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# Land Fragmentation, Technical Efficiency, and Adaptation to Climate Change by Farmers in the Gamo Highlands of Ethiopia

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**Abstract:** Although barley production is vulnerable to the impacts of climate change, households in the Gamo Highlands of Ethiopia rely on barley for their diet and allocate most of their highly-fragmented land to barley production. Moreover, farmers alter land management practices as a strategy to adjust to climate change and variability. However, to what extent land fragmentation and land management jointly influence the technical efficiency of barley production is unknown. In addition, it is unidentified whether technical efficiency is uniform across multiple separated plots. In this study, we adapted two stochastic frontier panel models on plot-level cross-sectional data to investigate this. The model results indicate that fragmentation influences the effect of land management practices on efficiency. The study found that efficiency was not uniform across different plots and for different farmers and showed the existence of large yield gaps. To close these gaps, policies designed to address the specific components of inefficiency need to be implemented.

**Keywords:** land fragmentation; climate change; adaptation; efficiency; barley; Ethiopia

## 1. Introduction

Climate change has a negative impact on agricultural productivity in Africa [1,2], significantly increasing the risk of hunger [3,4]. Sub-Saharan Africa (SSA) is the region most vulnerable to climate change in the world [5,6] and the region faces relatively huge challenges in adapting to the changing climate [7]. A meta-analysis of 52 studies forecasts that climate change will reduce the mean yield of eight crop types by 8% in Africa and South Asia by 2050 [8].

Adaptation to climate change is a possible way for farmers to live with a changing climate [9–11]. Adaptation is defined as an "adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities" [12]. Adaptation supports farmers to improve their access to food and livelihood security targets [13,14]. Adaptation also increases farm net revenue and food production in SSA, including in Ethiopia [15,16].

Given changes in land use [17], rising demand for agricultural products [18], and the adverse impacts of the changing climate on ecosystem functions and crop yield, a rising yield per hectare is important to Ethiopia because opportunities to bring additional virgin soil under cultivation are scant, especially in the densely occupied Gamo Highlands. Thus, sustainable intensification—defined as producing more yield from the same area of land while reducing adverse environmental impacts, but also increasing natural capital and ecosystem services—is needed [19]. There are different models of sustainable intensification, but in this study, we focus on sustainable land management (SLM), which is deployed as a strategy for sustainable adaptation to climate change and variability. For this, we collected information on the application of SLM practices at the level of individual plots; for example, we inventoried the quantity of manure applied and the number and age of indigenous trees planted per plot—indicators that are usually measured only at the farm level. By practicing SLM, farmers can invest in a yield rise while reducing the adverse impacts of agriculture on natural resources and ecosystem functions [20–22].

Agricultural fields in the Gamo Highlands of Ethiopia are notably fragmented [23,24], and fragmentation is expected to increase due to the population boom, customary land inheritance rules, and the usufruct rights of farmers [25]. Land fragmentation (LF) refers to the production of crops on disjointed multiple plots [26,27]. Previous studies have focused mainly on the effects of LF on productivity, inefficiency, and profit [28–31], overlooking how LF impacts on the technical inefficiency of SLM practices and how technical inefficiency can be plot-varying. This is the aim of this research. According to Koopmans [32], for a technically efficient producer it is impossible to increase output without increasing input or decreasing the production of at least one output. A technically inefficient farmer has room to produce the same level of output with less of at least one input or could produce more output with the same inputs.

To our knowledge, no study has examined the interaction between the effects of LF and SLM adaptation practices on technical inefficiency. Moreover, most previous studies analysed yield and inefficiency on the level of the agricultural holding, but not on a plot level [33]. The assumption in earlier farm-level studies that inefficiency is plot-invariant is quite a strong one; in contrast, we assume that inefficiency can be both plot-invariant and plot-varying for a given farmer owning multiple disjointed plots. Although barley is a staple crop for millions of people, and the yield is affected by the changing climate and variability, so far, studies like Tan et al. [34] have focused on the yield of cereals other than barley (such as rice, maize, and wheat). So, the purpose of this study is to examine how LF and SLM practices jointly influence technical inefficiency in barley production in the Gamo Highlands of Ethiopia. For this, we estimated (i) plot-invariant and plot-varying inefficiency and (ii) the interacted effects of LF and SLM practices on technical inefficiency. To explain these effects, we adapted stochastic frontier (SF) models for panel data (which are designed to work on farms observed over multiple periods) for use with cross-sectional data for farms with multiple plots. The paper is structured as follows: Section 2 provides the theoretical and empirical explanation for adapting the SF models for panel data for use with cross-sectional data. Sections 3 and 4 present the data and empirical model. Section 5 discusses the results and, finally, Section 6 presents the conclusion.

## 2. Theoretical Framework

Applications of SF models to examine productivity and efficiency dates back to Aigner et al. and Meeusen and van Den Broeck [35,36], and Rahmana, Niroula and Thapa and Tan et al. [31–33] have applied SF models to examine the effect of LF on output and technical efficiency. We assume that LF can either increase or reduce technical inefficiency. Moreover, we suppose that the effects of SLM practices on inefficiency are conditioned by the magnitude of the LF. First, fragmentation increases commuting costs and results in wastage of time and inputs (e.g., wastage of fertiliser due to leakage from containers when farmers work away from home). Furthermore, fragmentation holds farmers back from the maximisation of investments in land improvement in remote and small plots, and restricts available land use options and land management practices, which may lead to negative externality effects [37,38]. For instance, although indigenous tree planting potentially reduces soil erosion and composted leaves can improve soil fertility, tree planting can compete with crops for water and cause border disputes on fragmented plots. Moreover, farmers in the Gamo Highlands can be reluctant to grow heavy staple crops (such as potatoes and ensete) in remote fields due to the burden of transporting the final products, although remote plots are as suitable as homestead plots for the production of these crops. However, fragmentation can reduce output loss by spreading production risks [39].

In this study, we estimated two SF models for panel data: (i) an SF panel model with a multistage procedure developed by Kumbhakar et al. [40], hereafter called the "random effects stochastic frontier (RESF) model"; and (ii) a "true" fixed effects SF model proposed by Greene [41], hereafter called the "true fixed effects stochastic frontier (TFESF) model". The RESF and TFESF models are different; the former has two sources of inefficiency and the latter has one. We adapted these two panel models for a dataset containing cross-sectional plot-level data. As a consequence, in our model, the panel data has two dimensions: (i) the different farms and (ii) the two plots observed per farm. Collecting data on two plots for the same farmer allowed us to estimate both plot-invariant (persistent) efficiency and plot-varying (residual) efficiency.

First, the RESF model was adapted to divide technical inefficiency into persistent (plot-invariant) and residual (plot-varying) components. Moreover, the RESF model separates farmer effects from both persistent inefficiency and residual inefficiency. In doing so, the model avoids the upward bias in persistent inefficiency. Downward bias in overall efficiency is also avoided because persistent inefficiency is no longer confounded within farmer effects [40]. Persistent inefficiency is farmer specific (i.e., it reflects the effect of inputs like management and other unobserved inputs, which vary across farms). Persistent inefficiency can change only when there is a change in something that affects the management style of the farmer [42], for example, a change in land ownership or the provision of training to farmers on innovative SLM practices.

However, residual efficiency is both farm- and plot-specific. Efficiency can vary from plot to plot for the same farmer. A farmer can diversify the quality, quantity, and type of investment in soil fertility improvement between plots because of land fragmentation. For instance, a farmer could be reluctant to undertake tree planting on small fragmented plots. In addition, a farmer can vary the quality and quantity of land improvement in different plots, due to the variation in the distance to the plots, the size of the plots, the soil type and fertility level of the plots, the susceptibility of the plots to erosion, and the slope of the plots. Additionally, LF could lower the farmer's propensity to innovate in land management. For instance, a farmer could avoid ground-breaking and labour-intensive land management practices in remote plots. It is also important to note that some land management practices can be uniform across plots for a given farmer (i.e., use of manure). For this, identifying persistent and residual components of inefficiency is vital, because they have different policy implications.

The RESF model, which separates farmer effects, persistent inefficiency, and plot-varying inefficiency, is specified as follows:

$$y_{ij} = \beta_0 + x'_{ij}\beta + \mu_i - \eta_i + v_{ij} - u_{ij} \qquad i = 1, 2, \ldots, n \qquad j = 1,\ 2 \tag{1}$$

where, $y_{ij}$ is the ln of barley output per hectare (ha) for farm $i$ observed in plot $j$, and $x_{ij}$ (in ln) is the vector of inputs allocated to plot $j$ by the producer in farm $i$ to realize $y_{ij}$. A parameter vector $\beta$ characterises the structure of the production technology. The error term is decomposed into four constituents: $\mu_i$ *and* $v_{ij}$ are the noise while $\eta_i$ *and* $u_{ij}$ are non-negative inefficiency components. The random disturbance term $v_{ij}$ is included to capture the effect of statistical noise on observed yield per hectare as a result of measurement errors, omitted variables, and favourable and unfavourable exogenous production shocks that are out of the producer's control. Moreover, $\mu_i$ captures unobserved, producer-specific heterogeneities, which are plot-invariant. These random shocks can increase or decrease yield, ceteris paribus. However, $\eta_i$ *and* $u_{ij}$ account for plot-invariant and plot-varying technical managerial constraints, respectively, resulting in the actual yield of plot $j$ being different from its potential yield per hectare $y_{ij}$ (i.e., technical inefficiency).

We used a multistep procedure to estimate the model: the parameters of the production function, $\beta$, (other than intercept and variance components) were estimated first without setting distributional assumptions on the error components [40,43]. We used maximum likelihood in the next stage to estimate the efficiency components. To apply the procedure, we first had to rewrite Equation (1) as:

$$y_{ij} = \beta_0^* + x'_{ij}\beta + \alpha_i + \varepsilon_{ij} \tag{2}$$

where, $\beta_0^* = \beta_0 - E(\eta_i) - E(u_{ij})$; $\alpha_i = \mu_i - \eta_i + E(\eta_i)$ and $\varepsilon_{ij} = v_{ij} - u_{ij} + E(u_{ij})$. This specification allows a zero mean to be obtained, as well as constant variance for $\alpha_i$ and $\varepsilon_{ij}$ [40,42]. Following Kumbhakar et al. [40], Equation (2) can be estimated in three steps.

Step 1: Equation (2) is the commonly known specification for a random effects panel data model, thus the standard random effects panel regression yields estimated values for $\beta$ represented as $\hat{\beta}$. This step also allowed the estimated values of $\alpha_i$ and $\varepsilon_{ij}$ (represented as $\hat{\alpha}_i$ and $\hat{\varepsilon}_{ij}$) to be obtained.

Step 2: Plot-varying technical inefficiency, $u_{ij}$, was obtained using estimated values of $\varepsilon_{ij}$ from step 1, as:

$$\varepsilon_{ij} = v_{ij} - u_{ij} + E(u_{ij}) \tag{3}$$

and by assuming $v_{ij}$ is independent and identically distributed $N(0,\ \sigma_v^2)$ and $u_{ij}$ is $N^+(0,\ \sigma_u^2)$. This step gave a prediction of the plot-varying residual technical efficiency (RTE) component, $\hat{u}_{ij},\ RTE = \exp(-\hat{u}_{ij})$, for details see [40,44].

Step 3: To estimate plot-invariant or persistent technical efficiency, $\eta_i$, we followed a procedure similar to step 2. To do this, we used the best linear predictor of $\alpha_i$ from step 1, as:

$$\alpha_i = \mu_i - \eta_i + E(\eta_i) \tag{4}$$

and considering $\mu_i$ is independent and identically distributed $N(0,\ \sigma_\mu^2)$ and $\eta_i$ is $N^+(0,\ \sigma_\eta^2)$, Equation (4) was estimated using the standard normal-half-normal SF model cross-sectionally [40,44]. Estimates of the plot-invariant (i.e., persistent) technical inefficiency component, $\eta_i$, were obtained using the procedure suggested by Jondrow et al. [44]. Persistent technical efficiency (PTE) was obtained from $PTE = Exp(-\hat{\eta}_i)$. The overall technical efficiency (OTE) was then obtained from the product of PTE and RTE [42]. That is, $OTE = PTE \times RTE$.

Second, the true fixed effects stochastic frontier (TFESF) model proposed by W. Greene [41] was adapted to estimate the effect of plot-varying exogenous variables. The TFESF model was used, because in the RESF model with multistage procedure the means to accommodate heteroskedasticity has not yet been developed [40]. Moreover, the TFESF model allows the inefficiency to be heteroskedastic. For these reasons, we adapted the TFESF model to estimate the effect of exogenous covariates on technical inefficiency. For this, we analysed the TFESF model at two levels: (i) TFESF model I (i.e., restricted model, a model without interaction terms) and (ii) TFESF model II (i.e., unrestricted model, a model with interaction terms), comprising the effect of land fragmentation, SLM practices, and the interaction between LF and SLM practices on technical inefficiency. The TFESF model II was considered to examine whether or not the efficiency effects of SLM practices are conditioned by LF.

The specification of a TFESF model accounting for heteroskedasticity is:

$$y_{ij} = \alpha_i + x'_{ij}\beta + \varepsilon_{ij} \tag{5}$$

$$\varepsilon_{ij} = v_{ij} - u_{ij} \tag{6}$$

$$v_{ij} \sim N(0,\ \sigma_v^2) \tag{7}$$

$$u_{ij} \sim N^+(\mu_{ij},\ \sigma_{ij}^2) \tag{8}$$

$$\mu_{ij} = z_{ij}\delta \tag{9}$$

$$\sigma_{ij}^2 = \exp(z_{ij}\gamma) \tag{10}$$

where, $y_{ij}$ represents output per hectare for farm $i$ on plot $j$, $x_{ij}$ are vectors of inputs, $\beta$ is a technology parameter, $\alpha_i$, is farm-specific heterogeneity, $v_{ij}$ is the noise, and $u_{ij}$ is the inefficiency. The mean of inefficiency and heteroskedastic inefficiency are represented by $\mu_{ij}$ and $\sigma_{ij}^2$ respectively. The constant 1 and exogenous variables affecting inefficiency are represented by $z_{ij}$, while $\delta$ and $\gamma$ are the corresponding coefficient vectors, respectively.

## 3. The Study Area and Data

The study area, the Gamo Highlands, is located high above the East African Great Rift Valley. The mountain chains of the Gamo Highlands are characterised by a predominance of ensete and cereal-based cropping systems and livestock production. Barley is the predominant crop and is produced mainly for consumption rather than for market. Weaving is the second most dominant livelihood strategy.

Lack of working capital, limited endowments of agricultural land, and land fragmentation influence land use, investment in land improvement, and agricultural production in Ethiopia [45]. Moreover, farmers in Ethiopia have only land use rights, and land cannot be used as collateral. These limited land use rights decrease the propensity of farmers to invest in land improvement.

The data for this study was obtained from a household survey. Farmers' socioeconomic features and plot-level data were collected from Done kebele (a 'kebele' is a lower-level administrative unit in Ethiopia). Done kebele is part of Dita woreda (a 'woreda' is a higher-level administrative unit comparable to a province), which is located in the Gamo Highlands. Plot-level data collection was limited to a single kebele and two plots per farm, because gathering information on land management practices (e.g., the amount of manure applied and the number of native trees planted) for multiple plots per owner is demanding. Moreover, the two plots selected per farm were far from each other and it is difficult to trace plots, thus a guide from each farm was used to indicate the two plots selected per farm requiring substantial commuting costs. A stratified random sampling technique was followed to select plots. A hundred households were surveyed in the 2016 "meher" season (the main barley production season). Using a simple random sampling approach, two barley plots per farm were selected: a homestead plot close to home randomly selected from homestead barley plots per farm, and a remote (the furthest) plot from home randomly selected from remote barley plots. Farmers who had only either a homestead or a remote plot were not included. Plot-level data was fully collected for 184 plots belonging to 92 farmers. Geolocation data collected by experts employed by the local government using global positioning system (GPS) devices was used as secondary data to calculate farm-level fragmentation indicators. Table 1 presents a summary of the data used for this study.

**Table 1.** Summary statistics of variables.

| Variables | Description of Variables | % | Mean | SD | Min | Max |
|---|---|---|---|---|---|---|
| ln (Output) | Barley yield per ha observed in plot j, kg | | 7.43 | 0.91 | 4.47 | 10.69 |
| | **Inputs** | | | | | |
| ln (Manure) | Manure applied per ha on plot j, kg | | 3.96 | 2.06 | 0 | 7.73 |
| ln (Labour) | Family labour available to be used per ha on plot j in 2015, hours | | 5.92 | 1.22 | 2.17 | 8.95 |
| ln (Fertiliser) | Chemical fertiliser applied per ha on plot j, kg | | 5.39 | 1.87 | 0 | 10.03 |
| | **Plot-invariant causes of inefficiency** | | | | | |
| | **Education and experience** | | | | | |
| Literacy | 1 if household head can read and write | 25 | 0.25 | 0.43 | 0 | 1 |
| Experience | Farming experience, years | | 35.6 | 16.9 | 1 | 76 |
| | **Land fragmentation indicators** | | | | | |
| Plot | Number of plots | | 25.5 | 16.3 | 2 | 80 |
| SFI | Simpson index for land fragmentation | | 0.87 | 0.1 | 0.5 | 0.97 |
| Distance | Sum of non-overlapping distance from home to all plots, km | | 2.8 | 1.6 | 0.2 | 7.2 |
| Land | Total land holding size, ha | | 1.6 | 1.5 | 0.13 | 8.32 |
| | **Plot-varying causes of inefficiency** | | | | | |
| | **Plot characteristics** | | | | | |
| Slope | 1 if slope of barley plot j is steep | 26 | 0.26 | 0.44 | 0 | 1 |
| Fertility | 1 if barley plot j is fertile | 31 | 0.32 | 0.47 | 0 | 1 |
| Distance 1 | Distance to a barley plot j from home, km | | 0.71 | 0.66 | 0.001 | 2.7 |
| Land 1 | Plot j allocated for barley production, ha | | 0.08 | 0.09 | 0.002 | 0.61 |
| | **SLM practices** | | | | | |
| Legume | 1 if legume applied on plot j last year | 65 | 0.65 | 0.48 | 0 | 1 |
| Indigenous | 1 if indigenous tree planted on plot j | 46 | 0.46 | 0.50 | 0 | 1 |
| Seed | 1 if quality barley seed used on plot j | 42 | 0.42 | 0.50 | 0 | 1 |
| Obs. | Number of observations | | | | | 184 |

Source: survey data.

### 3.1. Output

The average annual barley yield of a plot was 2790 kg per hectare (ha) for the main crop production (e.g., *meher*) season 2015. Although investment in soil improvement in nearby plots is high, the average yield of a plot close to home was 2455 kg, which is not significantly different from the yield in a remote plot, which was 3126 kg per ha. Plots close to home were a mean distance of 0.36 km from home, while remote plots were 1.1 km away from home on average.

### 3.2. Inputs

The main inputs for barley production in the study area are land, labour, manure, and chemical fertiliser. Plot size is an important factor of production; on average, households farm 1.6 hectares of land on 26 plots. Scale inefficiencies in production and poor investment in land quality improvement are inevitable for small plots, leading to high production inefficiency. Family labour is the main source of labour. The availability of family labour is expected to increase yield by increasing the application of land management practices and post-harvest crop management that cuts down the loss of yield through insects and livestock. As labour use per plot is not known, we calculated it by multiplying the adult equivalent family labour size (adult equivalent labour = (0.25 × household size age 10–14) + (1 × household size age 15–65) + (0.75 × household size age > 65)) by the share of hours (share of hours a labourer worked = 52 weeks × 6 days × 8 hours × land 1 ÷ land (see Table 1 for land 1 and land)) members of the family worked on a specific barley plot.

### 3.3. Land Fragmentation Indicators

Although we have various indicators to measure LF to capture different dimensions of LF, we employed two plot-varying LF indicators, barley plot size and the distance to barley plot from home for estimation.

The non-overlapping distance from the homestead to the barley plot and the Simpson index for LF are plot-invariant indicators described in Table 1 to show the fragmentation status in the study area. We followed the approach of Hung et al. [46] to measure the Simpson index. The Simpson index value ranges from 0 (when a household has a single plot) to 1 (when a household has many plots). GPS devices were used to measure the distance to, and size of, the barley plots.

We considered two prominent debates on the relationship between LF and efficiency. First, that LF reduces efficiency [28,31,47,48] and, second, that multiple plot ownership increases technical efficiency, which was found to be the case in China [34], implying the existence of variation effects. LF decreases expected output but reduces output variation from year to year and increases the minimum output in the worst year in India [49]. Wan and Cheng [50] showed that the adverse effects of LF on returns to scale and output are too small in China to recommend radical land policy reform. Based on the finding of these previous studies, we expected that the notable LF in our study area would reduce technical efficiency.

### 3.4. SLM Practices

The SLM practices considered in this study are the practices that farmers apply to adapt to a changing climate and the climate variability that they have observed in the last 25 years. The selection of practices was as follows: first we surveyed 13 SLM practices that potentially increase soil fertility and control soil erosion. Second, we asked farmers whether or not they had perceived climate change and variability (i.e., a change in temperature, precipitation, or barley productivity) in the last 25 years. Third, farmers were asked whether or not they were altering practices with the intention of adapting to climate change and variability. Farmers who said that they had responded to perceived climate change were considered "adapters". If a farmer did not perceive climate change, but changed their SLM practices, (s)he was still considered to be an autonomous adapter. We collected plot-level data on four SLM practices that are significantly correlated with farmers' perceptions of climate change. These were manure application, indigenous tree planting, legume–barley rotation (e.g., planting legumes following barley production in the same plot in the next production season or year), and the use of quality seed (see Table 1).

The deployment of these practices is important in maintaining profitable agriculture and to sufficiently feed the growing population, while preserving the natural capital and ecosystem services [51]. Effective investment in land increases resilience and soil quality, which in turn leads to efficiency improvement. Land management practices, such as the amount of manure applied and local trees planted, are assumed to increase productivity and efficiency by compensating for, or decreasing, soil loss.

The technical efficiency effects of the interaction between SLM and LF indicators can either be positive or negative. LF could increase inefficiency as it increases commuting costs. LF also discourages innovation in the use of SLM practices and the quality of investment in soil upgrading could be higher in homestead plots than in remote plots. For instance, the amount of manure applied or age and number of local trees planted per hectare are expected to decrease as the plot gets far away from the homestead.

### *3.5. Plot Characteristics*

Plot characteristics are expressed using dummies for soil fertility and the slope of a plot. We assumed that the adverse effects of low soil fertility and slope on productivity and efficiency can be offset by effective land management practices.

### *3.6. Education and Experience*

Household education and farming experience influence technical efficiency by influencing the capacity and know-how of farmers to combine factors of production and utilise available technology [52,53]. However, these variables are plot-invariant and not used as explanatory variables for the main analysis.

## **4. Empirical Model**

For the stochastic production frontier, the translog specification for the yield of the $j$th plot of farm $i$ was selected:

$$j = \beta_0 + \sum_{m=1}^{3} \beta_m \ln\ x_{mij} + \frac{1}{2} \sum\nolimits_{m=1}^{3} \sum\nolimits_{r=1}^{3} \beta_{mr} \ln\ x_{mij} \cdot \ln\ x_{rij} + \mu_i - \eta_i + v_{ij} - u_{ij} \tag{11}$$

where, $\ln\left(y_{ij}\right)$ is the natural logarithm of output per ha for farm $i$ observed in plot $j$ in 2015 in the *meher* season, and $x_{mij}$ and $x_{rij}$ are the amounts of input $m$ or $r$ used for barley production on plot $j$ by farmer $i$, and $\beta$s are the coefficients for the inputs of the frontier model.

The technical inefficiency $u_{ij}$ of farm $i$ is expressed as follows:

$$u_{ij} = \delta_0 + \sum_{s=1}^{2} \delta_s LF_{sij} + \sum_{w=1}^{4} \tau_w SLM_{wij} + \sum_{s=1}^{2} \sum_{w=1}^{4} \pi_{sw} LF_{sij} \times SLM_{wij} + \sum_{k=1}^{2} \rho_k P_{kij} + \omega_{ij} \tag{12}$$

where, $u_{ij}$ is the non-negative, unobservable random variable that captures the technical inefficiency of farm $i$ for plot $j$. In $SLM_{wij}$, $w$ is the land management practice that is deployed as an adaptation strategy on plot $j$ of farm $i$, and $LF_{sij}$ is the plot-varying LF indicator $s$ for plot $j$ of farm $i$. The joint effect of LF indicators and SLM practices on barley output is given by $LF_{sij} \times SLM_{wij}$. $P_{kij}$ is fertility or slope level $k$ for plot $j$ of farm $i$. The letters of the Greek alphabet in Equation (12) stand for the coefficients of the covariates explaining inefficiency, while $\omega_{ij}$ is the error term for technical inefficiency. The maximum likelihood estimation for the RESF model, as discussed in Equations (1)–(4), was carried out to estimate Equation (11). The STATA ado file in STATA version 13.1 developed by Kumbhakar et al. [42] was used to execute the estimation of $\beta$s and the efficiency components (OTE, RTE, and PTE) in the multistep procedure. However, the maximum likelihood estimation for the TFESF model, as discussed in Equations (5)–(10), was carried out to estimate Equations (11) and (12) in one step. In this way, the $\beta$s and the coefficients of the inefficiency variables were estimated jointly. To estimate the parameters of the TFESF model, the 'sfpanel' syntax in the STATA version 13.1 was used.

The general likelihood ratio (LR) test statistic, $\lambda = 2[\ln\ L(H_1) - \ln L(H_0)$, is twice the difference between maximum log likelihood values of the unrestricted and restricted model. The LR test was applied: (i) to examine the existence of technical inefficiency, (ii) to determine functional form (i.e., translog versus Cobb–Douglas function), and (iii) to test the importance of SLM practices and LF or interaction between SLM and LF in explaining technical inefficiency.

## 5. Results and Discussion

The results are presented in the following four sub-sections. The first sub-section discusses the results of hypotheses tests (Table 2), the second discusses the output elasticities of the production frontier estimation (Table 3), the third describes the components of efficiency (Table 4), and the fourth discusses the causes of inefficiency for restricted (i.e., model I, for which the interaction terms are not controlled) and unrestricted (i.e., model II, for which the interaction terms are considered as factors affecting efficiency) TFESF models (Table 5). Two SLM practices, legume and quality seed use, were not considered as interaction terms as model II does not converge with inclusion of these two variables as interaction terms.

**Table 2.** Summary of hypotheses tests.

| Model | | Test Statistics | A.1 No Technical Inefficiency | A.2 TL Model vs. CD Model | A.3 Joint Effect of LF Indicators Is Zero | A.4 Joint Effect of SLM Practices Is Zero | A.5 No Interaction Effect |
|---|---|---|---|---|---|---|---|
| | | | | $\beta_{mr} = 0$ | $\delta_s = 0$ | $\tau_w = 0$ | $\pi_{sw} = 0$ |
| RESF | Equation (11) | $\lambda$ | 4.86 | 23.13 | | | |
| | | df | 1 | 6 | | | |
| | | $p$-value | 0.025 | 0.000 | | | |
| | | decision | rejected | rejected | | | |
| TFESF II | Equations (11) and (12) | $\lambda$ | 647.104 | 462.90 | 8.05 | 42.56 | 13.23 |
| | | df | 1 | 7 | 2 | 4 | 8 |
| | | $p$-value | 0.000 | 0.000 | 0.020 | 0.000 | 0.010 |
| | | decision | rejected | rejected | rejected | rejected | rejected |

**Table 3.** Yield elasticities.

| Variables | Model I | | Model II | |
|---|---|---|---|---|
| | Elasticities | SE | Elasticities | SE |
| ln (Labour) | 0.2280 *** | (0.0580) | 0.0970 | (0.0737) |
| ln (Manure) | 0.2125 *** | (0.0228) | 0.2133 *** | (0.0322) |
| ln (Fertiliser) | 0.5595 *** | (0.0499) | 0.5064 *** | (0.0543) |
| Seed | | | 0.0960 *** | (0.0233) |
| Indigenous | | | 0.0504 ** | (0.0212) |
| Legume | | | 0.0369 | (0.0272) |
| Returns to scale | 1.08 | | 1.00 | |

*** $p < 0.01$, ** $p < 0.05$.

**Table 4.** Technical efficiency sores.

| | Residual Efficiency | Persistent Efficiency | Overall Efficiency |
|---|---|---|---|
| Mean | 0.72 | 0.67 | 0.49 |
| SD | 0.09 | 0.16 | 0.16 |
| Min | 0.32 | 0.26 | 0.08 |
| Max | 0.91 | 0.91 | 0.82 |

**Table 5.** Estimation of parameters for TFESF model for barley production.

| Variable | Model I | | | | Model II | |
|---|---|---|---|---|---|---|
| **Production Function** | **Coef** | **SE** | **Coef** | **SE** | **Coef** | **SE** |
| ln (Labour) | 0.3579 *** | (0.0001) | 0.3581 *** | (0.0007) | 0.3130 *** | (0.0015) |
| ln (Manure) | 0.3052 *** | (0.0001) | 0.2867 *** | (0.0011) | 0.2882 *** | (0.0026) |
| ln (Fertiliser) | 0.3512 *** | (0.0001) | 0.3534 *** | (0.0010) | 0.3347 *** | (0.0021) |
| Seed | | | | | 0.8214 *** | (0.0087) |
| Indigenous | | | | | 0.2698 *** | (0.0116) |
| Legume | | | | | 0.3867 *** | (0.0145) |
| **Factors affecting inefficiency** | | | | | | |
| Land1 | 4.3284 *** | (1.5262) | 14.9436 *** | (3.4223) | 1.7271 | (8.2861) |
| Land 1 × land 1 | | | −28.0562 *** | (8.1049) | −19.7118 | (14.3803) |
| Distance 1 | 0.1215 | (0.1796) | −0.0782 | (0.1632) | −0.9651 * | (0.5051) |
| ln (Manure) | 0.4952 *** | (0.0839) | 0.2813 *** | (0.0545) | (0.19989 | (0.1977) |
| Seed | −0.5605 *** | (0.1862) | −0.3087 | (0.1909) | −0.4987 ** | (0.1974) |
| Indigenous | 0.1126 | (0.1813) | −0.0764 | (0.1778) | −0.7642 ** | (0.3771) |
| Legume | 0.2946 | (0.1919) | 0.2418 | (0.1889) | 0.7974 | (0.2210) |
| Slope | −0.4997 ** | (0.2100) | −0.1249 | (0.2237) | −0.3610 | (0.2736) |
| Fertility | −0.4291 ** | (0.1845) | −0.4033 ** | (0.1887) | −0.3919 ** | (0.2014) |
| Experience | −0.0060 | (0.0057) | −0.0128 ** | (0.0063) | −0.4556 | (0.2255) |
| Literacy | −0.3662 * | (0.1998) | −0.1207 | (0.1993) | 0.0008 ** | (.0002) |
| Labour | 0.0007 *** | (0.0002) | | | −0.3610 *** | (0.2736) |
| Land 1 × ln (Manure) | | | | | 1.5810 | (1.2991) |
| Land 1 × Indigenous | | | | | 4.2977 | (3.0124) |
| Distance 1 × ln (Manure) | | | | | −0.0042 | (0.1087) |
| Distance 1 × Indigenous | | | | | 1.1818 *** | (0.3702) |
| Constant | −24.6601 | (17.543) | 0.58461 | (0.5786) | 0.3439 | (1.2611) |
| Observations | 184 | 184 | 184 | 184 | 184 | 184 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

## 5.1. Hypotheses Tests

A summary of the hypotheses tests for Equations (11) and (12) is given in Table 2. The first hypothesis states that there is no inefficiency (i.e., ordinary least squares (OLS) is an ideal estimator). The second hypothesis is that the translog (TL) specification of Equation (11) is reduced to the Cobb–Douglas (CD) specification. To conduct the test statistics for Hypotheses 1 and 2, the log likelihood values of the OLS, RESF, and TFESF models for Equation (11) were used. The test results indicate the presence of technical inefficiency, because the null hypothesis of no inefficiency was rejected at the 1% significance level for the RESF and TFESF models (see column A.1 of Table 2). Moreover, the TL did not reduce to the CD specification, because the null hypothesis that the cross-products of input variables jointly equal zero was rejected for the TFESF and RESF models (see column A.2 of Table 2), but we decided to use the CD specification instead of the TL as the TL specification does not converge with inclusion of factors affecting inefficiency.

Hypotheses 3 to 5 were tested using the log likelihood value of the TFESF model for Equations (11) and (12). The third hypothesis is that LF indicators, for example, plot size used for barley production and distance to a barley plot, jointly do not affect technical efficiency. This null hypothesis was rejected at the 1% significance level (see column A.3 of Table 2). The fourth hypothesis is that the four SLM practices that are jointly deployed on the barley plots do not affect technical inefficiency. The fifth hypothesis states that the interaction terms (i.e., SLM and LF indicators) jointly do not affect efficiency.

The likelihood ratio test rejected the fourth and fifth null hypotheses at the 1% significance level (see columns A.4 and A.5 of Table 2, respectively). The hypotheses test results suggest that SLM practices, LF indicators, and their interactions with SLM practices are important determinants of technical efficiency.

### *5.2. Elasticities and Returns to Scale*

Table 3 presents the yield elasticities and standard errors (SE) of the TFESF models I and II. As the specification is TL for Equation (11), the elasticities are the first derivative of ln of output per ha, with respect to ln of an input. The results show that the sum of yield elasticities of the inputs was 1.08 and 1 for model I and model II respectively (see Table 3). This implies that a 1% increase in the use of inputs would result in a proportionate increase in yield.

The yield elasticities of the fertiliser were highest, followed by manure. Although the high yield elasticity of fertiliser is important to ensure food security, fertiliser is less environmentally friendly than manure. A kilogram increase in fertiliser use led to a 0.51 to 0.56% change in yield in the TFESF model. Moreover, the yield elasticity results of SLM practices were positive and significant (except legume), which is promising for the environment as the use of SLM practices is sustainable, as SLM practices are eco-friendly and economical for farmers. The yield elasticity of labour is comparable to the results of Seyoum [54] for maize production in Ethiopia.

### *5.3. Technical Efficiency Components*

The RESF model by Kumbhakar et al. [40] is able to distinctly report the magnitude of persistent plot-invariant efficiency (PTE) and plot-varying efficiency (RTE) components. Results show that efficiency varies greatly between plots, as well as between farmers (Table 4). The RTE was between 32% and 91%, whereas the PTE was between 26% and 91%, implying that efficiency variation is significant for both RTE and PTE. The mean value of RTE was 72%, i.e., higher than the mean value of PTE of 67%. This implies that although the mean inefficiency of 33% between farmers was higher than the mean inefficiency of 28% between plots, it is important to reduce inefficiency between farms and between plots to ensure sustainable production in a changing climate, as both inefficiency levels are significant. Moreover, this result confirms the findings of Kumbhakar et al. [40].

Moreover, the mean OTE of 49% (and its range from 8 to 82%) implies a large gap between actual and potential output; hence, farmers have room to increase output by more than 51% without increasing the use of inputs (such as labour) by adopting the technologies and techniques used on the best-managed fields.

### *5.4. Factors Affecting Inefficiency*

This section focuses on the estimation results of the two TFESF models: TFESF models I and II are presented in Table 5. LF indicators affect inefficiency. In particular, the size of the plot used for barley production reduced inefficiency after some threshold level (a plot size below 0.27 hectares increased inefficiency, while plots above this size decreased inefficiency). This indicates that larger plots could increase investment in land quality improvement. Farmers construct homes closer to larger plots to ease manure application and other forms of investments that enhance soil quality in these plots. This result implies that increasing the size of a plot, for example, by reducing LF through the voluntary exchange of plots, is critical to reduce inefficiency. This result is also supported by the findings of Niroula and Thapa [33].

Distance to the barley field from home either increases efficiency (TFESF model II) or has no effect on efficiency (TFESF model I). However, distance was found to decrease efficiency in studies by Tan et al. [55], and Rahmana [31] found that the larger the number of plots (i.e., LF) the lower the efficiency. The variation in results can be attributed to the fact that, as opposed to the expectation, investment in nearby plots was not higher than in remote plots. For example, the mean of manure and fertiliser applied per hectare in nearby plots was not significantly higher than for remote plots.

However, the mean of labour hours used per hectare for nearby plots was significantly (i.e., at the 5% level) lower than for remote plots. Moreover, higher altitude plots far away from home, which are more suitable for barley production, are more likely to be fallow.

SLM practices did have a significant effect on efficiency. For instance, increasing quality seed use was found to improve efficiency, while manure application decreased efficiency, as manure application is demanding, particularly on fragmented plots.

The technical efficiency effects of SLM practices were jointly conditioned by LF indicators. However, the effect of some specific SLM practices on efficiency was not conditioned by the level of LF. For instance, manure application on larger plots used for barley production neither improved nor lowered efficiency. Some possible explanations for this result are: first, although farmers commonly construct separate homes to increase manure application on larger plots located away from their main home [56], the amount of manure and fertiliser applied per hectare decreases significantly as the plot size increases. Second, increasing indigenous tree planting on larger plots did not change inefficiency, even though we hypothesised that planting trees on fragmented plots would lead to more border conflicts, creating a negative interaction effect.

This result may be explained by the fact that the age of trees planted and size of the plot used for barley production were not strongly correlated; in addition, the number of indigenous trees planted and the size of the plot used were also not significantly correlated. The average age of trees planted was eight years and the average number of trees planted per ha was 34, which was not sufficient to significantly alter erosion and soil fertility levels. Finally, manure application on distant plots did not affect efficiency: the reason for this is perhaps that an inadequate amount of manure is used, as applying this practice on remote plots is demanding.

The absence of a significant effect of most of the specific SLM practices and the interaction between most of the specific SLM and LF indicators on efficiency implies that SLM practices, or the way they are applied, are unable to improve efficiency. In particular, the lack of manure and resources to buy inputs (such as quality seed or tree seedlings) may be a cause for this. Moreover, the SLM practices employed by farmers may not be sufficiently effective in reducing the current impact of climate change. Support from agricultural experts and training of farmers to enhance innovation in land management and increasing access to credit to buy inputs are needed to make existing SLM practices more effective. Soil fertility enhancement was found to be efficiency improving, implying the positive long-term effect of SLM practices. The farming experiences of farmers and education levels increased efficiency, which is consistent with Tan et al. [34], while more labour hours used in fragmented plots discouraged efficiency implying the existence of surplus labour.

## 6. Conclusions

Increasing barley yield is imperative to feed the increasing population in the Gamo Highlands. However, a changing climate is expected to increase the gap between grain supply and demand, largely by decreasing yield per hectare. Smallholder farmers have limited options to meet the growing food demand but face ample restraints. For instance, adverse impacts of climate change are increasing while virgin land to increase production is unavailable or scarce. Farm fields are fragmented, which impedes the effective implementation of sustainable land management practices to deal with the impacts of climate change and to restore ecosystem functions, leading to production inefficiency. However, on the other hand, land fragmentation allows farmers to access various plots with heterogeneous soil types and distinct agroecological zones that are important to spread production risks. For these reasons, we hypothesised that LF and SLM practices jointly affect efficiency. Furthermore, we postulated that technical efficiency might not be constant across multiple separate plots for a given farmer.

We found that LF indicators did conjointly affect technical efficiency and that larger plot sizes improved efficiency. Furthermore, in a changing climate, we also found that SLM practices jointly affected technical efficiency, specifically, quality seed use improved efficiency, but manure application impeded efficiency as manure use is a demanding activity. Moreover, LF indicators and SLM practices cooperatively influenced technical efficiency. The overall result implies that SLM practices are not innovative enough to enhance efficiency or that there are constraints (e.g., lack of resources) that hinder their full potential to deal with climate change. Innovative SLM practices entail, for example, the planting of broadleaf indigenous trees and grasses on terraces to be used as fodder instead of bare terraces and composting instead of labour-intensive manure application.

The assumption that technical efficiency across multiple separate plots owned by the same farmer is equal needs to be reconsidered in efficiency studies. We found that technical efficiency varies across plots for farmers. The mean technical efficiency within plots was 72% and between farmers was 67%. The overall mean technical efficiency was 49%. This indicates that farmers have significant room to increase yield without using additional inputs, offering perspectives for increasing food supply in situations where virgin soil for food production is unavailable and limited.

This study introduced the joint effect of SLM practices as a climate change adaptation scheme and LF on technical efficiency as a contribution to existing studies. Moreover, the study proved that the assumption that efficiency is constant across multiple separate plots per farm leads to an inaccurate estimation of inefficiency levels. Efficiency is plot-invariant and plot-varying for farmers with multiple plots. Therefore, farmers can increase technical efficiency and yield if awareness is created about the drawbacks of fragmentation. Policy measures that reduce residual and persistent inefficiency are desirable as the magnitude of both inefficiency estimates is considerable. To achieve this, farmers can decrease LF by grouping small separate plots into larger dissimilar plots through bartering and leasing. To address the risk involved in land lease, sharecropping can be used. Moreover, constraints that limit the full potential of existing SLM practices should be lifted (e.g., resources provided to buy inputs) and new, more innovative SLM practices should be introduced to deal with the shifting climate. Agricultural experts can introduce ground-breaking SLM practices and maintenance of these practices to better cope with climate alteration and improve soil and vegetation coverage of farm lands. Future studies in the area can focus on the scale and allocative efficiency effects of land fragmentation. In this study we considered 2 plots per farm out of 26 plots per farm on average, due to resource reasons, but future studies could increase the number of plots studied to better explain the economic, social and environmental effects of land fragmentation.

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## References

1. Schlenker, W.; Lobell, D.B. Robust negative impacts of climate change on African agriculture. *Environ. Res. Lett.* **2010**, *5*, 014010. [CrossRef]
2. Deressa, T.T.; Hassan, R.M. Economic impact of climate change on crop production in Ethiopia: Evidence from cross-section measures. *J. Afr. Econ.* **2009**, *18*, 529–554. [CrossRef]
3. Parry, M.; Rosenzweig, C.; Iglesias, A.; Fischer, G.; Livermore, M. Climate change and world food security: A new assessment. *Glob. Environ. Chang.* **1999**, *9*, S51–S67. [CrossRef]
4. Wijeratne, M.A.; Anandacoomaraswamy, A.; Amarathunga, M.K.S.L.D.; Ratnasiri, J.; Basnayake, B.R.S.B.; Kalra, N. Assessment of impact of climate change on productivity of tea (*Camellia sinensis* L.) plantations in Sri Lanka. *Natl. Sci. Found. Sri Lanka* **2007**, *35*, 119–126. [CrossRef]
5. Challinor, A.; Wheeler, T.; Garforth, C.; Craufurd, P.; Kassam, A. Assessing the vulnerability of food crop systems in Africa to climate change. *Clim. Chang.* **2007**, *83*, 381–399. [CrossRef]

6. Kotir, H.J. Climate change and variability in Sub-Saharan Africa: A review of current and future trends and impacts on agriculture and food security. *Environ. Dev. Sustain.* **2011**, *13*, 587–605. [CrossRef]
7. Scholes, R.J.; Biggs, R. *Ecosystem Services in Southern Africa: A Regional Assessment*; Council for Scientific and Industrial Research: Pretoria, South Africa, 2004.
8. Knox, J.; Hess, T.; Daccache, A.; Wheeler, T. Climate change impacts on crop productivity in Africa and South Asia. *Environ. Res. Lett.* **2012**, *7*, 034032. [CrossRef]
9. Adger, W.N.; Huq, S.; Brown, K.; Conway, D.; Hulme, M. Adaptation to climate change in the developing world. *Prog. Dev. Stud.* **2003**, *3*, 179–195. [CrossRef]
10. Kurukulasuriya, P.; Mendelsohn, R. *A Ricardian Analysis of the Impact of Climate Change on African Cropland*; The World Bank: Washington, DC, USA, 2008; Volume 2.
11. IPCC. Climate Change: The Scientific Basis. In *Modelling the Turnover of Organic Matter in Long-Term Experiments at Rothamstedt*; Jenkinson, D.S., Hart, P.B.S., Rayner, J.H., Parry, L.C., Eds.; Cambridge University Press: Cambridge, UK; New York, NY, USA, 2001.
12. Parry, M.; Canziani, O.; Palutikof, J.; van der Linden, P.; Hanson, C. *Climate Change 2007: Impacts, Adaptation and Vulnerability*; Cambridge University Press: Cambridge, UK, 2007; Volume 4, pp. 1–976.
13. Kandlinkar, M.; Risbey, J. Agricultural impacts of climate change: If adaptation is the answer, what is the question? *Clim. Chang.* **2000**, *45*, 529–539. [CrossRef]
14. Vermeulen, S.J.; Aggarwal, P.K.; Ainslie, A.; Angelone, C.; Campbell, B.M.; Challinor, A.J.; Hansen, J.W.; Ingram, J.S.I.; Jarvis, A.; Kristjansonak, P.; et al. Options for support to agriculture and food security under climate change. *Environ. Sci. Policy* **2012**, *15*, 136–144. [CrossRef]
15. Di Falco, S. Adaptation to climate change in Sub-Saharan agriculture: Assessing the evidence and rethinking the drivers. *Eur. Rev. Agric. Econ.* **2014**, *41*, 405–430. [CrossRef]
16. Di Falco, S.; Veronesi, M.; Yesuf, M. Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *Am. J. Agric. Econ.* **2011**, *93*, 825–842. [CrossRef]
17. FAO. *FAO Statistical Yearbook 2012*; Food and Agricultural Organization of the United Nations: Rome, Italy, 2012.
18. Tolessa, T.; Senbeta, F.; Kidane, M. The impact of land use/land cover change on ecosystem services in the central highlands of Ethiopia. *Ecosyst. Serv.* **2017**, *23*, 47–54. [CrossRef]
19. Pretty, J.; Toulmin, C.; Williams, S. Sustainable intensification in African agriculture. *Int. J. Agric. Sustain.* **2011**, *9*, 5–24. [CrossRef]
20. Motavalli, P.; Nelson, K.; Udawatta, R.; Jose, S.; Bardhan, S. Global achievements in sustainable land management. *Int. Soil Water Conserv. Res.* **2013**, *1*, 1–10. [CrossRef]
21. Schirpke, U.; Kohler, M.; Leitinger, G.; Fontana, V.; Tasser, E.; Tappeiner, U. Future impacts of changing land-use and climate on ecosystem services of mountain grassland and their resilience. *Ecosyst. Serv.* **2017**, *26*, 79–94. [CrossRef] [PubMed]
22. Fernandes, E.C.; Burcroff, R. *Sustainable Land Management: Challenges, Opportunities, and Trade-offs*; World Bank: Washington, DC, USA, 2006.
23. Deininger, K.; Jin, S. Tenure security and land-related investment: Evidence from Ethiopia. *Eur. Econ. Rev.* **2006**, *50*, 1245–1277. [CrossRef]
24. Teshome, A.; de Graaff, J.; Ritsema, C.; Kassie, M. Farmers' perceptions about the influence of land quality, land fragmentation and tenure systems on sustainable land management in the north western Ethiopian highlands. *Land Degrad. Dev.* **2014**, *27*, 884–898. [CrossRef]
25. Gashaw, T.A. Agricultural land fragmentation and productivity in Ethiopia: Review. *Int. J. Adv. Sci. Res.* **2017**, *2*, 18–22.
26. Nguyen, T.; Cheng, E.; Findlay, C. Land fragmentation and productivity in China in the 1990s. *China Econ. Rev.* **1996**, *7*, 169–180. [CrossRef]
27. Kawasaki, K. The costs and benefits of land fragmentation of rice farms in Japan. *Aust. J. Agric. Resour. Econ.* **2010**, *54*, 509–526. [CrossRef]
28. Manjunatha, A.; Anik, R.A.; Speelman, S.; Nuppenau, E. Impact of land fragmentation, farm size, land ownership and crop diversity on profit and efficiency of irrigated farms in India. *Land Use Policy* **2013**, *31*, 397–405. [CrossRef]
29. Di Falco, S.; Penov, I.; Aleksiev, A.; Van Rensburg, T.M. Agrobiodiversity, farm profits and land fragmentation: Evidence from Bulgaria. *Land Use Policy* **2010**, *27*, 763–771. [CrossRef]

30. Reidsma, P.; Ewert, F.; Lansink, A.O.; Leemans, R. Adaptation to climate change and climate variability in European agriculture: The importance of farm level responses. *Eur. J. Agron.* **2010**, *32*, 91–102. [CrossRef]
31. Rahman, S.; Rahman, M. Impact of land fragmentation and resource ownership on productivity and efficiency: The case of rice producers in Bangladesh. *Land Use Policy* **2008**, *26*, 95–103. [CrossRef]
32. Koopmans, T.C. *An Analysis of Production as Efficient Combination of Activities*; John Wiley: New York, NY, USA, 1951.
33. Niroula, G.S.; Thapa, G.B. Impacts of land fragmentation on input use, crop yield and production efficiency in the mountains of Nepal. *Land Degrad. Dev.* **2007**, *18*, 237–248. [CrossRef]
34. Tan, S.; Heerink, N.; Kuyvenhoven, A.; Qu, F. Impact of land fragmentation on rice producers' technical efficiency in South-East China. *NJAS Wagening. J. Life Sci.* **2010**, *57*, 117–123. [CrossRef]
35. Aigner, D.; Lovell, C.A.K.; Schmidt, P. Formulation and estimation of stochastic frontier production function models. *J. Econom.* **1977**, *6*, 21–37. [CrossRef]
36. Meeusen, W.; van Den Broeck, J. Efficiency estimation from Cobb-Douglas production functions with composed error. *Int. Econ. Rev.* **1977**, *18*, 435–444. [CrossRef]
37. Bentley, J. Economic and ecological approaches to land fragmentation: In defense of a much-aligned phenomenon. *Annu. Rev. Anthropol.* **1987**, *16*, 31–67. [CrossRef]
38. De Lisle, D. Effects of distance on cropping patterns internal to the farm. *Ann. Assoc. Am. Geogr.* **1982**, *72*, 88–98. [CrossRef]
39. Blarel, B.; Hazell, P.; Place, F.; Quiggin, J. The economics of farm fragmentation: Evidence from Ghana and Rwanda. *World Bank Econ. Rev.* **1992**, *6*, 233–254. [CrossRef]
40. Kumbhakar, S.C.; Lien, G.; Hardaker, J.B. Technical efficiency in competing panel data models: A study of Norwegian grain farming. *J. Product. Anal.* **2014**, *41*, 321–337. [CrossRef]
41. Greene, W. Fixed and random effects in stochastic frontier models. *J. Product. Anal.* **2005**, *23*, 7–32. [CrossRef]
42. Kumbhakar, S.C.; Wang, H.; Horncastle, A.P. *A Practitioner's Guide to Stochastic Frontier Analysis Using Stata*; Cambridge University Press: New York, NY, USA, 2015.
43. Kumbhakar, S.C.; Heshmati, A. Efficiency measurement in Swedish dairy farms: An application of rotating panel data, 1976–88. *Am. J. Agric. Econ.* **1995**, *77*, 660–674. [CrossRef]
44. Jondrow, J.; Lovell, C.K.; Materov, I.S.; Schmidt, P. On the estimation of technical inefficiency in the stochastic frontier production function model. *J. Econom.* **1982**, *19*, 233–238. [CrossRef]
45. Belay, K.; Manig, W. Access to rural land in eastern Ethiopia: Mismatch between policy and reality. *Agric. Rural Dev. Trop. Subtrop.* **2004**, *105*, 123–138.
46. Hung, V.P.; MacAulay, T.G.; Marsh, P.S. The economics of land fragmentation in the north of Vietnam. *Aust. J. Agric. Resour. Econ.* **2007**, *51*, 195–211. [CrossRef]
47. Sherlund, S.M.; Barrett, C.B.; Adesina, A.A. Smallholder technical efficiency controlling for environmental production conditions. *J. Dev. Econ.* **2002**, *69*, 85–101. [CrossRef]
48. Bizimana, C.; Nieuwoudt, W.L.; Ferrer, S.R. Farm size, land fragmentation and economic efficiency in southern Rwanda. *Agrekon* **2004**, *43*, 244–262. [CrossRef]
49. Heston, A.; Kumar, D. The persistence of land fragmentation in peasant agriculture: An analysis of South Asian cases. *Explor. Econ. Hist.* **1983**, *20*, 199–230. [CrossRef]
50. Wan, G.; Cheng, E. Effects of land fragmentation and returns to scale in the Chinese farming sector. *Appl. Econ.* **2001**, *33*, 183–194. [CrossRef]
51. Tappan, G.; McGahuey, M. Tracking environmental dynamics and agricultural intensification in southern Mali. *Agric. Syst.* **2007**, *94*, 38–51. [CrossRef]
52. Wang, H. Heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model. *J. Product. Anal.* **2002**, *18*, 241–253. [CrossRef]
53. Battese, G.E.; Malik, S.J.; Gill, M.A. An investigation of technical inefficiencies of production of wheat farmers in four districts of Pakistan. *J. Agric. Econ.* **1996**, *47*, 37–49. [CrossRef]
54. Seyoum, E.T.; Battes, G.E.; Fleming, E.M. Technical efficiency and productivity of maize producers in eastern Ethiopia: A study of farmers within and outside the Sasakawa-Global 2000 project. *Agric. Econ.* **1998**, *19*, 341–348.
55. Tan, S.; Heerink, N.; Qu, F. Land fragmentation and its driving forces in China. *Land Use Policy* **2006**, *23*, 272–285. [CrossRef]

56. Cholo, T.; Fleskens, L.; Sietz, D.; Peerlings, J. Is land fragmentation facilitating or obstructing adoption of climate adaptation measures in Ethiopia? *Sustainability* **2018**, *10*, 2120. [CrossRef]