

## Article

# Does Farmer Knowledge of Soil Quality Influence Input Allocation Decisions and Productivity Outcomes? Implications for Sustainability

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## Abstract

Land degradation, characterized by declining soil fertility and erosion, is a major constraint of maize productivity in Malawi, where more than half of the arable land is degraded. Although knowledge of soil fertility is critical for efficient input allocation, most smallholder farmers rely on subjective assessments of soil quality, which could potentially lead to imprecise decisions. This study examines how farmers' perceptions of soil fertility and erosion influence input allocation and maize productivity among smallholder farmers in Malawi. Using plot-level data comprising 6370 maize plots from the Malawi Integrated Household Survey, we apply a Conditional Mixed Process estimator and stochastic frontier analysis to assess input use behaviour and technical efficiency. Results indicate that farmers allocate more labour and inorganic fertilizer to plots perceived as fertile, and adoption of improved maize varieties is lower on plots perceived as poor. Organic manure is more frequently applied on degraded plots to recondition the soils. Mean technical efficiency is estimated at 0.63, indicating substantial inefficiency relative to the production frontier. Further, technical efficiency declines with worsening soil conditions. These findings highlight sustainability risks associated with soil degradation and inefficient input allocation. Improved soil diagnostic services, integrated soil fertility management practices, and targeted extension programmes could promote sustainable land management and efficient matching of inputs to soil conditions.



Academic Editors: Jun (Justin) Li and Joanna Lemanowicz

Received: 2 April 2026

Revised: 22 May 2026

Accepted: 7 July 2026

Published: 14 July 2026

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**Keywords:** soil quality perceptions; input allocation decisions; technical efficiency; conditional mixed process; stochastic frontier analysis

## 1. Introduction

Maize (*Zea mays* L.) is a strategic food security crop in Malawi, serving as the staple for over 80% of the population [1,2]. Nationally, maize is cultivated on approximately 1.9 million hectares, yet productivity remains remarkably low [3]. For several decades, the average maize yields have stagnated at about 1.8 metric tons per hectare, far below the potential of

4–6 tons per hectare attainable under optimal agronomic conditions [2]. A number of production constraints have been discussed [3–5], and some of these challenges are recurring or escalating because of climate change. First, erratic rainfall patterns—largely driven by climate variability—disrupt planting schedules and reduce water availability during critical growth stages, and, hence, cause yield instability [4,5]. Second, pest infestations, mainly fall armyworm and stem borers, cause significant crop losses [5]. Third, chronic labour shortages during peak labour demand periods, namely planting and weeding which delay farm operations, result in crop productivity loss due to intense competition for nutrients between crops and weeds [6]. Lastly, approximately 40% of the country's soils are deficient in nutrients and soil organic matter due to eroded topsoil, unsustainable cropping practices and acidification [7,8]. Soil erosion rates in Malawi reach up to 30 tons per hectare annually, which is more than ten times the global average [7,9]. Ref. [10] argued that soil erosion and fertility loss have adverse impacts on productivity and welfare, and thus advocated for localized soil management strategies to address soil nutrient degradation and enhance sustainable crop production.

Amidst these escalating weather variability and soil fertility challenges, the adoption of best farm management practices such as cultivating the right crops and applying the right inputs in the right proportions becomes critical for maximizing production [3,8,11]. However, the adoption of suitable inputs, especially organic soil amendments, mineral fertilizer, and improved seeds, remain a critical constraint among smallholder maize farmers [3]. For example, the average fertilizer use of 90 kg per hectare is significantly below the global average estimated at 161.5 kg per hectare [12]. The observed low fertilizer use is despite the implementation of the Farm Input Subsidy Program (FISP), which has been largely focused on giving farmers access to affordable inorganic fertilizer, for close to two decades [13,14]. Similarly, organic fertilizer use also remains low at approximately 31% due to limited livestock ownership, bulkiness of manure, and high labour-intensity associated with its preparation and application [6]. Other critical inputs similarly show low adoption rates, whereby only 8% of farmers use chemical pesticides and 40% have adopted improved maize varieties [15,16].

The focus of the present study is to explore the nexus between knowledge of soil quality attributes, input allocation decisions, and technical efficiency among smallholder maize producers in Malawi. Farmers' decisions regarding where and why they allocate certain bundles of inputs to specific parcels of farmlands has not been extensively researched [11,17]. Fundamentally, the most important criteria guiding efficient input allocation decisions concern soil fertility status (i.e., indicative of crop suitability) and the desire to optimize returns, i.e., satisfy essential household requirements, e.g., food and cash. Thus, a profit-maximizing farmer will rationally allocate inputs in such a way that farm returns are optimized [11,18]. It is worth noting that returns for soil quality rehabilitation or productivity enhancement may be realized within a short-, medium- or long-term time horizon, depending on the state of nutrient degradation prevalent on the farm and the restorative capabilities of the selected technologies [8]. While a few farmers may have access to formal soil testing offered by agricultural research laboratories, the majority of rural farmers assess soil fertility using subjective methods such as visual inspection of soil conditions (colour and texture) and crop history in terms of previous crop yield and weed prevalence, or the presence of noxious weeds like witch-weed [19,20]. In essence, the farmer's determination of soil fertility influences the choice of crops to grow, and, subsequently, the type and quantity of inputs to use across different plots. Empirical evidence suggests that soil quality beliefs or knowledge can affect input use patterns and crop productivity, but results are rather mixed [11,14,18]. Typically, farmers tend to allocate better crops to better farmland to avoid wasting productive/costly inputs on land deemed

to be unresponsive to inputs, yet other studies show that farmers intensify input use on degraded plots to restore lost soil performance [18,21,22]. According to Ref. [22], inputs, such as organic fertilizers, are often applied to poorer soils rather than good ones due to their restorative properties and lower risk of economic loss.

This study extends the literature on input allocation decisions and technical efficiency by incorporating farmland quality as a critical driver of input allocation decisions besides risk aversion and access to modern technologies [11,18,23,24]. From a policy perspective, understanding the crop-input allocation decisions vis-à-vis soil fertility status could better inform policies and strategies advocating for soil testing services and extension advisories promoting integrated soil fertility management options for balanced soil nutrients. Ref. [9] noted that smallholder farmers often apply fertilizers without site-specific knowledge, which results in nutrient imbalances and suboptimal yields. With the low levels of sustainable input intensification in Malawi, more evidence is needed for the scaling of integrated soil fertility management options (ISFM). The depletion of soil organic matter due to poor agricultural practices, such as mono-cropping, causes nutrient deficiency because soils fail to hold nutrients and water, thereby resulting in poor crop growth during prolonged dry spells. Optimal fertilizer-use efficiency is achieved when organic soil amendments are integrated in the suite of soil fertility management practices to increase soil organic matter content and achieve agricultural sustainability [8]. Thus, the study is also closely aligned with several Sustainable Development Goals (SDGs), including SDG 2 (Zero Hunger), SDG 15 (Life on Land), and SDG 12 (Responsible Consumption and Production) [25].

## 2. Materials and Methods

### 2.1. Theoretical Motivation

Two interrelated economic perspectives inform this study: production theory and decision-making under uncertainty. Production theory provides the neoclassical foundation for understanding how inputs are transformed into output within a given technology set [18,26]. At its core, the production function represents the maximum attainable output from a given combination of inputs under a specified technology. In smallholder maize production systems, key inputs such as land, labour, seed, and fertilizer jointly determine potential output. A key implication of this framework is that farmers are viewed as optimizers who allocate inputs to maximize expected returns, subject to resource and technological constraints. In farming systems where farmers own multiple plots, this implies a heterogeneous allocation of inputs across plots, depending on known differences in marginal productivity. Accordingly, farmers are expected to allocate more inputs to plots perceived as more productive and fewer inputs to less productive plots [11], or totally abandon crop production where the land is deemed too degraded and has ceased to generate acceptable returns. However, the logic of precise input allocation relies on the assumption that farmers have accurate or unbiased information about plot-level productivity. In reality, smallholder farmers in Malawi operate under significant uncertainty, particularly regarding soil fertility and plot responsiveness. True soil quality is not directly observable, and, instead, farmers rely on nearly imperfect indicators such as soil colour, texture, weed pressure, crop vigour, and historical yields to infer plot-level productivity [19,20]. This introduces uncertainty into the decision-making process, where input allocation is guided by perceived rather than objectively measured plot conditions.

Thus, theories such as the Expected Utility Theory, Subjective Expected Utility Theory, and Prospect Theory help to shed light on how farmers behave under such scenarios. Expected Utility Theory establishes the principle that economic agents choose input combinations that maximize expected returns under risk [27,28]. Subjective Expected Utility extends this by allowing probabilities of outcomes to be formed subjectively when true

distributions are unknown, which is consistent with farmers relying on experiential and observable indicators to assess soil quality [29]. Prospect Theory further complements these perspectives by highlighting that decision-makers evaluate outcomes relative to reference points and exhibit loss aversion, leading to asymmetric responses to perceived gains and losses across plots [30,31].

These frameworks imply that input allocation reflects both profit-oriented optimization and information or knowledge about plot-level productivity. Farmers, therefore, condition input choices on observable soil characteristics or knowledge of soil quality and their expected returns. Within this setting, inputs such as improved seed and inorganic fertilizer are expected to be allocated preferentially to plots perceived to give higher expected returns, while soil-restorative inputs such as organic manure are more likely to be directed toward plots perceived as degraded but with potential for rehabilitation. Consequently, any systematic divergence between perceived and actual soil quality can generate misallocation of inputs across plots, leading to inefficiency and undermining production sustainability [32,33]. Technical inefficiency implies that farmers are unable to obtain maximum output from a given input-mix (land, labour, fertilizer, seed, and other agricultural inputs). Farmers' production inefficiency results in unnecessary input wastage and output contraction, and, hence, has serious implications for agricultural sustainability. For example, such production inefficiency (less output per unit inputs) may stimulate farmers' desire to produce more and, thus, intensify environmental externalities through cropland extensification, excessive soil nutrient mining, or the adoption of unsustainable agricultural intensification practices (e.g., agricultural chemical use). In this sense, sustainability within smallholder agriculture is closely linked to the efficient transformation of productive resources into output while minimizing avoidable environmental costs and maintaining long-term soil productivity [33,34].

## 2.2. Analytical Framework

The study applies two complementary empirical approaches to examine how farmers' subjective knowledge of soil quality influences input allocation decisions and maize output, namely: (1) the Conditional Mixed Process (CMP) estimator for modelling joint input choices, and (2) stochastic frontier analysis (SFA) for estimating technical efficiency and its determinants. Farmers' simultaneous input decisions are represented by a mix of discrete variables (e.g., use of pesticides and improved seed varieties), continuous variables (e.g., inorganic fertilizer and labour use), and zero left-censored organic fertilizer. Maize output and input allocations are evaluated at farm (plot) level.

### 2.2.1. Conditional Mixed Process

The determination of input choice across maize plots is modelled using the CMP estimator developed by David Roodman [35]. The framework provides a unified technique for estimating multiple equations of different functional forms, which is appropriate in our case because farmers' adoption and intensity decisions are made simultaneously. The CMP framework permits each dependent variable to assume its natural distribution while allowing the disturbance terms to follow a multivariate normal structure, thereby capturing cross-equation correlation in unobservable characteristics [36,37].

In this specification, the choice whether to use pesticides ( $y_{1i}$ ) and improved varieties ( $y_{2i}$ ) are treated as binary outcomes and are thus modelled using probit formulations. Inorganic fertilizer ( $y_{3i}$ ) and labour use ( $y_{5i}$ ) are specified as continuous linear equations, while organic fertilizer intensity ( $y_{4i}$ ) is a left-censored outcome due to the large proportion

of zero applications. Let the latent variable representation of the system be expressed as in Equation (1):

$$\begin{aligned} y_{1i}^* &= X_{1i}\beta_1 + \varepsilon_{1i}, y_{1i} = 1 \text{ if } y_{1i}^* > 0, \\ y_{2i}^* &= X_{2i}\beta_2 + \varepsilon_{2i}, y_{2i} = 1 \text{ if } y_{2i}^* > 0, \\ y_{3i} &= X_{3i}\beta_3 + \varepsilon_{3i}, \\ y_{4i}^* &= X_{4i}\beta_4 + \varepsilon_{4i}, y_{4i} = \max(0, y_{4i}^*), \\ y_{5i} &= X_{5i}\beta_5 + \varepsilon_{5i} \end{aligned} \quad (1)$$

where  $i$  indexes plots,  $y_{1i}$  and  $y_{2i}$  denote binary adoption outcomes,  $y_{3i}$  and  $y_{5i}$  represent continuous input intensities, and  $y_{4i}$  is a censored continuous variable. The vector  $X_{ki}$  comprises plot-level soil quality assessments, erosion indicators, agro-ecological controls, and household and institutional characteristics relevant to each decision. The joint error vector  $\varepsilon_i = (\varepsilon_{1i}, \dots, \varepsilon_{5i})'$  is assumed to follow a multivariate normal distribution with unrestricted covariance matrix, allowing the model to account for correlation arising from unobserved managerial ability, knowledge, or constraints that influence multiple input decisions simultaneously [35,38]. The suitability of the CMP framework was validated through the significance of the estimated cross-equation correlation coefficients ( $\rho$  parameters), which indicate the presence of interdependence among the input decisions. For the nonlinear components of the system, results are interpreted using average marginal effects.

### 2.2.2. Stochastic Frontier Analysis

To examine maize production and farmers' performance relative to best-practice production, we use the SFA, a parametric approach that distinguishes random production shocks from systematic shortfalls due to technical inefficiency [18,39,40]. Unlike conventional production functions, which assume that all deviations from maximum output arise from random noise, the stochastic frontier framework explicitly decomposes deviations from the production frontier into two components: statistical noise and technical inefficiency. Formally, maize output for the plot  $i$  is specified in Equation (2):

$$Q_i = f(X_{ik}; \beta) \exp(v_i - u_i), \quad i = 1, 2, 3, \dots, N \text{ and } v_i - u_i = \varepsilon_i \quad (2)$$

where  $Q_i$  denotes observed maize output;  $f(X_i; \beta)$  represents the deterministic production frontier that captures the maximum feasible output given the input vector  $X_i$ , and technology parameters  $\beta$ . The error term is composed of two parts. The symmetric term  $v_i \sim N(0, \sigma_v^2)$  captures random shocks beyond the farmer's control, such as weather variability and measurement error. On the other hand,  $u_i \geq 0$  represents technical inefficiency and measures the extent to which actual output falls short of the frontier due to suboptimal management or constraints [41–43].

Technical inefficiency ( $u_i$ ), therefore, reflects lost output relative to the best-practice frontier, holding inputs constant. Strictly stating,  $u_i$  is a monotonic transformation of technical efficiency (TE), which is the ratio of observed output to the maximum attainable output under the same input bundle (Equation (3)). Higher  $u_i$  mechanically translates into lower TE, and vice versa.

$$TE_i = \frac{Q_i}{Q_i^*} = \frac{f(X_{ij}; \beta) \exp(v_i - u_i)}{f(X_i; \beta) \exp(v_i)} = \exp(-u_i) \quad (3)$$

where  $Q_i^* = f(X_i; \beta) \exp(v_i)$  denotes frontier (potential) output. By construction, values of both TE and  $u_i$  lie between zero and one. By far, we are mainly interested in estimating  $f(X_i; \beta)$  and  $u_i$ , and consequently, TE.

There exist several functional forms for specifying  $f(X_i; \beta)$  within the stochastic frontier framework, including Cobb–Douglas, Translog, and other flexible specifications. In this

study, we adopt Translog specification (TL), which provided a superior fit to our data than the Cobb–Douglas functional form (LR  $\chi^2(15) = 252.14$ ;  $p < 0.001$ ). Accordingly, the TL production frontier is presented in Equation (4) [44–46]:

$$\ln Q_i = \beta_0 + \sum_{k=1}^K \beta_k \ln X_{ki} + \frac{1}{2} \sum_{k=1}^K \sum_{j=1}^K \beta_{kj} \ln X_{ki} \ln X_{ji} \quad (4)$$

where  $Q_i$  denotes observed maize output for plot  $i$ , and  $X_{ki}$  represents the quantity of input  $k$  used on plot  $i$ , where  $k = 1, 2, \dots, K$  (e.g., land, labour, seed, fertilizer, and pesticides). The parameter  $\beta_0$  is the intercept term capturing the baseline level of technology, while  $\beta_k$  denotes the first-order parameters that measure the output elasticities associated with each individual input. The coefficients  $\beta_{kj}$  represent second-order parameters that capture interaction effects between different inputs when  $k \neq j$ , as well as curvature effects when  $k = j$ , thereby allowing for flexible substitution and complementarity relationships among inputs.

To identify the determinants of inefficiency, the following specification is employed, in line with Refs. [39,47].

$$\mu_i = z_i \delta + \omega_i \quad (5)$$

where  $z_i$  is a vector of explanatory variables, which in our case, is capturing farmers' knowledge of soil quality (soil fertility status and erosion extent) and other controls,  $\delta$  is a vector of parameters to be estimated, and  $\omega_i$  is a non-negative random term. These variables do not shift the production frontier itself but influence how closely farmers operate relative to that frontier.

Our estimation of SFA components follows a one-step approach, as proposed by Ref. [47] and building on earlier models of Refs. [39,43,48]. More recent implementations and extensions include those by Refs. [49,50] as well as empirical applications by Refs. [51,52]. The approach refines the conventional stochastic frontier estimation by jointly estimating the production frontier and the inefficiency model in a single step through maximum likelihood estimation. This addresses a well-known shortcoming of the traditional two-step method used in earlier studies, such as those applying Data Envelope Analysis (DEA) and deterministic frontier, where inefficiency effects are regressed on explanatory variables in a second stage [39,47,53]. The two-step approach can yield inconsistent and inefficient estimates because the second-stage regressors are mostly correlated with the composite error term of the first stage. The one-step SFA framework addresses this issue by directly embedding inefficiency determinants into the likelihood function, thereby addressing potential endogeneity (The model was estimated using `sfcross` command in Stata 18 Standard Edition [49]).

### 2.2.3. Variables and Measurements

The study makes use of a comprehensive set of variables that capture soil characteristics, input choice, household socio-economic attributes, and maize productivity outcomes. Detailed definitions, coding schemes, and measurement units for all variables are presented in Table 1 for a clear understanding of the empirical approach.

To facilitate interpretation and reduce the influence of skewness and extreme values commonly observed in agricultural input data, continuous variables entered the models in logarithmic form where appropriate. However, because organic fertilizer application contained a large proportion of zero observations, the variable was transformed using the Inverse Hyperbolic Sine (IHS) transformation rather than the conventional logarithmic transformation [54,55]. Unlike the standard logarithmic transformation, the IHS approach accommodates zero-valued observations without requiring the addition of arbitrary constants, while still approximating logarithmic behaviour for large values. This transfor-

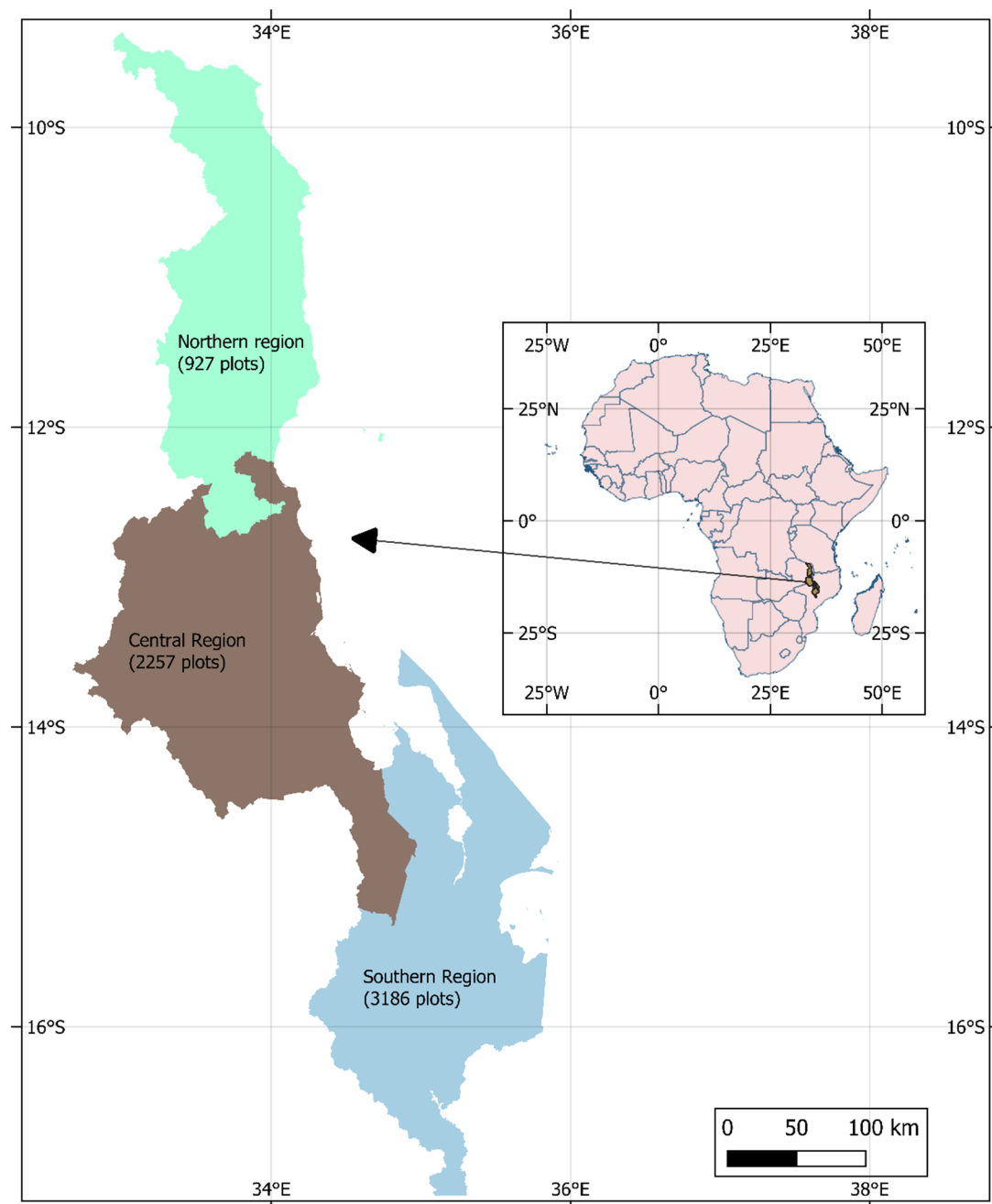
mation has increasingly been recommended in the applied econometric and agricultural economics literature when dealing with highly skewed variables containing many zeros [54–56].

**Table 1.** Variable definition, description, and measurement units.

| Variable                                  | Description                                                                             | Measurement Unit                                                                                                    |
|-------------------------------------------|-----------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------|
| Crop productivity                         | Total maize output obtained from the plot                                               | Kg                                                                                                                  |
| Plot area                                 | Total area of the cultivated plot                                                       | Acres                                                                                                               |
| Organic fertilizer                        | Quantity of organic manure or compost applied to the plot.                              | Kg                                                                                                                  |
| Inorganic fertilizer                      | Quantity of chemical fertilizer applied to the plot.                                    | Kg                                                                                                                  |
| Labour                                    | Total household and hired labour used on the plot.                                      | Man-hours                                                                                                           |
| Seed quantity                             | Total seed used for planting the plot.                                                  | Kg                                                                                                                  |
| Pesticides/herbicides use                 | Indicates whether a farmer applied pesticide or herbicide during the production season. | 1 = Yes; 0 = No                                                                                                     |
| Improved variety                          | Indicates whether an improved maize seed variety was planted.                           | 1 = Improved variety; 0 = Local                                                                                     |
| Soil quality                              | Farmer's subjective assessment of soil fertility condition.                             | 1 = Poor; 2 = Fair; 3 = Good                                                                                        |
| Soil erosion rate                         | Self-reported rate of soil erosion observed on the plot.                                | 1 = Severe; 2 = Moderate; 3 = Low; 4 = No erosion                                                                   |
| Agro-ecological zone                      | Climatic zone determined by temperature and rainfall regime.                            | 1 = Tropic-warm/semi-arid;<br>2 = Tropic-warm/sub-humid;<br>3 = Tropic-cool/semi-arid;<br>4 = Tropic-cool/sub-humid |
| Region                                    | Administrative region where the plot is located.                                        | 1 = Northern; 2 = Central;<br>3 = Southern                                                                          |
| Age                                       | Age of the plot manager                                                                 | Years                                                                                                               |
| Gender                                    | Gender of the plot manager                                                              | 1 = Male, 0 = Female                                                                                                |
| Extension                                 | At least received an extension message                                                  | 1 = Yes; 0 = No                                                                                                     |
| Extension contact on inorganic fertilizer | Household received extension advice on inorganic fertilizer use.                        | 1 = Yes; 0 = No                                                                                                     |
| Extension contact on organic fertilizer   | Household received extension advice on organic fertilizer.                              | 1 = Yes; 0 = No                                                                                                     |
| Extension contact on seed variety         | Household received extension advice on improved seeds.                                  | 1 = Yes; 0 = No                                                                                                     |
| Fertilizer coupon                         | Household accessed government fertilizer subsidy.                                       | 1 = Yes; 0 = No                                                                                                     |
| Livestock ownership                       | Household owns livestock.                                                               | 1 = Yes; 0 = No                                                                                                     |
| Household size                            | Number of household members residing in the household.                                  | Number of persons                                                                                                   |

### 2.3. Data Source

This study draws on data from the 2019 Malawi Integrated Household Survey (IHS-V), implemented by the National Statistical Office (NSO) under the Living Standards Measurement Study–Integrated Surveys on Agriculture (LSMS-ISA) programme [6]. The survey employed a nationally representative two-stage stratified sampling design, covering more than 12,000 households across 780 enumeration areas in the Northern, Central, and Southern regions of Malawi (Figure 1). The IHS-V provides comprehensive information on household characteristics, economic activities, and agricultural practices nationwide. For the purposes of this study, the analysis focuses on smallholder maize farmers, with the unit of analysis defined at individual maize-plot level. A total of 6370 maize plots were analyzed.



**Figure 1.** Maize plot-level observations by region.

### 3. Results

#### 3.1. Soil Conditions in Malawi

Farmers' evaluations of soil quality were mainly based on their own visual and experiential judgments, which mainly come from soil colour, texture, crop vigour, and weed composition. We group these subjective assessments into two categories: soil fertility and erosion rate. The results show that about half of all maize plots (55%) are perceived to have good soil quality, while 32% are rated as fair, and only 13% are rated as poor. Regarding erosion, approximately 59 percent of plots are reported to experience no visible erosion, 27 percent are classified under low erosion, 9 percent under moderate erosion, and only 5 percent as highly eroded. The extent of subjectively assessed soil erosion is lower than the rate reported by other studies, such as Ref. [57], which reports that over 75% of soils in the country are degraded primarily due to accelerated erosion, nutrient depletion, deforestation, and unsustainable land management practices.

#### 3.2. Maize Input Allocation and Maize Productivity

Patterns of input use across maize plots reveal a production system that is characterized by low levels of input intensification and a general tendency to allocate more inputs to plots endowed with better soil quality (Table 2). Overall, approximately 27 percent of plots received organic fertilizer, with an average application rate of 208 kg. Even though its use is more sustainable, the adoption level of organic fertilizer is low and reflects the structural limitations of smallholder systems. Ref. [1] attributed this mainly to restricted livestock ownership and the labour burden associated with preparing compost materials. The propensity to apply inorganic fertilizer is very high, but the quantity applied is meagre. Thus, synthetic fertilizer was applied on nearly all maize plots; however, the average application rate of 56 kg remains substantially below agronomic recommendations when assessed against the mean plot size of 0.88 acres. In particular, recommended application rates of 100–120 kg per acre are required to achieve optimal maize yields [58]. The use of pesticides and herbicides was observed in only 4 percent of plots, supporting the low adoption trends reported by Ref. [59]. Adoption of improved maize varieties was low, at only 48 percent: the uptake of improved varieties remains gradual and uneven, as many farmers continue to rely on recycled and local varieties, thereby limiting potential productivity gains [3,60]. Labour use per plot averaged 31.3 man-hours for the growing season. This input combination gives a mean maize output of 442 kg. Cross-tabulation by perceived soil quality and erosion mostly supports these systematic differences (Table 2).

**Table 2.** Plot-level mean input allocation and maize output by soil quality and erosion rate (Sample size (n) = 6370).

| Variable                | Soil Quality Categories |                   |                    |                  | Soil Erosion Categories |                   |                   | Overall           |
|-------------------------|-------------------------|-------------------|--------------------|------------------|-------------------------|-------------------|-------------------|-------------------|
|                         | Good                    | Fair              | Poor               | Severe           | High                    | Moderate          | No Erosion        |                   |
| Plot area (acres)       | 0.90<br>(0.01)          | 0.85<br>(0.01)    | 0.86<br>(0.02)     | 0.82<br>(0.03)   | 0.89<br>(0.05)          | 0.91<br>(0.02)    | 0.87<br>(0.01)    | 0.88<br>(0.01)    |
| Seeds (kg)              | 7.93<br>(0.11)          | 7.55<br>(0.14)    | 7.11<br>(0.19)     | 7.12<br>(0.31)   | 7.86<br>(0.28)          | 8.11<br>(0.17)    | 7.54<br>(0.10)    | 7.70<br>(0.08)    |
| Organic fertilizer (kg) | 227.93<br>(69.73)       | 122.90<br>(17.45) | 325.70<br>(212.07) | 77.96<br>(20.62) | 96.85<br>(18.96)        | 128.72<br>(19.86) | 273.46<br>(81.50) | 208.02<br>(48.17) |
| Fertilizer total        | 58.23<br>(1.06)         | 55.47<br>(1.40)   | 48.27<br>(1.77)    | 49.94<br>(2.51)  | 49.64<br>(2.29)         | 58.20<br>(1.46)   | 56.55<br>(1.05)   | 56.02<br>(0.77)   |
| Labour man-hours        | 32.33<br>(0.39)         | 30.28<br>(0.47)   | 29.16<br>(0.65)    | 31.74<br>(1.18)  | 32.04<br>(0.85)         | 32.49<br>(0.55)   | 30.53<br>(0.37)   | 31.26<br>(0.28)   |

Table 2. Cont.

| Variable                 | Soil Quality Categories |                   |                   |                   | Soil Erosion Categories |                   |                   | Overall          |
|--------------------------|-------------------------|-------------------|-------------------|-------------------|-------------------------|-------------------|-------------------|------------------|
|                          | Good                    | Fair              | Poor              | Severe            | High                    | Moderate          | No Erosion        |                  |
| Pesticides               | 0.04<br>(0.004)         | 0.045<br>(0.01)   | 0.045<br>(0.01)   | 0.06<br>(0.01)    | 0.037<br>(0.01)         | 0.05<br>(0.01)    | 0.04<br>(0.003)   | 0.04<br>(0.003)  |
| Improved maize varieties | 0.49<br>(0.01)          | 0.47<br>(0.01)    | 0.46<br>(0.02)    | 0.43<br>(0.03)    | 0.39<br>(0.02)          | 0.48<br>(0.01)    | 0.50<br>(0.01)    | 0.48<br>(0.01)   |
| Maize output (kg)        | 471.57<br>(12.94)       | 420.66<br>(14.15) | 372.63<br>(20.09) | 292.50<br>(18.34) | 397.90<br>(28.86)       | 449.05<br>(15.97) | 459.35<br>(12.26) | 442.20<br>(8.85) |

Note: plot-level means estimated using survey weights (svy).

### 3.3. Effect of Subjective Soil Assessments on Maize Input Use

Table 3 presents the estimates from the CMP model, which integrates a probit specification for pesticide use and improved seed variety adoption, linear regression for inorganic fertilizer and labour use intensity, and a censored Tobit model for organic fertilizer use. All models were statistically significant at the 1 percent level (Wald  $\chi^2$  test), demonstrating that the explanatory variables collectively account for variation in input adoption behaviour.

**Table 3.** Estimated effects from CMP regression models (probit, censored Tobit, and linear) for input decisions among maize farmers.

| Variable                        | Pesticide Use      | Improved Variety    | Organic Fertilizer (IHS)     | Inorganic Fertilizer (ln) | Labour Hours (ln)    |
|---------------------------------|--------------------|---------------------|------------------------------|---------------------------|----------------------|
|                                 | Probit (dy/dx)     | Probit (dy/dx)      | Censored Tobit (Coefficient) | Linear (Coefficient)      | Linear (Coefficient) |
| Soil quality                    |                    |                     |                              |                           |                      |
| Poor                            | −0.004<br>(0.087)  | −0.04<br>(0.05)     | 0.63 *<br>(0.35)             | −0.22 ***<br>(0.04)       | −0.14 ***<br>(0.02)  |
| Fair                            | 0.05<br>(0.06)     | −0.04 (0.04)        | 0.27<br>(0.25)               | −0.11 ***<br>(0.03)       | −0.07 ***<br>(0.02)  |
| Soil erosion                    |                    |                     |                              |                           |                      |
| Severe                          | 0.14<br>(0.11)     | −0.12<br>(0.07)     | −0.16<br>(0.50)              | 0.02<br>(0.05)            | 0.09 ***<br>(0.03)   |
| Moderate                        | −0.02<br>(0.10)    | −0.14 **<br>(0.06)  | 0.64<br>(0.40)               | 0.03<br>(0.04)            | 0.11 ***<br>(0.03)   |
| Low                             | 0.10<br>(0.06)     | −0.01<br>(0.04)     | 0.64 **<br>(0.26)            | 0.09 ***<br>(0.03)        | 0.09 ***<br>(0.02)   |
| Region                          |                    |                     |                              |                           |                      |
| Central                         | 0.02<br>(0.12)     | −0.14 **<br>(0.07)  | —                            | —                         | —                    |
| Southern                        | 0.07<br>(0.11)     | −0.52 ***<br>(0.07) | —                            | —                         | —                    |
| Extension on pest control       | 0.31 ***<br>(0.06) | —                   | —                            | —                         | —                    |
| Extension on improved varieties | —                  | 0.27 ***<br>(0.04)  | —                            | —                         | —                    |
| Extension on organic fertilizer | —                  | —                   | 1.84 ***<br>(0.24)           | —                         | —                    |

Table 3. Cont.

| Variable                          | Pesticide Use      | Improved Variety    | Organic Fertilizer (IHS)     | Inorganic Fertilizer (ln) | Labour Hours (ln)    |
|-----------------------------------|--------------------|---------------------|------------------------------|---------------------------|----------------------|
|                                   | Probit (dy/dx)     | Probit (dy/dx)      | Censored Tobit (Coefficient) | Linear (Coefficient)      | Linear (Coefficient) |
| Extension on inorganic fertilizer | —                  | —                   | —                            | 0.10 ***<br>(0.03)        | —                    |
| Inorganic fertilizer coupon       | —                  | —                   | —                            | 0.10 ***<br>(0.03)        | —                    |
| Livestock ownership               | —                  | —                   | 0.03<br>(0.24)               | —                         | —                    |
| Household size                    | —                  | —                   | —                            | —                         | 0.11 ***<br>(0.003)  |
| Tropic-warm/sub-humid             | 0.22 ***<br>(0.07) | −0.11 ***<br>(0.04) | −0.99 *** (0.25)             | −0.23 ***<br>(0.03)       | −0.13 ***<br>(0.02)  |
| Tropic-cool/semi-arid             | −0.01<br>(0.10)    | −0.26 ***<br>(0.05) | −1.89 ***<br>(0.38)          | 0.24 ***<br>(0.04)        | 0.09 ***<br>(0.02)   |
| Tropic-cool/sub-humid             | 0.19<br>(0.14)     | −0.13<br>(0.08)     | −4.02 ***<br>(0.48)          | 0.67 ***<br>(0.04)        | 0.04<br>(0.03)       |
| $\rho_{12}$                       | 0.13 ***           |                     |                              |                           |                      |
| $\rho_{13}$                       | 0.18 ***           |                     |                              |                           |                      |
| $\rho_{14}$                       | 0.08 **            |                     |                              |                           |                      |
| $\rho_{15}$                       | 0.01               |                     |                              |                           |                      |
| $\rho_{23}$                       | 0.08 ***           |                     |                              |                           |                      |
| $\rho_{24}$                       | 0.002              |                     |                              |                           |                      |
| $\rho_{25}$                       | −0.02              |                     |                              |                           |                      |
| $\rho_{34}$                       | −0.13 ***          |                     |                              |                           |                      |
| $\rho_{35}$                       | 0.24 ***           |                     |                              |                           |                      |
| $\rho_{45}$                       | 0.01               |                     |                              |                           |                      |
| $\sigma_3$                        | 0.95 ***           |                     |                              |                           |                      |
| $\sigma_4$                        | 7.17 ***           |                     |                              |                           |                      |
| $\sigma_5$                        | 0.55 ***           |                     |                              |                           |                      |
| Wald $\chi^2$                     | 2097.06 ***        |                     |                              |                           |                      |
| Log likelihood                    | −27,279.63         |                     |                              |                           |                      |
| Observations                      | 6370               | 6370                | 6370                         | 6370                      | 6370                 |

Notes: IHS = Inverse Hyperbolic Sine. Standard errors (clustered at household level) in parentheses. \*, \*\*, and \*\*\* denote significance at 10%, 5%, and 1% levels, respectively. Reference groups for categorical covariates: soil quality = good; erosion = no erosion; region = northern; agro-ecological zone = tropic-warm/semi-arid. “—” indicates that the variable was not included in the respective equation.

We find evidence that farmers tend to apply more organic fertilizer on degraded plots by 0.63% relative to good soils, implying that farmers may view organic application as a restorative input for degraded lands. At the same time, poor soil quality is a disincentive to inorganic fertilizer use: plots with poor soil fertility receive significantly lower quantities of inorganic fertilizer by 0.22% and lower labour allocation (0.14%), indicating a tendency to withdraw costly inputs from plots perceived as having low responsiveness to conventional inputs.

Similarly, soil erosion perceptions also influence input use behaviour significantly. Some presence of soil erosion is associated with a higher likelihood of applying organic fertilizers compared to soils without erosion. Maize plots with some presence of erosion are likely to be applied with significantly more organic fertilizer by 0.57%, and farmers are less likely to cultivate improved varieties in farms exhibiting moderate erosion (14%) compared to non-eroded soils. Relative to plots with no erosion, inorganic fertilizer use increases significantly under low erosion, while labour use rises significantly across all erosion levels.

Beyond soil quality indicators, several controls behave as expected. Of interest is receiving extension on new seed varieties, which raises improved seed adoption by 27%, whereas extension advice on pesticide use increases pesticide adoption by 31%. Lastly, an increase in household size by one member increases labour availability by 0.11%.

### 3.4. Effect of Knowledge of Soil Quality Attributes on Maize Productivity

The Translog SFA model results for maize production are presented in Table 4. The overall stochastic model was statistically significant at the 1% significance level, confirming that the included variables jointly explain variations in maize output and technical efficiency among smallholder farmers.

**Table 4.** Translog stochastic frontier production and inefficiency model for maize output.

| Output (ln)                               | Production Frontier | Inefficiency Model |
|-------------------------------------------|---------------------|--------------------|
| Acreage (ln)                              | 0.14 (0.13)         | —                  |
| Seed (ln)                                 | 0.57 *** (0.10)     | —                  |
| Labour (ln)                               | 0.21 * (0.12)       | —                  |
| Organic fertilizer (IHS)                  | −0.05 * (0.03)      | —                  |
| Inorganic fertilizer (ln)                 | 0.02 (0.08)         | —                  |
| Pesticides                                | 0.10 ** (0.04)      | —                  |
| Improved variety                          | 0.18 *** (0.02)     | —                  |
| Acreage <sup>2</sup>                      | 0.05 (0.05)         | —                  |
| Seed <sup>2</sup>                         | −0.06 (0.04)        | —                  |
| Labour <sup>2</sup>                       | 0.05 (0.03)         | —                  |
| Organic fertilizer <sup>2</sup>           | 0.03 *** (0.004)    | —                  |
| Inorganic fertilizer <sup>2</sup>         | 0.22 *** (0.02)     | —                  |
| Acreage × Seed                            | 0.06 * (0.03)       | —                  |
| Acreage × Labour                          | 0.03 (0.03)         | —                  |
| Acreage × Organic fertilizer              | 0.002 (0.007)       | —                  |
| Acreage × Inorganic fertilizer            | −0.04 * (0.02)      | —                  |
| Seed × Labour                             | 0.003 (0.03)        | —                  |
| Seed × Organic fertilizer                 | 0.001 (0.007)       | —                  |
| Seed × Inorganic fertilizer               | −0.04 * (0.02)      | —                  |
| Labour × Organic fertilizer               | −0.001 (0.006)      | —                  |
| Labour × Inorganic fertilizer             | −0.07 *** (0.02)    | —                  |
| Organic fertilizer × Inorganic fertilizer | −0.01 *** (0.005)   | —                  |
| Constant                                  | 3.65 *** (0.26)     | —                  |
| Soil quality                              |                     |                    |
| Fair                                      | —                   | 0.19 ** (0.07)     |
| Poor                                      | —                   | 0.40 *** (0.10)    |
| Soil erosion                              |                     |                    |
| Low                                       | —                   | 0.09 (0.08)        |
| Moderate                                  | —                   | 0.47 *** (0.11)    |
| Severe                                    | —                   | 0.71 *** (0.13)    |
| Gender                                    | —                   | −0.24 *** (0.07)   |
| Age                                       | —                   | 0.01 *** (0.002)   |

Table 4. Cont.

| Output (ln)               | Production Frontier | Inefficiency Model |
|---------------------------|---------------------|--------------------|
| Extension access          | —                   | −0.20 *** (0.07)   |
| Constant (ln $\sigma_u$ ) |                     | −1.58 *** (0.14)   |
| Constant (ln $\sigma_v$ ) |                     | −1.30 *** (0.03)   |
| $E(\sigma_u)$             | 0.54 ***            |                    |
| $\sigma_v$                | 0.52 *** (0.009)    |                    |
| Wald $\chi^2(22)$         | 8389.32 ***         |                    |
| Log likelihood            | −6983.58            |                    |
| Observations              | 6370                | 6370               |

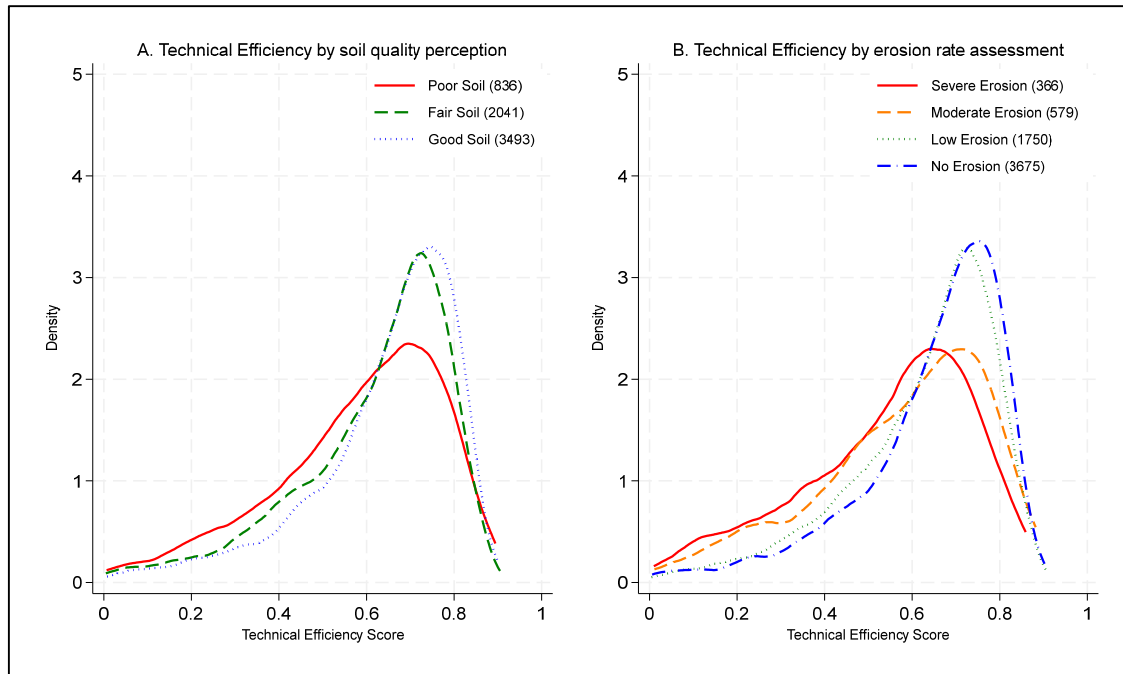
Notes: IHS = Inverse Hyperbolic Sine. Variables denoted by superscript <sup>2</sup> represent squared terms included in the Translog production function. Standard errors (clustered at household level) in parentheses. Reference groups for categorical covariates: soil quality = good; erosion = no erosion; \*, \*\*, and \*\*\* denote significance at 10%, 5%, and 1% levels, respectively. “—” indicates that the variable was not included in the respective equation.

The production frontier results indicate that seed quantity, labour, pesticide application and improved maize varieties are significantly associated with increased maize output. Specifically, a 1% increase in seed use increases maize output by approximately 0.57%, while a 1% increase in labour raises output by about 0.21%. Plots where pesticides were applied produced significantly higher output by 0.10%, relative to plots without pesticide use ( $p < 0.05$ ). Similarly, the adoption of improved maize varieties increased maize output by 0.18%. Organic fertilizer exhibited a negative first-order coefficient, suggesting that at the current application levels, increases in organic fertilizer use were associated with reduced maize output. This might be a short-term effect.

The Translog estimates further reveal significant nonlinearities in production relationships. The squared terms for organic fertilizer ( $\beta = 0.03$ ;  $p < 0.01$ ) and inorganic fertilizer ( $\beta = 0.22$ ;  $p < 0.01$ ) were positive and statistically significant, indicating nonlinear productivity effects associated with fertilizer application. Several interaction terms were also statistically significant. The interaction between acreage and seed was positive, while the interaction terms between acreage and inorganic fertilizer, seed and inorganic fertilizer, labour and inorganic fertilizer, and organic fertilizer and inorganic fertilizer were negative and significant. Positive interaction effects indicate complementarity between inputs, while negative interaction effect suggests substitutability or inefficiency, where combining the inputs reduces their marginal productivity. Returns to scale (RTS), computed as the sum of the first-order elasticities of acreage, seed, labour, organic fertilizer and inorganic fertilizer, was estimated at approximately 0.89. This indicates decreasing returns to scale, implying that a proportional increase in all production inputs results in a less than proportional increase in maize output.

Evidence from the inefficiency component of the stochastic frontier model highlights the critical role of land quality perception in shaping farmers’ production performance. The results show that plots with poor soil quality are associated with higher technical inefficiency ( $p < 0.05$ ). Similarly, moderate and high erosion rates increase inefficiency, implying that, despite the positive influence of factors of production, land degradation reduces farmers’ ability to achieve maximum yields. As observed in related studies, including Refs. [18,23,24], poor soil quality is undermining the productive capacity of maize farmers. For example, Ref. [18] also observed that German farmers in locations with better soil quality achieved greater outputs. Our results support the evidence found in the soil science literature that optimal fertilizer use efficiency cannot be achieved under heavily degraded soils [8]. This suggests that applying both organic and inorganic fertilizers may be the best approach for reconditioning the soil, enhancing the production of maize cropping systems, and improving their sustainability.

Figure 2 links the frontier estimates to the distribution of technical efficiency across soil conditions. Better soil conditions are associated with rightward shifts in the efficiency distribution, higher mean efficiency, and reduced dispersion, whereas adverse soil conditions are associated with flatter and left-skewed distributions of technical efficiency, which indicate greater inefficiency heterogeneity.



**Figure 2.** Technical efficiency by soil quality and erosion rate.

The ANOVA results presented in Table 5 further substantiate the stochastic frontier findings by demonstrating systematic differences in technical efficiency across perceived soil quality and erosion categories at different percentiles. The overall mean technical efficiency stands at 0.63, indicating that maize farmers operate, on average, about 37% below the production frontier, and therefore do not fully exploit the output potential achievable with the existing input combinations. Mean technical efficiency declines monotonically with worsening soil conditions, falling from 0.76 on plots perceived as having good soil quality to 0.53 on fair soils and as low as 0.47 on poor soils, with all pairwise differences statistically significant at the 1% level. A similar pattern is observed with respect to erosion, where mean efficiency is 0.76 for non-eroded plots and decreases to 0.43 on highly eroded plots.

**Table 5.** ANOVA results of technical efficiency by soil quality and erosion rate.

| Soil Assessment | Technical Efficiency |      |             |             |             | ANOVA<br><i>p</i> -Value |
|-----------------|----------------------|------|-------------|-------------|-------------|--------------------------|
|                 | n                    | Mean | <i>p</i> 25 | <i>p</i> 50 | <i>p</i> 75 |                          |
| a. Soil quality |                      |      |             |             |             |                          |
| Poor            | 836                  | 0.58 | 0.47        | 0.62        | 0.73        | 0.000                    |
| Fair            | 2041                 | 0.62 | 0.53        | 0.67        | 0.74        |                          |
| Good            | 3493                 | 0.64 | 0.57        | 0.69        | 0.76        |                          |
| b. Erosion rate |                      |      |             |             |             |                          |
| Severe          | 366                  | 0.54 | 0.43        | 0.58        | 0.68        | 0.000                    |
| Moderate        | 579                  | 0.57 | 0.46        | 0.61        | 0.72        |                          |
| Low             | 1750                 | 0.62 | 0.54        | 0.67        | 0.75        |                          |
| No erosion      | 3675                 | 0.64 | 0.57        | 0.69        | 0.76        |                          |
| Total           | 6370                 | 0.63 |             |             |             |                          |

Notes: p25, p50, and p75 refer to the 25th, 50th (median), and 75th percentiles, respectively.

#### 4. Discussion

This article examined how farmers' knowledge of soil quality (soil fertility and erosion extent) affects input allocation decisions and, in turn, maize productivity among smallholder farmers in Malawi. The policy intent of enhancing productivity to stimulate agriculture commercialization and poverty reduction would not be fully realized if smallholder farmers are technically inefficient [3]. The findings demonstrate that knowledge of soil quality attributes play a decisive role in determining how farmers allocate scarce resources across plots. This suggests that farmers' plot management behaviour is largely guided by their expectations of soil responsiveness and potential crop harvest or crop outputs. In this sense, the results are consistent with the principles of EUT applied in this study, in which decisions are based on personal beliefs under uncertainty [61].

Specifically, we observe that farmers' probability of adopting improved seed varieties is significantly lower on plots perceived to have less fertile soils compared to those rated as good. Considering that improved varieties are costly, which contributes to low adoption among farmers in Malawi, this finding may suggest that farmers doubt the yield potential of improved varieties on soils they consider suboptimal and, to avoid wasting scarce resources, they allocate improved seeds primarily to plots with better perceived fertility [14]. This aligns with the findings of Ref. [11], who posited that farmers are reluctant to apply expensive inputs on lands where they anticipate minimal response, as the perceived risk of economic loss becomes a constraint. However, Ref. [62] found that when improved technologies are demonstrably matched to soil conditions through integrated soil fertility management, adoption can increase even on less fertile lands. Such adoption of integrated soil fertility management would lead to improved sustainability. Likewise, plots judged to have poor soil quality receive substantially less inorganic fertilizer and labour. This finding is supported by Ref. [9], who observed that Malawian macadamia farmers reduced fertilizer applications on plots they perceived as degraded. This behaviour contrasts with evidence from Ref. [63] in Nigeria, where farmers intensified labour and input use on poorer soils to compensate for low fertility.

Poor soil quality and the presence of erosion on the plot appear to stimulate the adoption of certain inputs, including the increased application of organic fertilizer on such plots, hence indicating that farmers apply strategies to protect and enhance the productivity of land that is still in relatively good condition. This agrees with the studies done by Ref. [64] in Kenya, and that of Ref. [65] on organic fertilizer adoption, as these studies note that farmers mainly apply fertilizer on much-degraded plots as soil-restorative mechanisms. The mixed results suggest that farmers need guidance, e.g., from extension agents on the use of organic fertilizer and the management of soil degradation through soil erosion, especially in relation to production system sustainability.

The stochastic frontier results further reveal important structural characteristics of maize production among smallholder farmers in Malawi. The diminishing RTS suggests that the productivity gains from further input intensification are becoming constrained by underlying structural and environmental limitations within the production system. In smallholder agriculture, diminishing returns commonly emerge when key complementary factors such as soil fertility, moisture retention, and agronomic management are inadequate to support efficient input transformation. Evidence from Malawi and other African countries shows that continued cultivation under declining soil fertility conditions reduces the responsiveness of maize output to additional fertilizer and labour inputs, thereby limiting productivity gains from intensification strategies [3,66,67]. Ref. [68] argued that many African soils have become "non-responsive" due to prolonged nutrient depletion and low organic matter, such that increases in fertilizer and labour no longer generate proportionate yield improvements. Similar evidence from Ref. [11] demonstrated that

fertilizer productivity declines significantly on degraded soils with poor soil organic matter conditions. In Malawi, studies by Ref. [67] found that reliance on inorganic fertilizer alone under degraded soil conditions leads to lower yield response compared to integrated soil fertility management systems. Likewise, Refs. [3,11] suggested that narrow fertilizer-led intensification has contributed to stagnant or declining land productivity because of persistent soil degradation and inadequate rehabilitation investments.

The inefficiency component shows that perceived poor soil quality and erosion significantly increase technical inefficiency. This implies that farmers operating on degraded or eroded plots are mostly unable to achieve the same level of output from given inputs relative to their counterparts endowed with better soils. Given the observed input allocation among farmers, it is not surprising to witness such a scenario, as it shows that farmers are taking little effort to improve the status of eroded lands. Similar findings are reported by Refs. [9,10], who separately showed that poor lands registered higher inefficiencies, and that soil erosion had significant negative distributional impacts on welfare. Thus, failure to account for environmental production conditions such as weather, soils, pests, etc., could confound technical efficiency estimates, especially in smallholder systems where farmers lack the adaptive capacity to mitigate or manage natural shocks [18,23,24]. For example, the results show that the use of pesticides can increase yields and reduce the risk of harvest loss. Better quality soils possess better nutrient and water retention properties, and, hence, more stable yields can be achieved in comparison with poorer soils. Ref. [11] showed that fertilizer use among smallholders in Kenya is highly conditional on soil organic matter, with meaningful uptake occurring only on plots with sufficient soil carbon. On degraded plots, fertilizer offers little yield benefit, rendering economic incentives such as subsidies or credit largely ineffective. Complementing this, Ref. [69] provided experimental evidence from Madagascar showing that farmers who were informed that their plots were likely to respond well to nitrogen applied more fertilizer and achieved higher yields and incomes. Ref. [62] demonstrated that integrated soil fertility management (ISFM) practices, when aligned with farmer perception, led to higher maize and cowpea yields in on-farm trials, suggesting that perception-informed interventions can enhance productivity. Encouraging integrated soil fertility management would increase system sustainability.

## 5. Conclusions and Policy Implications

This study concludes that farmers' subjective knowledge of soil fertility and erosion significantly influences input allocation decisions and technical efficiency among smallholder maize farmers in Malawi. Farmers tend to allocate improved seed, inorganic fertilizer, and labour to plots perceived as fertile, while organic fertilizer is more frequently directed toward degraded plots as a restorative strategy. However, the results further reveal that poor soil quality and soil erosion significantly reduce technical efficiency and maize productivity, thereby undermining the sustainability of maize-based farming systems. The findings suggest that reliance on subjective soil assessments may contribute to inefficient input allocation and persistent productivity gaps. Therefore, the study recommends strengthening access to plot soil diagnostic services and expanding extension programmes that promote integrated soil fertility management practices combining organic and inorganic soil amendments. Policies should also prioritize soil restoration, erosion control measures, and farmer training on sustainable land management to improve input use efficiency, enhance maize productivity, and support agricultural sustainability in Malawi.

## 6. Limitations of the Study

An important limitation of this study is its reliance on farmers' subjective assessments of soil fertility and erosion in the absence of plot-level biophysical soil measurements. Although the study was initially designed to undertake a comparative analysis of subjective perceptions and objective soil quality indicators, such as nutrient content, soil organic matter, or pH, this was not feasible due to data constraints. As a result, the analysis cannot evaluate the extent to which farmers' perceptions accurately reflect underlying soil conditions. Future research that integrates household survey data with objective soil diagnostics would enable a more comprehensive assessment of how perception gaps influence input allocation behaviour, technical efficiency, and productivity outcomes.

**Author Contributions:** All authors contributed to the conception and design of the study, data analysis, interpretation of results, and drafting and revision of the manuscript. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The cleaned dataset and the Stata do-files used to generate the results in this study are available from the corresponding author upon reasonable request.

**Acknowledgments:** The authors gratefully acknowledge the Malawi National Statistical Office (NSO) and the World Bank Living Standards Measurement Study–Integrated Surveys on Agriculture (LSMS-ISA) programme for providing access to the Malawi Integrated Household Survey 2019–2020 (IHS5) dataset used in this study. The analysis and interpretations presented in this manuscript are solely those of the authors and do not necessarily reflect the views of NSO or the World Bank. The authors declare that generative artificial intelligence tools, including OpenAI's ChatGPT-5.5 and Microsoft M365 Copilot, were used solely to assist with language editing and grammatical refinement of the manuscript. The tools were not used to generate scientific content, analyze data, interpret results or develop arguments. All substantive ideas, analyses, interpretations and conclusions presented in this article are entirely the authors' own.

**Conflicts of Interest:** The authors declare no conflicts of interest.

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