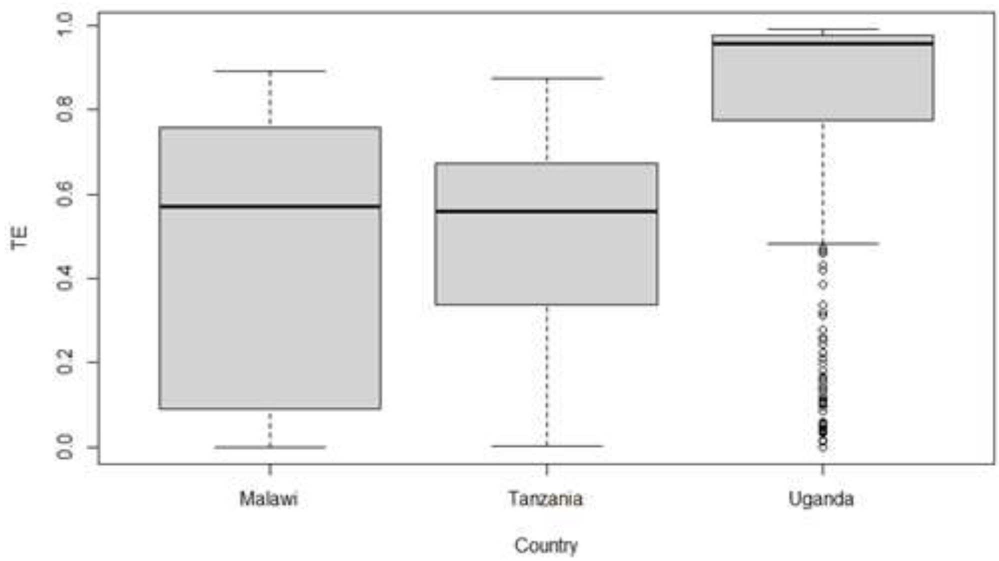

Figure 3. Distribution of TE scores of smallholder cassava farmers.
Source: Farmer surveys (2015/2016).

Table 6. Technical efficiency summary statistics.

Country/variables	Malawi		Tanzania		Uganda	
	Without env. factors	With env. factors	Without env. factors	With env. factors	Without env. factors	With env. factors
Mean	0.36	0.58	0.50	0.53	0.39	0.77
95% CI	0.01-0.99	0.01-0.99	0.01-0.99	0.01-0.91	0.01-0.89	0.01-0.98
Median	0.37	0.59	0.57	0.58	0.42	0.92
Minimum	0.01	0.03	0.01	0.01	0.01	0.01
Maximum	0.91	0.99	0.90	0.91	0.73	0.98

Source: Farmer surveys (2015/2016).

improved cassava varieties had a positive and significant influence on cassava output TE across the three countries.[5] This result is consistent with those of Debede et al. (2015) and Girma et al. (2017) in Ethiopia. The results suggest that farmers tended to be more efficient in monocropping fields than intercropping systems in Malawi and Tanzania. Intercropping also had a negative influence on TE in Uganda but the coefficient was not

[5] The most widely adopted varieties in Uganda were NASE 14 (31%), followed by NASE 3 (13%), NASE 13 (13%) and TME (10%) because of their high productivity. Similarly, in Malawi, the most commonly planted improved cassava varieties were Manyokola (24%), Gomani (23%), Sauti (17%) and Beatrice (11%). In Tanzania, Mkombozi was the most common improved cassava variety used by farmers.

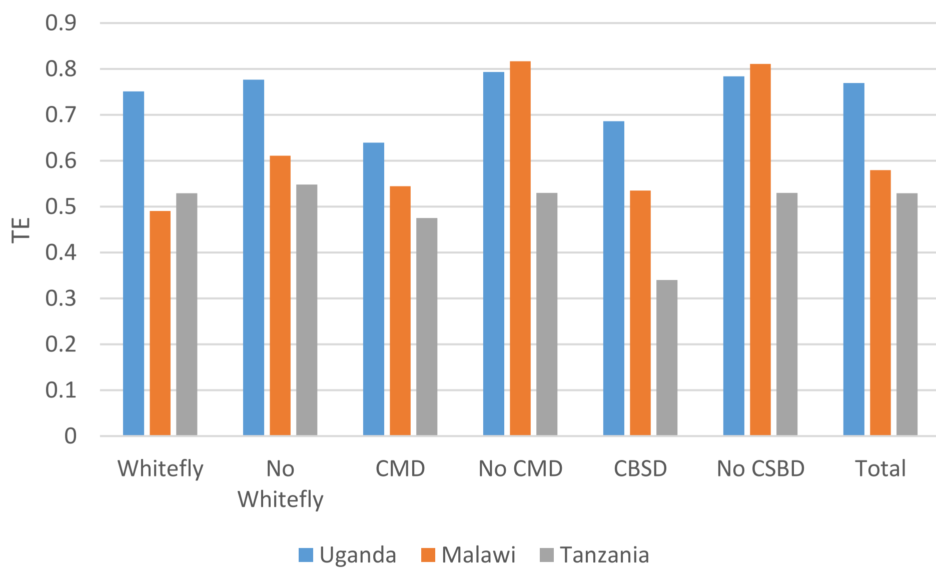

Figure 4. Distribution of technical (TE) in Malawi, Tanzania, and Uganda based on infestation status. A value of zero indicates that current technologies are not used effectively and a value of one indicates full use and efficiency of the available technology.
Source: Farmer surveys (2015/2016).

statistically significant at the 5% level. Studies suggest that intercropping systems can both negatively and positively affect technical inefficiency (Alene et al., 2006; Hong et al., 2019). Intercropping systems generally have higher land-use efficiencies than mono-cropping systems (Alene et al., 2006). However, this may be achieved at the expense of the other inputs, such as labor (Huang et al., 2015). Alene et al. (2006) estimated the mean TE of maize–coffee intercropping systems in Ethiopia to be 91%. They showed that farmers make efficient use of land and other resources through innovative cropping systems. A similar study by Dlamini et al. (2012) showed that integrating maize with other species increased the TE of farmers in Swaziland. Hong et al. (2019) reported that intercropping contributed to a higher TE in smallholder farming in China. However, Tchale and Sauer (2007) found a significant negative impact on TE when maize-based smallholder farmers in Malawi practised intercropping. Therefore, the results may be crop and location specific. Plot altitude was not significant across the study countries.

Education, farming experience, household size, membership of associations, credit, farm size, land ownership, extension, and distance to markets also significantly affected the TE of cassava farmers. Farming experience had a statistically significant and negative effect on inefficiency. This indicates that cassava farmers with many years of production are more efficient than those with fewer years of farming experience. This result is consistent with *a priori* expectations and showed that farmers use their experience to utilize their scarce resources efficiently. As expected, education years also had a negative and significant ($p < 0.05$) effect on inefficiency in all the countries. This indicates that farmers with more formal education were more efficient in cassava production than those with fewer years. This finding agrees with those of Kumbhakar et al. (1991) of US dairy farms, which showed that education increased labor and land productivity. A study by Huang and Kalirajan (1997) also reported that average household education level was positively correlated with TE levels for both maize and rice production in China. Similarly, household size had a significant negative effect on inefficiency in most study countries. This implies that household size led to increased efficiency through its positive correlation with the availability of family labor (Mignouna et al., 2012).

As anticipated, farm size had a statistically significant effect on inefficiency. To examine possible non-linearities of the impact of farm size on TE, we included the square of the farm size as an additional explanatory variable in the model. The coefficient of farm size had a significant positive effect on inefficiency, while the squared farm size had a significant negative impact (Table 7). This finding suggests a non-linear relationship between farm size and TE, consistent with Hong et al. (2019) study. An extensive literature on this issue has produced mixed reports on the relationship between efficiency and farm size. Several studies have indicated that small farm sizes have a positive effect on farm-level efficiency because of their simplicity of management and lower costs than larger farms. Ahmad and Bravo-Ureta (1995) reported a negative correlation between herd size and TE in a study of US dairy farms. Parikh et al. (1995) found that cost

Table 7. Sources of technical inefficiency of cassava farmers in the study countries.

Variable	Malawi	Tanzania	Uganda	Pooled
Improved cassava variety	-1.31 (1.05)*	-0.50 (0.02)	-0.40 (0.48)*	-1.08 (0.82)*
Intercropping systems	0.87 (1.19)*	1.68 (1.09)*	0.22 (0.37)	0.74 (0.35)
Whitefly impacts	0.59 (0.51)*	1.98 (0.98)*	0.32 (0.21)*	1.86 (0.66)**
Male farm head	-0.41 (0.06)	-1.01 (0.95)*	-0.10 (0.46)*	-0.25 (0.87)
Farming experience	-0.50 (0.11) *	-1.17 (0.65)*	-0.41 (0.25)*	-0.94 (0.57)*
Education years	-0.50 (0.92)**	-1.22 (0.59)*	0.49 (0.44)*	-0.75 (0.89)*
Household size	-0.32 (0.15)*	-0.32 (0.94)*	0.36 (0.35)*	-1.49 (0.94)*
Farm size	0.77 (0.27)	0.12 (0.42)	0.10 (0.11)	1.81 (1.74)
Farm size^2	-2.55 (0.06) *	-0.10 (0.09)*	-0.16 (0.42)*	-0.51 (0.44)*
Land tenure				
Freehold ownership	-3.41 (3.14)*	-2.56 (1.19)*	-0.73 (1.17)*	-1.60 (1.29)*
Leasehold ownership	-2.34 (2.93)*	-	-2.65 (1.74)*	-4.57 (2.65)*
Customary ownership	-0.87 (1.01)*	-2.65 (1.51)*	-3.35 (1.51)*	-4.19 (1.31)*
Member of organisation	-0.83 (1.13)*	-0.04 (0.05)*	-0.80 (0.37)*	-1.10 (0.78)*
Extension visits	-0.87 (0.98)	-2.01 (1.26)*	-0.27 (0.46)	-0.77 (0.91)*
Credit	-2.07 (0.89)*	-0.07(-0.25)*	-0.33 (0.39) *	-0.32 (0.84)*
Altitude	0.10 (0.18)	-0.17 (0.28)	0.59 (0.64)	-1.04 (0.88)
Distance to market	1.01 (0.42)*	0.46 (0.47)**	0.33 (0.22)*	0.30 (0.54)*
Distance to District HQ	0.44 (0.26)*	1.20 (0.67)*	0.12 (0.26) *	0.53 (0.51)*
Obs.	400	350	450	1200

Standard errors in parentheses.Significance levels: * $p<0.05$; ** $p<0.01$; *** $p<0.001$. Country fixed effects used in the pooled regressions.
Source: Farmer surveys (2015/2016).

inefficiency increased with farm size. Debebe et al. (2015) found that the landholding size has a negative and significant effect on the efficiency of maize production in Ethiopia. However, other authors have reported the opposite result showing a positive and statistically significant relationship between farm size and TE. This may be the case because larger farms are more likely to employ modern agricultural technologies and be more efficient due to the advantages of economies of scale and scope (Debebe et al., 2015). Kumbhakar et al. (1991) showed that larger farms are generally more efficient. Alvarez and Arias (2004) found a positive relationship between TE and the size of dairy farms in Spain. Huang and Kalirajan (1997) showed that the size of household arable land was positively related to TE in maize, rice, and wheat production in China.

Regarding gender, male farmers in Uganda and Tanzania had a significant ($p< 0.05$) and negative effect on inefficiency. This suggests that the average household tended to have a lower inefficiency effect if it had a male head and *vice versa*. We found similar results in Malawi, although the variable was not statistically significant. Our findings agree with those of Liu and Myer (2009) which found that maize producing households in Kenya had a lower efficiency level if it had a female head. They observed that the effects of gender could be related to the land ownership patterns in these countries, which tend to favor men, and that female heads may be subjected to various forms of social discrimination associated with access to extension services, education, and access to good quality planting material. However, Kareem et al. (2017) showed that female cassava farmers contributed more to cassava production efficiency (0.59) than male farmers (0.54) in Ogun state in Nigeria. Okoye et al. (2016) reported a similar finding that female farmers were more technically efficient than male farmers among smallholder farmers in Madagascar. Missiame et al. (2021) showed that female-managed cassava farms in Ghana were technically more efficient than male managed farms, with average TE of 0.92 and 0.23, respectively. Their findings depicted a relatively more efficient use of resources by female farmers compared to male farmers. There is evidence that when individual characteristics and access to inputs are controlled, female managed farms are equally efficient as male managed farms (Seymour, 2017; Missiame et al., 2021). The difference was attributed to factors such as access to inputs and resource endowments.

Land tenure was found to have a significant effect on inefficiency. The results show that, compared to the squatters and other ownership forms, the coefficients on freehold, leasehold and customary ownership was negative and statistically significant. This implies that these forms of land tenure reduced technical inefficiency compared with squatters and other forms. This finding agrees with those of Ahmed et al. (2002) for Ethiopia, Koirala et al. (2016) for the Philippines and Ma et al. (2017) for China, which showed that tenure security contributes to higher TE. Secure tenure can induce more investment (such as soil conservation) and increase TE in the long run (Place and Hazell, 1993; Deininger and Jin, 2006; Deininger *et al.*, 2008). Place and Hazell (1993) showed that land tenure is important to investment and productivity in Rwanda. Studies on Uganda and Ethiopia found that tenure security has a positive impact on productivity (Deininger and Jin, 2006; Deininger et al., 2008).

Similarly, membership of a farmers' organisation and having access to credit and extension services had significant negative effects on inefficiency. Membership of farmers' organisations allows farmers to interact and exchange information on new technologies, innovations, and management practices with other farmers. Thus, becoming a member of a farmers' organisation could help increase TE of cassava farmers.

The coefficient of extension access was negative, which implies that access to agricultural extension services leads to a reduction in the farmers' technical inefficiency. This finding is intuitive since agricultural extension agents are the primary sources of information on new and improved agricultural technologies for farmers in the three study countries. Extension agents provide training and guidance to cassava farmers on the best farm management practices. Therefore, farmers who have access to extension tend to be more efficient in their resource use.

This finding aligns with that of Missiame et al. (2021), who found that access to extension services improves the technical efficiency of smallholder cassava farmers in Ghana. Lastly, the coefficients of distance to market and district headquarters were positive and significant across the three countries. This indicates that the average household tended to have larger inefficiency levels if located farther from markets. This result may be attributed to the fact that farmers in close proximity to markets have the advantage of easy and timely access to production inputs. Conversely, farmers located further from markets may incur additional costs in acquiring such inputs which may deter those farmers from making the investments, thereby affecting their efficiency. This finding is consistent with that of Missiame et al. (2021) who found that proximity to market areas significantly improved the TE of smallholder cassava farmers in Ghana.

CONCLUSIONS AND POLICY IMPLICATIONS

This study applied a SPF model to examine the impacts of cassava whitefly pests on smallholder farmers' productivity and TE in areas of high infestation in Malawi, Tanzania and Uganda. We showed that cassava output was significantly correlated with land area and quantity of cuttings and labor used. We showed that whitefly infestations and socio-economic factors such as farming experience, education, household size, farm size, land tenure, membership of associations, extension, credit, and distance to markets were significant in explaining the technical inefficiency of cassava farmers. Whitefly and disease infestations contributed to higher levels of technical inefficiency of cassava farmers. These findings underscore the need for policies to ensure that cassava farmers have better access to improved inputs, especially clean planting materials, and the knowledge to integrate this technology into their farming system. To increase the productivity of cassava farmers, the following recommendations are made:

(i) Since cassava output was significantly correlated with cuttings, the issue is how to provide farmers better access to improved cuttings. One strategy is by making "clean, disease-free" and resistant varieties available across the major cassava-producing districts to distribute to smallholder farmers at affordable prices. It is recommended that the government should provide input subsidies so that farmers can use improved inputs to increase their productivity and provide a better return on the labour used for cassava production. The government should expand the current efforts by local and international non-governmental organisations (NGOs) to develop sustainable, market-oriented cassava seed systems for smallholder farmers in Uganda and Tanzania.

(ii) Since the number of years spent in education positively influenced farmers' TE, we recommend policies that encourage cassava farmers to acquire more education primarily related to biotic threats such as whitefly pests and diseases in smallholder cassava production systems. Therefore, it is recommended to increase extension contacts in the major cassava-producing districts and include information on whitefly and disease management strategies.

(iii) There is a need for governments to address the issue of high labor use in smallholder cassava production systems. The average labor use of 142–185 person-days per acre shows that cassava farmers depend heavily on human labor to carry out most farming activities. Labor reducing technologies are needed, with additional training required to help increase labor productivity. Boosting cassava production by prioritizing female farmers to improve their production efficiency is recommended.

(iv) The productivity of cassava farmers can be increased by implementing better access to credit and infrastructure. More farmers should be encouraged to become members of farmers' groups. Institutional factors such as providing more access to extension services may increase the adoption of improved cassava varieties.

(v) Finally, since this was a "baseline" study, it is recommended that it be repeated in five years to collect panel data that can be used to determine productivity change over time.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

ACKNOWLDGEMENTS

This study was funded by the Bill & Melinda Gates Foundation through the Natural Resources Institute, University of Greenwich (Grant number#OPP1058938). We thank staff and extension workers from local research institutions who collected the data from cassava farmers in Malawi, Tanzania and Uganda.

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