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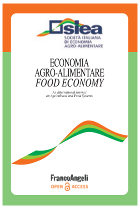

Enhancing Technical Efficiency and Economic Welfare: A Case Study of Smallholder Potato Farming in the Western Highlands of Guatemala

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Abstract

Smallholder farmers in the Western Highlands of Guatemala grow potatoes for subsistence and as a cash crop but their current productivity is 29% lower than the world average. The objective of this study is to provide policy recommendations for improving potato productivity through enhancing technical efficiency in smallholder potato farming in the Western Highlands of Guatemala. In doing so, this study examines the determinants of potato productivity and identifies the sources of technical inefficiency in smallholder potato farming. In addition, the study evaluates the economic welfare impact of potato farm operations and provides policy recommendations for increasing smallholder potato productivity through enhancing technical efficiency. Stochastic production frontier analysis showed that on average farmers are at 57% efficiency. Hence, there is a considerable room for improving efficiency in potato farming. The sources of inefficiency of the farmers were determined to be caused by higher elevation, smaller farm size, and location of the farms. Welfare gains from reaching potential efficiency is US$ 8.79 million in terms of producer surplus per year in Guatemala. Hence, this study provides valuable

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information for policy makers and farmers for improving technical efficiency and producer surplus. Likewise, providing better conservation practices by extension will ameliorate the low productivity associated with higher elevation and locations that are lower in technical efficiency.

Introduction

One of the sustainable development goals adopted by the United Nations in 2015 was to eliminate global starvation and to reach zero hunger by 2030 (Wu *et al*., 2018). This goal faces great challenges with increasing global food demand due to rapid population growth and climate change. According to some estimates, the global agricultural production will be required to increase by about 70-110% to achieve such a goal (Wu *et al*., 2018). Agricultural land expansion has played a significant role in increasing food production in developing countries during the last few decades (Neumann, 2010; Wu *et al*., 2018). However, in recent years, expansion of agricultural land area to satisfy global food demand is at odds with the intention of biodiversity conservation and urban development. This conflict requires identification of other options to increase agricultural production without further expansion of cultivated land area (Neumann, 2010; Wu *et al*., 2018).

Furthermore, FAO (2017) indicated that world under nourished people increased from 777 million in 2015 to 815 million people in 2016. The report revealed that the world should increase global food production by 50% to ensure the food security of additional two billion people, who will add to the world population by 2050. An increase in world food demand will require individual countries to enhance their food production to ensure food security. However, it is not likely food production will increase through increasing cultivated land area due to trade-offs associated with food production, biodiversity conservation, and greenhouse gas emission mitigation (Wu *et al*., 2018). Hence, sustained productivity growth is vital for poverty reduction and improving food security in developing countries (World Bank, 2007). Thiam (2001) showed that technical inefficiency ratio in agricultural sector lies from 32% to 63% in developing countries. A high level of technical inefficiency in agriculture causes low productivity, low income, and food insecurity among farming households. Particularly, low productivity in agriculture is one of the major constraints in meeting future food demand in the world (World Bank, 2007; Conceicao *et al*., 2016). Hence, improving technical efficiency in agriculture remains as a necessary condition for increasing agricultural productivity in developing countries to meet the increasing demand for global food production (Neumann, 2010; Sokolova *et al*., 2017; Wu *et al*., 2018).

Guatemala had a per capita income of US$ 8,200 in 2017 (UNDP, 2018). The agricultural sector employed 31% of the labor force with 13.5% contribution to GDP in 2018. The Human Development Report in 2018 shows that 29% of total population in Guatemala lives below the poverty line, which is US$ 1.9 per day (UNDP, 2018). Despite moderate economic growth of 3% real GDP in 2018, Guatemala records high level of poverty, inequality, child malnutrition, and child mortality (UNDP, 2018). These socio-economic conditions are worse in rural areas, where indigenous people reside and, where agriculture plays a considerable role in income generation and employment creation compared to urban areas (Sokolova *et al*., 2017; FAO, 2018). Potato is one of the major cash and staple food crops in Guatemala. Eighty eight percent of rural households engage in potato cultivation and the potato sector provides permanent and semi-permanent employment opportunities to over 70 thousand rural families (Sokolova *et al*., 2017). Potato production 29% lower (25 tons/ha) than the world yields (35 tons/ha) and 69% lower than European and North American yield (80 tons/ha). (FAO, 2018; Widanage *et al*., 2019). Thus, Guatemalan potato productivity remains at a low level. In addition, there is a high risk of further declining productivity of potato farming due to the persistence of crop diseases and pests, lack of irrigation and failure to follow the best agricultural practices (Sain *et al*., 2017; Chan *et al*., 2018). Guatemalan potato cultivation has been suffering from a crop disease called "potato cyst nematode (PCN)". Our interviews with farmers in 2016 revealed that about 50% of the yield reduction can be attributed to PCN. This has led to USAID, a development agency, to provide an assistance for finding a solution for the PCN problem. In addition, low productivity associated with crop diseases and high degree of poverty emphasize the importance of improving technical efficiency in smallholder potato farming in Guatemala. In the light of these observations, this study answers to the following research questions:

i. What are determinants of smallholder potato productivity in the Western Highlands of Guatemala?
ii. What are the sources of technical inefficiency in smallholder potato farming?
iii. What is the economic welfare impact on potato farmers due to improving technical efficiency?
iv. What are the policy recommendations of this study for improving potato productivity through enhancing technical efficiency in smallholder potato farming?

In answering those research questions, this study intends to achieve the following overall and specific research objectives.

1.1. *Objectives of the Study*

With the overall objective of providing policy recommendations to enhance potato productivity through improving technical efficiency in smallholder potato farms in the Western Highlands of Guatemala, the specific objectives of this study are two-folds. Firstly, this study aims to investigate the determinants of smallholder potato productivity and to identify the sources of technical inefficiency in potato farming. Secondly, the study evaluates the economic welfare impacts of farm operations on the smallholder potato producers and provides policy recommendations for enhancing potato productivity through improving technical efficiency and for increasing economic welfare of smallholder potato farmers in the Western Highlands of Guatemala.

1.2. *Importance of the Study*

Measuring technical efficiency and associated economic welfare impact of smallholder potato farming has vital importance for both farm managers and policy makers. Particularly, the agricultural sector in developing countries like Guatemala, which faces considerable budgetary constraints of investing in productivity growth. Thus, the primary concern of both farmers and policy makers is to identify strategies to enhance productivity through improving technical efficiency without employing additional resources and new technologies. Hence, the policy recommendations derived from this study can be applied to curtail unnecessary production costs and save both financial and physical resources in smallholder potato farming in the Western Highlands of Guatemala.

The concept of farm level technical efficiency analysis provides information to produce maximum level of output through optimal allocation of resources following the best agricultural practices. These strategies bring valuable policy insight for farm managers, who aim to maximize profit in the presence of market constraints, high input costs and slow adoption of new technologies. In addition, these findings are important for policy makers concerned with enhancing productivity, competitiveness, and sustainable resource use in smallholder potato farming.

Furthermore, the findings of this study can be applied to improve technical efficiency in smallholder potato farming in other developing countries, where similar socio-economic and agro-climatic characteristics are found.

This paper is organized as follows: section two provides a conceptual framework of the method of analysis. Then, section three describes the project sites, data collection and the empirical models used for data analysis.

In section four, we present results and discussions. Lastly, section five provides a conclusion and policy implications of the study.

2. Conceptual Framework

2.1. *Stochastic production function and inefficiency model*

Production theory indicates that all observations are on a single production function, when a sample of farms are specified in input-output space, with a given technology. However, empirical estimation of a production function does not meet such a theoretical expectation due to random variations and farm specific differences in technical efficiency (TE) (Aigner *et al.*, 1977; Kalirajan, 1981; Battese, 1992). Economic efficiency is defined as a combination of TE and AE (Allocative efficiency). AE indicates the ability of producing a given level of output at a minimum cost of input. In this study, TE is defined as the ability of a farming unit to produce maximum output given a set of inputs and technology (Kalirajan and Shand, 1986; Thiam *et al.*, 2001). Farm specific TE means that there are farms more successful than others in using farming technology efficiently.

Random variations in production have no important economic meaning in describing productivity differences because it accounts for efficiency differences among farms due to random factors. Many production function analyses focused on such random efficiency differences. Those studies used Ordinary Least Square (OLS) method, which permit observations to lie on both side of estimated production function (Kalirajan, 1981; Battese, 1992). Hence, such an estimation method was not consistent with the Neo-classical definition of production function.

Farm specific variations in technical efficiency cause for productivity differences among sample observations. These productivity differences reflect farm specific variability related with decision making as individual farming unit, who employs the available technology efficiently. If a farming unit employs their technology efficiently, then the sample observations locate on the estimated production function (Kalirajan, 1981; Battese, 1992). Similarly, observations locate below the estimated production function if a farming unit employs their technology inefficiently. This study extends the conventional specification of production function to explicitly account for random and farm specific variabilities for investigating productivity differences. In doing so, we employ a stochastic frontier production function to measure technical efficiency in potato farming of Western Highland of Guatemala. The stochastic frontier production function has become a widely used tool in applied production analysis because it is consistent with the notion of profit maximization and cost minimization (Thiam *et al.*, 2001).

These stochastic frontier models incorporate a composed error structure, which combines a two-sided symmetric term and a one-sided error component (Battese, 1992; Battese and Coelli, 1995; Thiam *et al.*, 2001) In our frontier model, one-sided error component reflects inefficiency and two-sided error captures the random effects, which are outside the control of potato farmers.

Random effects include measurement errors and other statistical noise, which comes from unexplained variability of the estimated empirical relationship. The estimated stochastic frontier model addresses the noise problem characterized in previous deterministic models, which over-estimated the inefficiency component (Battese, 1992; Battese and Coelli, 1995).

The merit of this approach is not only accounts for random variation in production as in conventional methods, but also explicitly considers for the inter-farm variability in using the technology (Kalirajan, 1981; Battese and Coelli, 1995). It is our opinion that this is a more appropriate methodology for investigating the issue of productivity differences compared to conventional production function, which was used in most econometric studies. According to this approach, individual farmer variability or technical inefficiency is the major cause of yield variability not the random variability. Individual farmer variability in production is within the control of farming unit. Hence, TE analysis provides an important policy insight for choosing strategies to improve technical efficiency in agricultural production. One of the weaknesses of this approach is that allocative efficiency of sample farmers cannot be examined because the stochastic frontier production function is estimated using only inputs and output (Kalirajan and Shand, 1986; Thiam *et al.*, 2001). In addition, technical efficiency in this study is a relative concept and such an optimum efficiency comes from the sample examined. Hence, it is not the absolute efficiency for all farms located in the Western Highlands of Guatemala. Policy makers should keep this in mind when they apply our findings to improve technical efficiency in potato farming in the study area.

This paper applies the stochastic frontier production function and the technical inefficiency model to evaluate the determinants of potato productivity and the sources of inefficiency in farm operations to answer research questions (1) and (2) respectively. In this analysis, we assume that farmers are profit maximizers and they aim to maximize profits subject to the given technology, constant input level and output prices (Varian, 1992). Furthermore, there are n number of farmers who use k number of inputs to produce single output potato. Assuming a Cobb-Douglas production relationship, the stochastic frontier production function is specified as follows:

$$Y_i = f(X_i; \beta_i) \exp(V_i - U_i) \quad i = 1, 2, \ldots\ldots\ldots\ldots\ldots N; \tag{1}$$

where Y_i is the level of potato output of the i th plot, which is $(n \times 1)$ column vector. X_i is a $(n \times k)$ matrix of the production inputs associated with potato yield. β_i is $(n \times 1)$ column vector of unknown parameters to be estimated using equation (1). V_i is a random error term having zero mean, which is associated with random factors such as measurement errors in production and other random shocks. These random factors are not under the control of farm households. If there are no such stochastic elements and the influence of external factors on potato production is minimal, then the stochastic error term becomes zero ($V_i = 0$) (Battese, 1992; Battese and Coelli, 1995). Under such conditions, the random errors are assumed to be independently and identically distributed with zero mean and the constant variance as $N(0, \sigma^2)$. The presence of V_i in this model implies that the technical efficiency may vary randomly across the farms or over time across the same farm. Similarly, if there are no functional form errors and influence of stochastic factors, the deviation of potential output from actual output is determined by the level of efficiency in agricultural practices followed by the farmers. If the actual output is less than the potential output, a farmer faces technical inefficiency. The U_i accounts for the technical inefficiency, which measures the deviation of frontier output (Y_i^*) from the actual output (Y_i). Ui s are non-negative and identically distributed variables, which are independent from V_i (Battese, 1992; Battese and Coelli, 1995). The merit of this approach is that the relative variability of U_i and V_i provides an indicator to identify the sources of the technical inefficiency (Kalirajan, 1982; Kalirajan and Shand, 1986; Battese, 1992).

Technical efficiency of an individual plot can be stated as a ratio of the actual output to the corresponding potential output at the level of inputs used by a specific farm (Battese, 1992; Kalirajan, 1990; Neumann *et al.*, 2010). Based on the stochastic frontier production function (1), the technical efficiency of farm i can be estimated as follows:

$$TE_i = Y_i/Y^* = f(X_i; \beta_i) \exp(V_i - U_i) / f(X_i; \beta_i + V_i) \tag{2}$$

$$TE_i = \exp(-U_i) = Y_i/Y^* \tag{3}$$

From equation (3) the term $\exp(-U_i)$ derives the ratio of the actual output (Y_i) to the potential output (Y^*). The ratio Y/Y^* is called technical efficiency of an individual plot i (Kumbhakar and Wang, 1994)[1]. Since $U_i > 0$; the ratio

1. We can approximate $\exp(-U_i)$ by $1 - U_i$ which gives $TE = \exp(-U_i) = 1 - TI$ (technical inefficiency).

Y_i/Y^* lies between 0 and 1. If the value is equal to 1, then the potato farm productivity is 100% efficient and if the value is equal to zero, then it implies the potato farm productivity is 0% efficient.

The relative variability of U_i and V_i provides an indicator to statistically examine the sources of differences between the farm plot actual yield and the yield estimated by the stochastic frontier production function. Equation (4) shows the variance ratio parameter (γ), which is the ratio of variance of U_i and the total variability of U_i and V_i (Kalirajan, 1981; Battese, 1992).

$$\gamma = \sigma^2 U_i \; / \; \sigma^2 U_i + \sigma^2 V_i \tag{4}$$

where $\sigma^2 U_i$ = variance of U_i; $\sigma^2 V_i$ = variance of V_i.

The numerator and denominator of equation (4) represents the variance of U_i and the total variance of the estimated model respectively. As defined in equation (1), V_i represents random variation and U_i accounts for technical inefficiency. If the variance of $V_i = 0$; then the variance ratio becomes 1. This indicates that the output of sampled farms differs from the maximum output mainly because of the differences in technical efficiency. If the variance of $U_i = 0$; then the variance ratio will become 0. Hence, the random factors are the main sources of productivity differences among farms. We use the conceptual model in equation (1) to estimate the empirical model in section 3.3.

Many studies have identified various socio-economic and bio-physical factors that influence technical inefficiency in agricultural production (Bettese and Coellei 1992; Thiam *et al*., 2001; Takeshima, 2019). Based on those analyses, the technical inefficiency model can be specified as follows:

$$U_i = f\,(X_i;\, \alpha_i) + w_i \tag{5}$$

where X_i s are the factors that influence technical inefficiency. The literature shows that X_i includes socio-economic factors, biophysical factors, and agroclimatic factors (Thiam, 2001; Neumann *et al*., 2010). α_i represent the parameter of each explanatory variable; w_i is an error term with zero mean and constant variance. The technical inefficiency model in equation (5) is used to identify the factors that contribute to the technical inefficiency.

2.2. *Measuring economic welfare of farm operations using producer surplus*

Economists use producer surplus to measure the economic welfare impacts of farm operations. Economic profit or producer surplus is known as the difference between total revenue (TR) and total cost (TC). In this paper, we use the producer surplus to measure the economic welfare impacts of farm efficiencies. When a farm achieves economic efficiency, it generates an economic surplus. The value of producer surplus can be used to examine the static economic efficiency of farm operations. Hence, in this analysis, we use the producer surplus to answer research question (3). The producer surplus of a potato farm is given as follows:

$$\text{Producer Surplus (PS)} = \text{Total Revenue (TR)} - \text{Total Cost (TC)} \qquad (6)$$

Total revenue earned by a potato crop in quintal (100 kg) per unit area in cuerda (0.393 ha) can be calculated as follows:

$$TR = P_p * Q_p \qquad (7)$$

where P_p = Price of one quintal (100 kg) of potato in quetzal (US$ 0.13) and Q_p = Quantity of potato (in quintal) per unit area in cuerda (0.393 ha).

Total cost in quetzal (US$ 0.13) occurred to a potato farm per unit are in cuerda (0.393 ha) can be measured as follows:

$$\begin{aligned} TC = {} & \text{Cost of seed} + \text{Cost of fertilizer} + \text{Cost of weed and pest control} \\ & + \text{Cost of manure} + \text{Labor cost} \end{aligned} \qquad (8)$$

The difference between producer surplus generated at the efficient level of output (TR_E) estimated from equation 3 and the actual level of output (TR_A) is the change in the economic efficiency of potato farms if farmers allocate its inputs optimally. Hence the calculation of change in producer surplus due to achieving efficient output is given as follows:

$$\Delta PS = TR_E - TR_A \qquad (9)$$

where ΔPS is the change in producer surplus per cuerda (0.393 ha). Equations (7)-(9) will be used to calculate values in Table 5 in section 4.4. In measuring the economic welfare impact of farm operations on the small-scale potato producers, we make several assumptions for our analysis. The assumptions are farmers face perfectly competitive markets both for inputs and output and, since farmers grow potato on farms they own, we do not count the land rent as a cost of production.

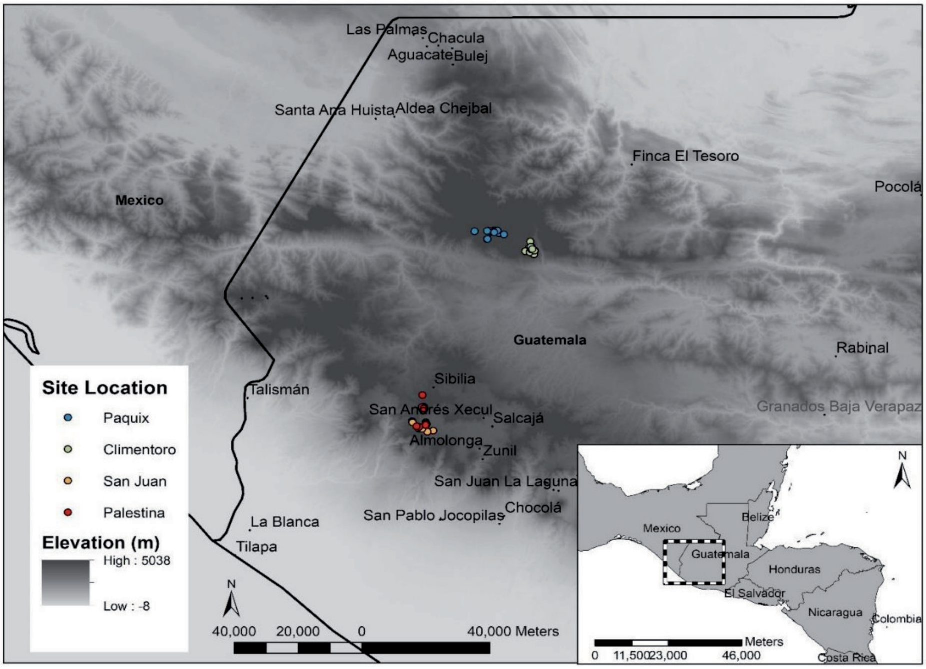
In the next section, we will provide a description of socio-economic and farm characteristics of study sites, data collection methods, and empirical model estimates.

3. Materials and methods

3.1. *Map of the study location*

The field survey was conducted in four potato production locations after consultation with local partners from the Faculty of Agriculture at the University of San Carlos of Guatemala. The four locations are: Palestina, Paquix, San Juan, and Climentoro in the Western Highlands of Guatemala (see Figure 1).

Figure 1 - Locations of study farm sites in the Western Highlands of Guatemala



3.2. Sample and data collection

Farm households were selected for the face-to-face interviews with the assistance of our local partners. Interviews were conducted at farmer cooperative centers or personal visits to the farm. Using a structured questionnaire, the interview was conducted to collect data on socio-economic conditions, demographic characteristics, production, costs, yields and agricultural practices in potato farming in the study areas. One hundred and four household surveys were completed, and 6 questionnaires were discarded due to incomplete information. Then, 16 observations were removed due to the absence of latitude and longitude data. Thus, the total number of observations is 82. The interviews occurred during the years of 2017 and 2018. The lead interviewer who is from the University of San Carlos of Guatemala is fluent in both English and Spanish. Training sessions with local enumerators prior to surveying the farmers were conducted in Spanish.

3.3. *Empirical model*

According to our field survey experience and focus on main potato growing regions, potato production technology used by farm households in the study area reflects similar characteristics.

Hence, we specified one production boundary for analyzing technical efficiency among farm households in four regions. we were not able to run single models for each region due to the small number of observations. However, we conducted ANOVA (see Table 3 on page 16) and it indicated that there is a difference in technical efficiency between regions. According to our field observation and the review of spatial data, our farms in one region are located within the similar range of latitude and longitude. Thus, there is no considerable variation in climate and soil between farms within the same region. To identify the causes for the difference in inefficiency of potato production across the regions, we included location dummy variable SAN JUAN (DL3) (see Table 4 on page 17) in the inefficiency model.

As mentioned in section 2.1, the stochastic frontier production function is used to estimate the technical relationship between inputs and potato production in the Western Highlands of Guatemala. In this model, we assume that smallholder potato farmers are profit maximizers and the potato market is perfectly competitive. Hence, the input and output prices are given for a smallholder potato farmer and his/her marginal revenue is positive. The technical inefficiency model shows a linear relationship between technical inefficiency and the socio-economic, bio-physical and agroclimatic variables. In this study, the stochastic frontier production function and technical inefficiency model are simultaneously estimated using maximum likelihood method.

Based on equation (1), the stochastic frontier production function can be specified as follows:

$$PTY_{\mathrm{i}} = \beta_0 + \beta_1 PLS_i + \beta_2 COS_i + \beta_3 THL_i + \beta_4 COWP_i + \beta_5 THL_i^2 + \beta_6 CNPK_i + \beta_7 CMNU_i + V_i - U_i \tag{10}$$

where PTY_i = Total potato output in quintal (1 ton = 9.07 quintal) of plot *i*; PLS_i = Farm plot size in cuerda (1 cuerda = 0.393 hectare); THL_i = Total hours of labor used in plot *i;* THL^2 = Total hours of labor squared term; $COWP_i$ = Cost of weed and pest control in quetzal in a plot *i* (1 quetzal 0.13 US$); COS_i = Cost of seeds in quetzal in plot *i;* NPK_i = Cost of fertilizer in quetzal in plot *i;* $CMNU_i$ = Cost of manure in quetzal in plot *i;* V_i = Random error term in plot *i*; and U_i = Technical inefficiency term in plot *i*.

Equation (10) shows the technical relationship between inputs and potato output of plot *i*. PTY_i is the dependent variable in the model. Plot size (PLS_i), total labor hours (THL_i), cost of seeds (COS_i), cost of fertilizer ($CNPK_i$), and the cost of weed and pest control ($COWP_i$) and cost of manure ($CMNU_i$) are explanatory variables in the production function. The betas of stochastic frontier production function analysis intend to examine the contribution of each factor inputs to changes in potato production. V_i is assumed to be independently and identically distributed random variable. It accounts for a deviation of frontier output from the actual output due to the random shocks and measurement errors. U_i is assumed to be identically distributed non-negative variables independent of V_i. U_i accounts for a deviation of frontier output from the actual output due to the technical inefficiency. A prediction of technical inefficiency can be made by decomposing the combined error term ($V_i - U_i$), into its components to obtain farm specific technical inefficiency. The farm specific technical inefficiency is calculated using the prediction of the conditional distribution of U_i given that the combined random error ($V_i - U_i$) is observable.

The technical inefficiency model captures the determinants of variation in technical inefficiency. Based on the equation (5) the technical inefficiency model is specified as follows:

$$U_i = \alpha_0 + \alpha_1 FSZ_i + \alpha_2 DL3_i + \alpha_3 ELEV_i + \alpha_4 CARST5_i + \alpha_5 FSZ_i + w_i \quad (11)$$

where U_i is the farm level technical inefficiency in plot *i;* FSZ_i is farm size in cuerda; $DL3_i$ is a location dummy variable with San Juan = 1 and other locations = 0; $ELEV_i$ is the elevation of potato farm plot *i* from 3D elevation (1m resolution); $CARST5_i$ is the soil carbon stock in ton per/ha at the 5 cm soil depth in plot *i;* α_i s are the contributions of each explanatory variables to create technical inefficiency and w_i is a randomly distributed error term in plot *i*.

Equations (10) and (11) are used to estimate the coefficients of the stochastic frontier production function and technical inefficiency model respectively. Results are given in Table 1 and 4 respectively.

4. Results and Discussion

4.1. *Determinants of potato productivity in the western Highlands of Guatemala*

The stochastic frontier production function and inefficiency model were estimated using STATA version 15.1. As discussed previously, the stochastic frontier production function was applied to describe producer behavior in potato farming. The results of the estimated stochastic frontier production function are given in Table 1.

Table 1 - Estimated coefficients of stochastic frontier production function of Western Highland of Guatemala
Dependent Variable = Total potato output

Explanatory Variables	**Coefficient**	**Standard Error**	**p Value**
Constant	0.477	16.80	0.977
Plot size	13.17	2.29	0.000*
Cost of seed	-0.005	0.008	0.495
Total labor hours	0.185	0.059	0.002*
Total labor hours square	-0.0001	0.0003	0.004*
Cost of weed and pest control	0.0301	0.0082	0.000*
Cost of fertilizer	0.0283	0.0185	0.126
Cost of manure	-0.0249	0.0173	0.152

* *Statistically significant at 1% level of significance* Source: Field survey data collected in 2017 and 2018 Number of observations = 82.
Log-Likelihood Ratio = -461.51
Wald chai (2)6 = 60.89 Prob $\chi^2 > 0.000$

According to the estimated model results, plot size (*PLS*), total labor hours (*THL*), weed and pest control (*COWP*) have positive relationships as expected with the Total potato output (*PTY*). Similarly, these explanatory variables are statistically significant at the 1% level. The labor squared term (THL^2) has the expected negative sign and it is also statistically significant at 1% level indicating that labor contributes to increase total potato production up to a certain point and then, begins to decline. This result of the labor variables is consistent with the law of diminishing marginal productivity in the agricultural sector of developing countries, where there is slow technological progress.

Furthermore, the estimated model shows that both fertilizer use (*CNPK*) and the cost of seed (*COS*) have the expected signs, but they are not statistically significant. The insignificance of (*CNPK*) could be due to the budget constraint of farmers compromising, their ability to purchase sufficient fertilizer and their subsequently failure to apply the recommended rate of nutrients.

Similarly, the cost of seed (*COS*) may not have a consistent significant influence on increasing potato yield in the Western Highlands of Guatemala as some farmers do not spend money on seeds or planting materials but use seeds saved from the last year's harvest. In the estimated frontier model, the coefficient of cost of manure (*CMNU*) has a negative sign but it is not statistically significant. This could be due to some farmers using farm manure and others using commercial fertilizer with varying levels of impact to yield. The Log-Likelihood ratio test indicates that the overall model is statistically significant at the 1% level. Thus, the estimated frontier model is consistent with both theoretical and statistical criteria.

Likelihood ratio test (*LR*) was used to determine the presence of technical inefficiency in potato farming. The null hypothesis of this test was formulated as H_0: $\lambda = 0$, where lambda is the ratio of standard deviation of the inefficiency error term to the random error term (i.e. $\lambda = \sigma_u/\sigma_v$). The test indicates no significant technical efficiency at farm level potato production. A rejection of null hypothesis indicates that all the deviation from potential output is due to systematic variation in potato production. The log-likelihood function values of the Ordinary Least Squares and stochastic frontier model were used for the test. The *LR* test is given as follows:

$$LR = -2\ (LLF_R - LLF_u) \tag{12}$$

where LLF_R and LLF_u represents the log-likelihood function values for the restricted (OLS) and unrestricted (Stochastic Frontier) model respectively. LR = -2(-522.23-461.51) = -121.44 is compared with Kodde and Palm (1986) critical values of mixed chi-squared distribution 5.41 at the one percent level of significance with one degrees of freedom. We reject the null hypothesis that there is no technical inefficiency. Thus, the estimated stochastic frontier production function is the most appropriate model to represent the field survey data.

4.2. *Technical efficiency in potato production across study sites*

The potential output was estimated using frontier production function represented by equation (10) in section 3.3. Equation (2) in section 2.1 was used to estimate the technical efficiency (*TE*). Our estimates show that the technical efficiency in the Western Highlands of Guatemala lies between 0.1 to 0.97. According to the frontier production function analysis, the average technical efficiency is 0.57. This means that farmers' actual output is 43% below the level of potential output. These findings reveal that potato farms in the Western Highlands of Guatemala are quite inefficient. Thus, there is considerable room for policy interventions to enhance technical efficiency. Furthermore, the findings of this study show that there are differences in technical efficiency across the four study sites (see Table 2).

Table 2 - Technical efficiency (TE) across four study sites in the Western Highlands of Guatemala

TE value	**San Juan**	**Climentoro**	**Palestina**	**Paquix**
Average	0.66	0.46	0.52	0.64
Standard Deviation	0.29	0.28	0.32	0.17
MaxMin	0.97	0.93	0.89	0.85
	0.11	0.12	0.09	0.28

Source: Field survey data collected in 2017 and 2018.

Table 2 shows that the average technical efficiencies in Climentoro (0.46) and Palestina (0.52) are smaller than the overall average of four study sites (0.57). Similarly, the average level of technical efficiencies in San Juan and Paquix are greater than the overall average of four study sites. In addition, minimum and maximum values of technical efficiencies in San Juan, Climentoro, and Palestina show that there is a considerable range of technical efficiencies within these three study sites compared to Paquix. Likewise, the analysis of variance was used to examine the variation of all the technical efficiency across the four study sites (see Table 3). Our analysis shows that there is a statistically significant variation in technical efficiency between four study sites. Climentaro and Paquix (high elevation) are Mollisols (high organic matter). Palestina and San Juan (lower attitudes) are Andisols (less organic matter), but yield was higher in the latter than in the former. This suggest that not grower or soils, but other unaccounted climatic factors may be contributing to the differences. This kind of analysis provides information to choose appropriate areas for necessary policy interventions for improving technical efficiency in potato farming.

Table 3 - Variation in technical efficiency of potato farming across four study sites in Guatemala

Source	**Sum of squares**	**Degrees of freedom**	**Mean square**	**F**	**p value**
Between study sites	0.5977	3	0.1992	2.91	0.044
Within study sites	3.4285	50	0.0685		
Total	4.0262	53			

Bartlett's test for equal variances: $\chi^2(3) = 7.6896$ Probability > $\chi^2 = 0.053$.

4.3. *Socio-economic and agroclimatic determinants of technical inefficiency*

Next, we estimated the inefficiency model to find the significant socio-economic and agroclimatic factors that determine technical inefficiency in smallholder potato farming. To begin, we normalized the calculated *TE* values (actual output/potential output) using the highest *TE* value in the sample as 1. Then, we used the normalized *TE* value (*NTE*) to estimate the technical inefficiency index (*TIE*) derived from *1-NTE*. The estimated *TIE* index was used as a dependent variable in the inefficiency model.

Equation (11) is used to estimate the inefficiency model and results are found in Table 4.

According to Table 4, all the estimated coefficients have the correct signs and are significant except carbon stock at the 5cm soil depth (*CARST5*). San Juan (*DL3*) has a negative and statistically significant relationship with technical inefficiency, which makes sense as the area has much higher yield and larger plot size than most of the study sites. This result indicates that San Juan (*DL3*) contributes to a lower technical inefficiency. Similarly, larger farm size (*FSZ*) has negative impacts on technical inefficiency, and it is statistically significant at 1% level. This is as expected due to the economies of scale generated by large-scale farms. Elevation (*ELEV*) has a statistically significant positive relationship with technical inefficiency in smallholder potato farming. This is consistent with the theoretical expectation since high elevation sloping areas have more erosion and run-off problems that would cause lower potato productivity (Wang *et al.*, 2002; Mahil *et al.*, 2016).

Furthermore, soil carbon stock (*CARST5*) had the correct sign but was not significant, perhaps this is due to the generally poor soil of farms and failure to capture the complexity of soil carbon content. Hence, we argue that the estimated inefficiency model is consistent with both theoretical and statistical criteria.

Table 4 - Estimated coefficients of the inefficiency model. Dependent variable = Technical Inefficiency Index (TIE)

Explanatory Variables	**Estimated Co-efficient**	**Standard Error**	**p Value**
Constant	-5.38	45	0.905
San Juan	-30.91	9.61	0.001*
Elevation	0.034	0.014	0.023**
Farm size	-0.172	0.081	0.037**
Soil carbon stock	-0.224	0.359	0.535

* Statistically significant at 1% level and ** statistically significant at 5% level.
Source: Field survey, 2017 and 2018.

4.4. *Evaluating the economic welfare impact of farm operations*

As mentioned in section 4.2, smallholder potato farmers attempt to maximize profits. Hence, in this analysis, we use profit or producer surplus generated from farm operations to measure welfare impact of farm operations on smallholder potato producers. The calculated producer surplus values per cuerda (0.393 ha) across four study sites are given in Table 5 under two scenarios, where the wage rate per hour is 10 quetzal in scenario 1 and the wage rate is 5 quetzal per hour in scenario 2. Five quetzal represents the current wage rate, which farmers use to pay their family labor and 10 quetzal is the current wage rate which is used to pay for hired labor[2]. Equations (7) to (9) in section 2.2 are used to calculate statistics in Table 5.

According to Table 5, all the study sites record positive producer surpluses under both wage rate scenarios with current level of productivity. This indicates that though farm operations currently have positive economic returns from potato farming, farmers could increase their economic returns if they are more efficient. There are considerable differences among the four sites in generating producer surpluses, Climentoro has very low producer surplus due to its generally low yield but since its potential yield is comparable to the other study sites so gain will be the greatest for Climentoro if farmers there strive to achieve their potential yield. Using the result of the change in regional average gain in producer surplus 1,246 quetzal from Table 5 and multiplying by the total area harvested in Guatemala in 2017 (21,156 hectares (potatopro.com) and dividing by 0.39 to convert hectare to

2. These wage rates are obtained by e-mail communication with Alfredo Mejia at The University of San Carlos of Guatemala.

cuerda, the aggregate gain in producer surplus for the Western Highland of Guatemala is 67.59 million quetzal or US$ 8.79 million per year. These are substantial gains and returns to producers and to Guatemala. Hence, positive change in producer surplus across study sites reveal that policy interventions are desirable to make potato farms are more efficient production units.

Table 5 - Producer surplus per cuerda (in quetzal)[3] across study sites

	San Juan	Climentoro	Palestina	Paquix	Regional
$Output_E$ (quintal)	29	28	19	29	28
$Output_A$ (quintal)	19	13	10	19	17
Wage rate (10 quetzal)					
TR_E	3190	3080	2090	3190	3080
TR_A	2143	1380	1077	2044	1834
TC	790	1262	459	829	874
PS_E	2400	1818	1631	2361	2206
PS_A	1335	118	618	1215	960
ΔPS	1047	1700	1013	1146	1246
Wage rate (5 quetzal)					
TC	571	767	540	478	468
PS_E	2619	2313	1550	2712	2612
PS_A	1572	613	537	1566	1366
ΔPS	1047	1700	1013	1146	1246

Source: Field survey, 2017 and 2018, market wage rates were obtained through personal communication had with Alfredo Mejia from the University of San Carlos of Guatemala.

where $Output_E$ = Efficient output per cuerda (in quintal); $Output_A$ = Actual output per cuerda (in quintal); TR_E = Total revenue at the efficient level of output; TR_A = Total revenue at the actual level of output; TC = Total cost of production; PS_E = Producer surplus at the efficient level of output; PS_A = Producer surplus at the actual level of output; and ΔPS = Difference between the efficient and actual level of producer surplus.

3. 1 Quetzal = 0.13 USD.

5. Conclusion and Policy Implications

5.1. *Conclusion*

Guatemala is a country which records a moderate economic growth but high level of poverty and food insecurity. Potato is one of the most important staple and cash crops in Guatemala. Hence, the potato sector is an important area for income generation, poverty reduction and improving food security. Results of this study show that farmers' actual output is 43% below the potential output, indicating that smallholder potato farming operations in the Western Highlands of Guatemala are quite inefficient and have room for improvement. However, technical efficiency in this study is a relative concept and such an optimum efficiency comes from the sample examined. Hence, it is not the absolute efficiency for all farms located in the Western Highlands of Guatemala. The estimated coefficients of stochastic frontier production function indicate that increasing the extent of plot size, transferring labor from potato farming to other non-farm sectors, and increasing financial resources on weed and pest control lead to increase the level of potato production in the Western Highlands of Guatemala. When evaluating the causal factors of inefficiency, farm size, farm elevation, and farm location were the primary driving factors. These results strongly suggest potential opportunities exist to offset input use inefficiencies and other non- input factor inefficiency. In addition, welfare gain from reaching potential efficiency is US$ 8.79 million in terms of producer surplus per year in Guatemala. Furthermore, our sensitivity analysis on wage rate indicates that input subsidies, crop insurance, revenue stabilization, and tax relief lead to increase economic surplus generation for smallholder potato farmers. Similarly better conservation practices through promoting extension may lead to increase potato productivity in higher elevation. Below are policy recommendations.

5.2. *Policy Recommendations*

1. The estimated model results in Table 4 indicate that there is an inverse relationship between technical inefficiency and farm size. This is as expected in economic theory due to the economies of scale generated by large-scale farms. Therefore, large-scale potato cultivation may be an economically efficient farming strategy for improving technical efficiency in smallholder potato farming in the Western Highlands of Guatemala.
2. The estimated frontier model results (see Table 1) show that an increase in labor inputs increases potato productivity. However, the estimated total

labor square coefficient (THL^2) indicates that the contribution of labor to potato productivity becomes negative after a certain level of production. This could be due to the marginal diminishing returns, which occurs from employing too much labor for cultivating a fixed amount of potato land. Hence, it is recommended to either decrease labor use or increase plot size to remove diminishing marginal returns and improve resource use efficiency in smallholder potato farming. In addition, labor transferring from potato farming to non-agricultural sector may lead to remove diminishing returns and increases the marginal labor productivity in potato cultivation.

3. As mentioned previously, the crop disease, PCN significantly reduces potato yield. The estimated frontier model shows that investing more and more resource for weed and pest control makes a positive contribution to increased potato production. An increase in expenditure on weed and pest control implies that there is an increase in quantity used because this econometric analysis is a static partial equilibrium approach. Hence, increasing allocation of financial resources to weed and pest control for improving soil health will increase potato production.
4. Our estimated inefficiency model (see Table 4) shows that potato farming at high elevation on steep sloping lands leads to inefficiency in resource use. Elevation would have additional affects like cooler daily temperatures, a shorter growing season and greater ultraviolet lights exposure to plants. These could all be confounding or contributing "elevation factors". Generally, it is not unreasonable to expect lower yield from higher elevations compared to yield at lower elevations. Higher elevation does not necessarily mean that a place must have greater slope – there are high elevation flat plateaus. Climentaro had sloping land, where the potato was cultivated. I think that some of the potato land in other high elevation site was not as sloping. Previous studies also indicated that high elevation gives low productivity and low elevation gives high productivity (Wang *et al.*, 2002; Malhi *et al.*, 2016). Hence, adopting erosion control methods may be a good strategy for increasing technical efficiency in potato farming. Furthermore, our interviews and model results reveal that well-developed infrastructure such as good road network, marketing facilities, and extension services favorably impact technical efficiency. Hence, it is worthwhile to conduct more workshops on the best agronomic practices particularly in Climentoro and Paquix because our interviews and direct observations revealed that these sites have relatively less infrastructure compared to Palestina and San Juan. As mentioned in the introduction, smallholder potato farmers suffer from poverty, and they do not have financial resources for investing in improving marketing facilities or extension services in the study area. Thus, it is recommended for the

Guatemalan government or non-governmental organizations like USAID to invest in those services because such investment may lead to improve productivity of potato farming through enhancing technical efficiency.
5. Economic welfare analysis of smallholder potato farming on high elevation slopes reveals that all the farms across the four study sites generate producer surpluses but are below the economically efficient level. Some land tenure is communal, residing with the tribe and not individuals, especially in indigenous communities. To capitalize on this, the government might consider designing appropriate policy interventions to facilitate and encourage farmers to expand their potato production areas.
6. Sensitivity analysis of changes in agricultural wage indicates that high input cost and low commodity prices reduce economic surplus. Thus, the provision of input subsidies, crop insurance, revenue stabilization and tax relief on the farm income are recommended to increase economic surplus generation for smallholder potato farmers.

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