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ARTICLE

The Interplay of Rural-Urban Migration, Climate-Smart Agriculture, and Technical Efficiency in Maize Production: Insights from Rural Malawi

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ABSTRACT

Rural-Urban Migration (RUM) has increasingly become a key adaptation strategy to climate and weather-related shocks in rural communities. Through rural-urban migration (RUM, households gain access to remittances, which are often reinvested in climate-smart agriculture (CSA) practices. However, the outcomes of such investments are not straightforward, as RUM can lead to either a loss or a gain in labor productivity depending on accompanying interventions. This study examines the impact of RUM on technical efficiency and productivity among maize smallholder farmers using panel data constructed from nationally representative Integrated Household Surveys (2010–2017). The findings show that RUM, when not accompanied by CSA practices such as soil and water conservation, agroforestry, and conservation agriculture, leads to a significant reduction in technical efficiency, averaging 9%, with sharper declines in 2010 and 2013 (18%) and a more moderate effect in 2016/2017 (7%). Conversely,

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when RUM is combined with CSA adoption, it has a positive effect on technical efficiency, carrying important policy implications. They thus highlight the need for policymakers to carefully monitor labor outmigration while avoiding restrictive migration policies that overlook the economic pressures driving RUM. Instead, policies should focus on balanced strategies that retain part of the rural labor force and enhance households' ability to convert remittances into productive agricultural investments. Key interventions include strengthening rural labor markets, promoting mechanization and labor-saving technologies, as well as enabling the effective use of remittances through financial literacy, improved extension services, and targeted support for CSA adoption.

Keywords: Stochastic Frontier Model; Technical Efficiencies; Rural-Urban Migration; Climate and Weather-related Shocks; Climate Smart Agricultural Practices

1. Study Context

Agricultural production has demonstrated a worldwide upward trajectory over the past few decades, with global maize output nearly doubling from about half a million metric tons in 1989 to slightly above a million metric tons in 2016 [1], following the increased use of chemical fertilizers and improved maize seed varieties. In Africa, where agriculture is the cornerstone of economic growth [2], its performance in Sub-Saharan Africa (SSA) reveals a declining trend, with total agricultural production reducing from 12.8 million metric tons in 1989 to 8.0 million metric tons in 2016 [3]. An interplay of several constraints, including limited use of fertilizers, continued reliance on traditional crop varieties, dependence on rain-fed agriculture, fragmented landholding sizes, and recurring extreme weather events, is attributed to the underperformance of the agricultural sector [4]. To address these challenges, many SSA countries have aligned their national agrifood systems strategies with continental frameworks, such as the Comprehensive Africa Agriculture Development Programme (CAADP), currently the Kampala Declaration, which advocates for allocating at least 10% of resources to reinforce agricultural resilience to climate shocks [5].

In line with other countries in the SSA region, agriculture is still the backbone of economy in Malawi, contributing approximately 22.3% of GDP, 64% of employment, 80% of export earnings, and 85% of the livelihoods in rural areas [6]. However, smallholder farming, contributing 70% to the agricultural sector, is customary and rain-fed dependent. Recent registration of farm households reveals that there are slightly more than 3.4 million farming households, with 90% of them cultivating maize [6]. Smallholder farmers are constrained by soil fertility depletion, land fragmentation, and insecure land tenure, particularly among women who cultivate less than 0.45 of a hectare [7]. Given these constraints, scholars and policymakers have advocated for a shift of agricultural productivity growth as the primary pathway out of food insecurity in developing countries like Malawi [8]. On the contrary, climate and extreme weather events, such as droughts, floods, and pest outbreaks, have intensified further compromising efforts in the agricultural sector [9].

Following extreme weather events and their associated effects on agricultural production, rural households have sent some of their members to engage in rural-urban migration (RUM) as an adaptive response [10]. The National Statistical Office (NSO, 2020) highlighted that over 40% of rural population in Malawi had migrated to urban centers in search of income and remittances to support their households in adopting climate-resilient agricultural practices. RUM-induced remittances have become a critical source of livelihood support and an enabler of investment in climate-smart agriculture (CSA) practices, namely, soil and water conservation, drought-resistant maize varieties, conservation agriculture, soil amendments, and agroforestry systems [10,11]. Between 2002 and 2016, remittance inflows to rural areas increased significantly, from US$0.84 million to approximately US$40 million, resulting in a rise in rural income from 1% in 2000 to over 23% in 2020 [11].

Nevertheless, empirical evidence on the impact of RUM and remittances on agricultural productivity remains inconclusive [11]. Some studies report positive outcomes, including improved access to inputs and increased knowledge sharing. In contrast, others document adverse effects, including reduced household labor availability, insecure land tenure, and weakened agricultural decision-making [11,12]. For example, in Mexico, households have primarily used remittances for consumption rather than productive investments. In Ghana, RUM has reduced the availability of family labor for agricultural production, as well as led to changes in household headship. These contradictory findings limit policymakers' ability to design targeted interventions that harness RUM as a tool for enhancing agricultural resilience and productivity [12]. In Malawi, empirical studies examining the link between RUM and farm productivity, particularly maize, the staple crop, remain sparse and fragmented. This gap hinders a comprehensive understanding of the full potential of RUM as an adaptive strategy and its role in promoting long-term agricultural development and food security, particularly in the context of increasing youth migration from rural Malawi to more developed countries such as Israel and South Africa [12,13].

This study thus makes a timely and policy-relevant contribution to the growing but fragmented literature on the nexus between climate-induced rainfall uncertainty (RUM), remittances, and agricultural productivity in Malawi [14]. While previous research has broadly examined the socio-economic impacts of RUM and remittance flows in developing countries, the evidence remains inconclusive, particularly concerning their influence on farm-level productivity outcomes [14]. Firstly, much of the existing literature has focused either on the welfare or consumption effects of remittances or on the labor substitution effects of remittances on agricultural output, often overlooking the complex and dynamic role that remittances can play in facilitating investment in conservation agriculture (CSA) practices. By linking RUM to maize productivity outcomes, this study addresses a critical gap in understanding whether and how RUM can serve as an adaptive strategy to mitigate the impacts of extreme weather events in smallholder farming systems.

Secondly, while recent studies have explored the role of climate-smart agriculture (CSA) in enhancing resilience and productivity, the literature has not sufficiently integrated the role of RUM-financed CSA practices on farm productivity [15,16]. Thus, this paper provides new empirical evidence on how rural households can leverage remittances to invest in CSA practices. By doing so, the study extends the discourse on CSA to include remittance flows as enablers of sustainable agricultural intensification. Thirdly, there is limited empirical work in Malawi that rigorously assesses the labor or productivity implications of RUM using panel-constructed data to control for unobserved heterogeneity, selection bias, and endogeneity concerns. Ultimately, the study examines the interplay between RUM, climate smart agriculture, and technical efficiency of maize production in rural Malawi. Besides, the paper contributes to broader policy and academic discussions on how RUM can be re-framed not just as a coping mechanism but also as an investment strategy for the agrifood systems in the global fight against hunger and climate stress.

2. Study Methods

2.1. Study Area and Household Data

This study focuses on rural areas of Malawi, a landlocked country in southeastern Africa bordered by Tanzania, Mozambique, and Zambia. Administratively, Malawi is divided into three main regions, Northern, Central, and Southern, which are further subdivided into 28 districts, including four major urban centers that function as economic and administrative hubs, see **Figure 1**. The country experiences a single rainy season each year, typically from October to April, which plays a crucial role in shaping agricultural activities and cropping calendars. Malawi's diverse topography, with elevations ranging from below 500 to over 1,500 meters above sea level, creates significant climatic variation across regions. These elevation differences lead to wide disparities in average temperatures and rainfall patterns during the growing season, thereby influencing crop productivity and farming practices. According to the World Bank (2020), average temperatures during the cropping season generally range between 23 °C and 25 °C. Annual rainfall, however, varies significantly by location and year, averaging between approximately 86 mm and 238 mm. This variability in climatic conditions presents both opportunities and constraints for agricultural production, especially for staple crops such as maize, which are highly sensitive to weather fluctuations. A nuanced understanding of Malawi's agroecological and climatic context is therefore essential for analyzing rural livelihoods, evaluating adaptive strategies, and assessing the impacts of climate variability on agricultural performance.

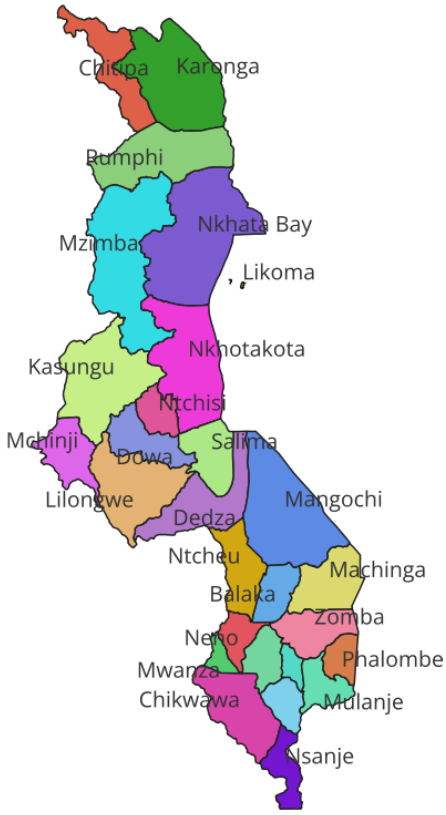

Figure 1. Map showing study districts in Malawi.

This study draws on data from the Integrated Household Panel Survey (IHPS), administered by Malawi's National Statistical Office (NSO) in partnership with the World Bank over three waves between 2010 and 2017. The IHPS employed a multi-stage stratified sampling design, beginning with the division of the country into districts, followed by subdivisions into traditional authorities and enumeration areas. From these, approximately 3865 households were randomly selected for participation [16,17]. A balanced panel of 1300 households was constructed by tracking and matching respondents across the 2010/2011, 2013 (n = 1272), and 2016/2017 (n = 1289) survey rounds. The IHPS collects comprehensive household-level data on demographics, education, labor and time use, food security, income, credit access, consumption, asset ownership, migration, and non-farm enterprises. It also includes information on institutional factors such as access to land, input and output markets, credit facilities, and agricultural extension services. Farm-level data cover land characteristics, input use, crop production, post-harvest storage, and sales. In the context of migration, the IHPS captures whether any household member has relocated to another area, including urban destinations. For this study, households reporting at least one migrant, regardless of whether remittances were received, are classified as households with a migrant (HWM), while those without any migrant members are designated as households with no migrant (HNM). These classifications are consistently applied across all three IHPS waves.

2.2. Theoretical and Empirical Strategy

Rural-urban migration (RUM) has long been recognized in academic literature, as early as the 1900s, as a key livelihood strategy, particularly for income diversification among rural households [18,19]. Yet, despite its prominence in development discourse, the implications of climate-induced RUM for agricultural performance, especially the technical efficiency of staple crops like maize, remain underexplored [20]. This study seeks to fill that gap by investigating how climate variability influences migration decisions and, in turn, affects maize production efficiency. **Figure 2** presents a conceptual framework illustrating the interplay between extreme weather events, climate-driven RUM, adoption of climate-smart agriculture (CSA) practices, and their combined effects on maize productivity. The framework underscores how both household- and farm-level characteristics shape migration choices, determine the likelihood of adopting CSA technologies, and ultimately influence the technical efficiency of maize production [20]. We assume that households receive remittances from migrated members, which is further invested in CSA related practices. In addition, the study conceptually postulates that increased farm productivity at the household level can influence climate-induced rural-urban migration, potentially triggering either positive or negative feedback loops [20,21].

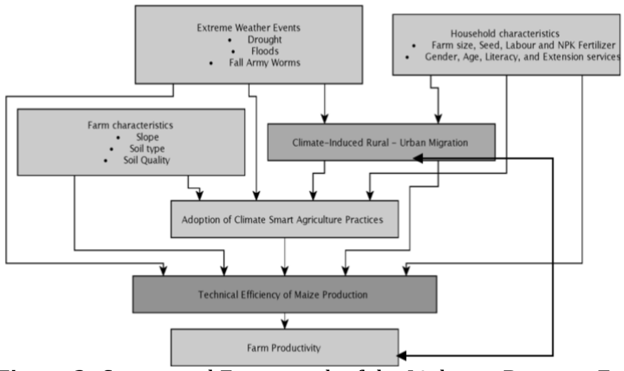

Figure 2. Conceptual Framework of the Linkages Between Extreme Weather, RUM, and Climate-Smart Agriculture Adoption.

To empirically evaluate these relationships, the study applies a panel-based Cobb-Douglas Stochastic Frontier Analysis (SFA) alongside a two-stage Tobit regression. Other than the Cobb-Douglas, several Stochastic Frontier Analysis (SFA) models can be applied, including the linear, Translog, and the general Constant Elasticity of Substitution (CES) forms. However, this study opts for the Cobb-Douglas functional form, as it allows for an initial estimation of technical efficiency attributed solely to physical production factors [22]. This provides a clear foundation for subsequently analyzing the impact of rural-urban migration (RUM) on the technical efficiency of maize production [23].

The analytical approach is grounded in a household decision-making model premised on random utility maximization, where migration occurs when the perceived benefits of relocating to an urban area outweigh those of remaining in a rural setting. The study further posits that rural households are increasingly exposed to erratic and frequent climate shocks. In adapting to these stresses, some households engage in migration as a risk management strategy. Remittances received from migrant members are often reinvested into CSA-related technologies, such as improved seed varieties or soil conservation practices, with the aim of boosting productivity and resilience.

Farm production analysis can be approached through either parametric or non-parametric frontier methodologies, each with distinct analytical strengths and assumptions [23]. Non-parametric methods, most notably Data Envelopment Analysis (DEA), do not require the specification of a particular functional form for the production function, nor do they rely on assumptions about the statistical distribution of error terms. Instead, DEA constructs a piecewise linear frontier based on observed input-output combinations, making it well-suited for identifying relative efficiency without imposing strong parametric constraints. In contrast, parametric frontier models specify a functional form of a priori and make explicit assumptions about the distribution of the composite error term, typically distinguishing between random noise and inefficiency. Among the most commonly applied functional forms in parametric analysis are the Cobb-Douglas (CD), Translog, Generalized, and Transcendental production functions [24]. These models are widely used due to their ability to accommodate multiple inputs, capture technical inefficiency, and allow for hypothesis testing within a stochastic framework.

Production functions represent the maximum output that can be achieved from a given combination of inputs under prevailing technological conditions. This study adopts a theoretical framework informed by the works of Battese [24], which conceptualize production as a process of transforming inputs into outputs. Central to this framework is the notion of the *production frontier*, the theoretical upper bound of output attainable when inputs are used with full technical efficiency. While production functions themselves may lack direct economic interpretation, they provide a powerful mathematical foundation for analyzing optimization behavior in production settings. These functions are characterized by essential properties such as weak monotonicity, quasi-concavity, non-negativity, and essentiality, all of which support their application in empirical economic analysis. In this study, production is modeled through an optimization framework based on a latent utility function, which is maximized under a maize-specific Translog production technology. The optimization is subject to spatial and temporal constraints on input availability, most notably capital and labor. The econometric basis for estimating technical efficiency stems from the pioneering work of Farrell [25], who introduced the concept of a production frontier. This approach was later formalized into the Stochastic Frontier Analysis (SFA) framework and later allowed for the decomposition of deviations from the frontier into inefficiency and statistical noise [26,27]. The specific SFA model employed in this study is detailed in Equation (1).

$$y_{ijt}=f\left(x_{ijkt},,t\right)\equiv lny_{ijt}=\beta_j\sum x_{ijt}+\beta_t t+v_{itk}, \quad (1)$$

Let y_{ijkt} denote the non-negative farm productivity of a household on a plot or farm at time. The vector $x_{ijt}(i{=}1,2....,J)$ represents the quantity of input used by each household on a farm at a time, including conventional inputs as well as rural-urban migration (RUM) as a potential determinant of productivity. The parameters, , are unknown coefficients to be estimated by the model. To analyze the marginal effects of inputs, we apply standard production theory assumptions. Specifically, we derive the first and second partial derivatives of output with respect to a single input holding all other inputs constant. As established in Fuss et al. (1978), these are given by: dy_{ijt}/dx_{jt} ≥ 0 and $d^2y_{ijt}/dx_{jt}^2<0$, of one input while fixing the other inputs. These conditions ensure that the production function satisfies weak monotonicity and concavity in inputs, which are foundational for estimating economically meaningful production frontiers. As per the SFA construction assumption, the v_{itk} is the error term is composed of two parts: a symmetric random error term (ε_{itk}) that captures statistical noise (such as measurement errors or external shocks beyond the farmerquotesingle s control), and a one-sided inefficiency term (u_{itk}) that reflects the shortfall in output due to technical inefficiency [27,28]. The random error term is typically assumed to follow a normal distribution, while the inefficiency term is assumed to follow a non-negative distribution, such as half-normal, truncated-normal, or exponential. This separation of the error components allows the model to distinguish between inefficiency and random variation, making it crucial to clearly specify the distributional assumptions and justify their appropriateness for the data at hand [27,28].

Technical inefficiency occurs when a household fails to attain the maximum possible output given its set of inputs, thereby operating below the production frontier. It reflects the shortfall between actual and potential productivity [28]. A household is deemed technically inefficient if it could either produce more output (y) with the same input bundle (x) or achieve the same output level using fewer inputs. In essence, technical inefficiency signals suboptimal input utilization relative to the efficient frontier. Although the impact of rural-urban migration (RUM) on the technical efficiency of maize production can be estimated using a cross-sectional Stochastic Frontier Analysis (SFA), this approach presents notable limitations. Specifically, cross-sectional models often suffer from endogeneity and fail to capture temporal variations in efficiency. Furthermore, unless corrected through methods such as Corrected Ordinary Least Squares (COLS), these models rely on strong distributional assumptions and typically conflate inefficiency with random noise. Panel data models offer a more robust alternative by accounting for unobserved heterogeneity, time-specific effects, and potential state dependence. They enable more accurate estimation of efficiency dynamics over time by controlling household-specific factors that remain constant across periods, as well as time-varying shocks. In this study, the Cobb-Douglas production function is employed as the empirical specification due to its analytical simplicity, ease of interpretation, and compatibility with frontier estimation techniques other than its counterparts: Translog or Ordinary Least Squares Linear function forms [29]. When linearized, the model facilitates the identification of RUM's impact on maize production efficiency, allowing for distinctions between households with migrants (HWM) and those without migrants (HNM). The panel-based SFA model is formally presented in Equation (2).

$$u_{itk}=\beta_0+\sum_{i=1}^{N}\beta_j lnP_{itk}+\sum_{i=1}^{N}\beta_j lnZ_{itk}+\omega RUM_{it}+\Omega CSA*RUM_{it}+e_{it} \quad (2)$$

In the model, the β, ω and Ω represent vectors of unknown parameters to be estimated. The term u_{it} captures the technical inefficiency associated with maize production for households at a time. The vector P_{itk} represents production inputs, including labor (measured in person-days), seed quantity (in kilograms), total landholding size (in hectares), and chemical fertilizer use (in kilograms). The vector Z_{itk} includes household-level socioeconomic characteristics hypothesized to influence technical inefficiency, such as education, access to extension services, and asset ownership. The error term e_{it} represents white noise, capturing measurement error and other random shocks not attributable to inefficiency. To investigate the effect of rural-urban migration (RUM) on technical efficiency, a two-stage Tobit regression approach is employed. In the first stage, technical efficiency scores are estimated from the Stochastic Frontier Analysis (SFA) model [29,30]. The SFA can only be applied if the data is negatively skewed [31], which becomes a testable hypothesis before estimation. In the second stage, following Pangapanga-Phiri [2], a Tobit regression is used to examine how RUM and other household characteristics influence the predicted technical efficiency scores. This two-stage framework accounts for the censored nature of efficiency scores, which are bounded between zero (0) and 1, and allows for the identification of factors driving inefficiency in maize production [31]. bfTable 1 shows variables used during modeling of the interplay between RUM, CSA, and technical efficiency of maize production in rural Malawi as empirically guided [31]. Variables include physical factors of production like seed, land, fertilizers, and labour, socio-institutional factors like age, gender, education, access to credit, extension services, and markets like ADMARC, as well as land characteristics like soil type (ST), soil quality (SQ), and slope (SP).

Table 1. Data variables used in the study.

Variables	Expected Sign	Definition
Farm Productivity		Yield in/ha
Seeds planted	+	Seed in kg
Labour	+	Personal labour days
Fertilizer applied	+	Fertilizer in kg
Land holding sizes	+/−	Farm size in ha
Age of household (HH) head	+/−	Age of HH head in years
Access to credit	+/−	Credit access = 1 if yes
Distance to ADMARC	+/−	Kilometer
Distance to main road	+/−	Kilometer
Attended any level of education	+/−	Attended education = 1 if yes
Highest education class	+/−	Years
Access to extension services	+	Extension access = 1 if yes
Gender	+/−	Gender of the hh head
Household size	+/−	Counts
Organic fertilizers	+	kg
CSA	+	CSA = 1 if adopted CSA practices
RUM	+/−	RUM = 1 if one HH member migrated
Mobile phone	+/−	Own a mobile phone = 1 if yes
Remittance receipt	+/−	Received remittance = 1 if yes
Flat slope	+/−	Yes if flat slope
Gentle slope	+/−	Yes if gentle slope
Steep slope	+/−	Yes if steep slope
Very steep slope	+/−	Yes if very steep slope
Yes if good soil quality	+	Yes if good soil quality
Fair soil quality	−	Yes if fair soil quality
Yes if poor soil quality	−	Yes if poor soil quality
Clay soil type	+/−	Yes if clay soil type
Loamy soil type	+	Yes if loamy soil type
Sandy soil type	+/−	Yes if sandy soil type
Loamy sandy soil type	+/−	Yes if loamy sandy soil type

Note: +/− denotes the variables has either positive (+) or negative (−).

3. Results and Discussion

3.1. Descriptive Summary of Household Characteristics

Table 2 provides a comprehensive summary of household and farm-level characteristics, comparing households with migrants (HWM) and those without migrants (HNM) over the period from 2010 to 2016/2017. The data show that roughly 40% of the sampled households have at least one member who has migrated to urban areas, predominantly driven by various economic incentives. Male-headed households constitute about

75% of the sample, though this proportion has declined slightly from nearly 78% in 2010 to approximately 72% in 2016/2017. This shift likely reflects demographic changes influenced by RUM dynamics. The average age of household heads is 46 years overall; however, HWM are typically headed by older individuals, averaging 57 years, compared to an average age of 38 years among HNM. This age gap suggests that younger, more economically active members tend to migrate to urban centers in pursuit of better opportunities, leaving older household members to manage farm operations. RUM shows an upward trend, increasing from 35% in 2010 to just over 40% by 2016/2017. Education levels reveal that over two-thirds of households have attained some formal schooling, typically up to grade five, indicating moderate literacy rates among the rural population. Meanwhile, mobile phone ownership has risen dramatically from 58% in 2010 to 88% in 2016/2017, reflecting enhanced access to communication technologies that facilitate remittance transfers and information exchange as highlighted in Pangapanga-Phiri [2]. Regarding remittances, about 33% of households with migrants reported receiving financial support from their urban-based members, accounting for 13% of the total households surveyed. These findings are consistent with prior studies and underscore the increasing importance of migration and remittance flows in shaping agricultural investment decisions [32].

Table 2. Descriptive statistics of the household and plot-level characteristics.

	HNM	HWM	POOLED		HNM vs HWM
Variables	Mean	Mean	Mean	Std. Dev.	*P*-value
Seed in kg	9.588	10.56	9.974	9.519	***
Yield in/ha	1463	1538	1,493.251	1,144.091	**
Personal labour days	27.01	30.58	28.438	20.358	***
Fertilizer in kg	46.43	47.52	46.864	59.554	
Farm size in ha	0.478	0.550	0.507	0.473	***
Age of hh head in years	37.93	57.17	45.614	15.369	***
Credit access	0.127	0.116	0.123	0.329	
Distance to the admark in km	7.497	7.500	7.498	5.163	
Distance to the main road in km	9.369	9.676	9.492	9.867	
Attended education	0.876	0.751	0.826	0.379	***
Highest education class	6.001	4.368	5.349	4.262	***
Extension access	0.628	0.674	0.646	0.478	***
Gender of the hh head	0.804	0.674	0.752	0.432	***
Hh size	5.459	5.156	5.338	2.301	***
Organic fertilizer in kg	110.6	147.9	125.5	2.513	***
Mobile phone	0.722	0.678	0.705	1.022	
Remittance receipt	0.00	0.334	0.133	0.340	***
Flat slope	0.673	0.650	0.664	0.472	
Gentle slope	0.264	0.275	0.269	0.443	
Steep slope	0.0460	0.0590	0.051	0.221	*
Very steep slope	0.0160	0.0160	0.016	0.126	
Good soil quality	0.493	0.499	0.495	0.500	
Fair soil quality	0.377	0.389	0.382	0.486	
Poor soil quality	0.130	0.112	0.123	0.328	
Clay soil type	0.211	0.210	0.210	0.408	
Loamy soil type	0.545	0.519	0.535	0.499	
Sandy soil type	0.218	0.243	0.228	0.420	*
Loamy sandy soil type	0.0250	0.0280	0.026	0.160	

Note: *t* statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

The study further examines how households allocate key productive resources and the resulting impact on maize production outcomes. On average, households cultivate 0.52 hectares of maize, with those having migrant members (HWM) tending to farm slightly larger plots, about 0.55 hectares, compared to 0.48 hectares cultivated by households without migrants (HNM). Differences in productivity are also apparent: the average maize yield across all households stands at 1493 kg per hectare, but HWM achieve a notably higher mean yield of approximately 1556 kg/ha, surpassing the 1463 kg/ha recorded for HNM. This yield gap of roughly 83 kg/ha likely reflects the positive influence of remittances, among other factors, which may enable greater investment in improved inputs and farming practices. Labor allocation follows a similar pattern, with HWM dedicating an average of 30 person-days per season to farm work, slightly more than the 27 person-days reported by HNM. Fertilizer use also differs, albeit marginally; both groups typically apply about one 50 kg bag of inorganic fertilizer per plot, with HWM averaging 48 kg of NPK fertilizer compared to 46 kg by HNM. More pronounced variation is evident in organic fertilizer application, where HWM apply an average of 148 kg per plot, substantially exceeding the 110 kg applied by HNM. Additionally, approximately 65% of households report receiving agricultural extension services, indicating a moderately widespread level of technical support across the sample. Collectively, these disparities in resource allocation and access to extension services help explain the observed differences in maize productivity and technical efficiency between migrant and non-migrant households [33].

Figure 3 provides a comprehensive overview of household and plot-level characteristics across the 2010 to 2017 survey periods. A striking trend is the substantial increase in household access to agricultural extension services. In 2010, only 41% of households reported receiving extension support; this figure rose sharply to 70% in 2013 and further climbed to 90% by 2016. This pronounced growth signals a strengthened institutional commitment to smallholder farmers, likely facilitating broader dissemination and adoption of modern and climate-resilient agricultural practices. Regarding farm characteristics, approximately 66% of households cultivated land on flat terrain, while 27% farmed on gently sloping (SP) land. These topographical variations carry important agronomic implications, influencing factors such as soil erosion and water retention, both critical for sustainable maize production. Perceptions of soil quality (SQ) varied across the sample, with nearly half of households rating their soil as good, and 38% describing it as fair. Encouragingly, perceived soil quality showed a gradual improvement over the survey years, likely driven by increased adoption of sustainable land management (SLM) practices such as soil and water conservation, organic fertilization, and agroforestry. In terms of soil types (ST), 54% of households cultivated on loamy soils, known for their favorable texture and nutrient-holding capacity, making them ideal for crop production. Conversely, 23% farmed on sandy soils, which generally have lower fertility and are more prone to nutrient leaching. These findings highlight the critical need to tailor soil improvement interventions and extension services to local conditions, thereby enhancing farm productivity and resilience [34,35].

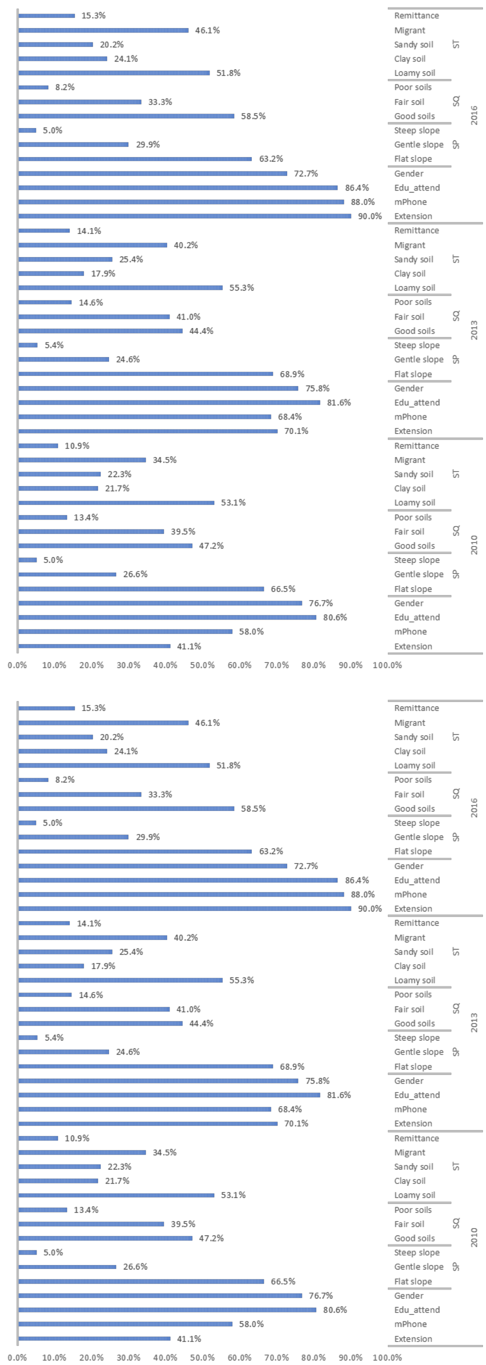

Figure 3. Household and Plot-level Characteristics: Proportional Trends from 2010 to 2017.

3.2. Stochastic Frontier Analysis and Robustness

Before estimating the empirical models, the study undertakes a series of diagnostic tests to ensure the robustness of both the data and the selected model specifications. A crucial preliminary step involves applying the Schmid and Lin residual test to determine the suitability of using the Stochastic Frontier Analysis (SFA) framework[35]. This test requires that residuals from an Ordinary Least Squares (OLS) regression exhibit negative skewness, indicating the presence of a one-sided error component attributable to technical inefficiency, a key assumption underlying the SFA model. As illustrated in **Figure 4**, the skewness and kurtosis test results confirm this condition. Specifically, residuals from both fixed-effects and random-effects panel models demonstrate significant negative skewness, consistent with the asymmetric error structure inherent to SFA. This allows us to confidently reject the null hypothesis of symmetry and supports the appropriateness of employing the SFA framework for analyzing technical inefficiency in maize production. Moreover, the kurtosis statistics show positive values, indicating distributions with heavier tails than a normal distribution. This suggests the existence of outliers or extreme inefficiency scores, which the SFA methodology is designed to handle effectively. Taken together, these diagnostic outcomes underscore the reliability and robustness of the empirical approach adopted in this study.

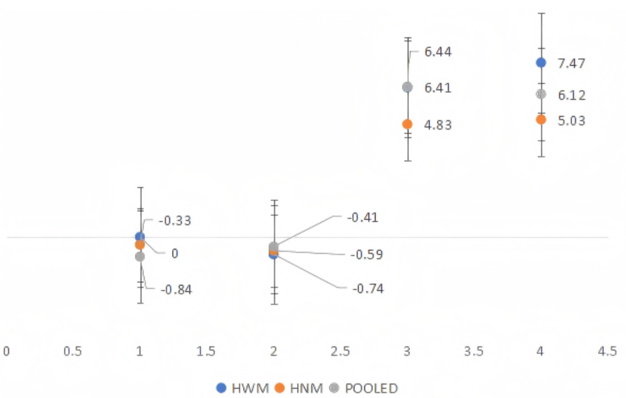

Figure 4. Skewness and kurtosis tests.

The study further evaluated the validity and robustness of the Stochastic Frontier Analysis (SFA) model specification through the log-likelihood ratio (LR) test, which examines the presence of inefficiency effects by testing the null hypothesis that no one-sided error component exists. This test is conducted following model estimation via the Maximum Likelihood (ML) method. At one percent significance level, the LR test statistics for both households with migrants (HWM) and those without migrants (HNM) significantly exceeded the critical value of 5.412, providing strong evidence to reject the null hypothesis of zero technical inefficiency. This confirms that the SFA model is well-suited to capture inefficiency in maize production. In addition to the LR test, panel unit root tests were performed to verify the stationarity of the data, a necessary condition to avoid spurious regression results. Both the Levin-Lin-Chu and Im-Pesaran-Shin tests were applied, and neither indicated the presence of unit roots at the one percent significance level. These findings confirm that the variables included in the model are stationary, thereby reinforcing the reliability of the panel data estimations. Together, these diagnostic procedures strengthen the credibility of the model and bolster confidence in the robustness of the empirical results[35]. Furthermore, the use of panel data in two-stage selection models helps address potential endogeneity arising from unobserved variables[35]. In addition, the study employs several variants of the SFA-Cobb-Douglas model as robustness checks to validate the results. This includes estimating technical efficiency and applying a two-stage Tobit selection model, using both pooled data and separate estimations across different waves to ensure consistency and reliability of the findings.

3.3. Do Rural-Urban Migration and Adoption of Climate-Smart Agriculture Practices Enhance Maize Productivity?

This study posits that remittances from rural-urban migration (RUM) facilitate the adoption of climate-smart agriculture (CSA) practices, which in turn enhance maize productivity amid climate variability and extreme weather events. However, we hypothesize that the positive effect of RUM-related remittances on agricultural productivity manifests primarily when coupled with the adoption of CSA technologies. To investigate this, a two-stage Tobit sample selection regression approach is employed to estimate the impact of RUM on the technical efficiency of maize production under adverse climatic conditions as presented in Pangapanga-Phiri [2], while controlling for any potential presence of endogeneity due to unobservable covariates [36,37], with results summarized in **Table 3**. In the first stage, the Battese and Coelli (1995) Cobb-Douglas Stochastic Frontier Analysis (SFA) is applied separately to households with migrants (HWM) and those without migrants (HNM). This step assesses the contribution of various physical inputs to maize productivity and generates household-level technical efficiency scores, which serve as the dependent variable in the second stage. The second stage utilizes a panel-based Tobit regression to examine how RUM influences these technical efficiency scores. Qualitative evidence supports the notion that households engage in RUM as a coping mechanism to offset the adverse effects of extreme weather, channelling remittances into CSA practices that bolster maize yields. **Table 3** presents the findings, with Columns (1–4) showing the SFA estimation results and Columns (5–8) displaying the Tobit regression outcomes. The model's log-likelihood ratio test is highly significant at the one percent level, confirming the robustness of the specification and its suitability for capturing productivity differences between HWM and HNM households. The subsequent discussion focuses primarily on the key insights derived from Columns (1–3). However, the study does not examine the effect of land productivity on rural-urban migration as much of the focus is placed on whether labour outmigration influences land productivity in rural communities.

Several key factors drive maize productivity, with farm size emerging as a particularly strong and statistically significant determinant. The results reveal that, holding other variables constant, an increase of one acre in cultivated land corresponds to a 12% rise in maize productivity at the one percent significance level. This effect is notably more pronounced among households with high maize yields (HWM), who experience a 45% increase, compared to only an 8% gain for households with low maize yields (HNM). This disparity suggests that land constraints may more severely limit productivity improvements among HNM households. Beyond land size, input use plays a critical role in shaping productivity outcomes. The analysis shows that an additional 100 kilograms of seed usage increases maize productivity by 8%, all else equal. Inorganic fertilizer application has an even stronger impact, boosting productivity by 36%. Labor input, measured in person-days, also contributes significantly to productivity for both HWM and HNM households. However, the marginal gain per additional labor day is much smaller for HWM households, 3% compared to 22% for HNM households, potentially reflecting differences in labor quality, efficiency, or management practices. These findings are consistent with earlier research, reinforcing the importance of land availability, input intensity, and labor effectiveness in driving maize productivity [36,37].

Rural-urban migration (RUM) does not directly increase maize productivity levels but significantly influences maize production through its impact on technical efficiency [37]. This distinction is important because RUM primarily alters the availability and allocation of productive household labor, which affects the efficiency with which inputs are used. The Tobit regression results reported in **Table 3** (Columns 5–8) reveal that the coefficient for RUM is statistically significant at one percent level, demonstrating the model's robustness and sensitivity in capturing even subtle effects of migration on efficiency. This strong statistical evidence supports the intuition that RUM plays a meaningful role in enhancing the effectiveness of maize production rather than merely increasing output quantity.

The study reveals that RUM has a statistically significant and negative impact on the technical efficiency of maize production in Malawi, primarily due to reductions in labor productivity. This negative effect is largely driven by the decreased availability of productive family labor, which is vital for labor-intensive tasks such as timely weeding, fertilizer and organic manure application, and other essential agronomic practices. These activities are crucial for buffering maize yields against weather variability, especially in smallholder farming systems where mechanization options are limited. The results indicate that, holding other factors constant, RUM reduces technical efficiency by an average of 9% over the study period. When examined by year, the negative impact is more pronounced between 2010 and

2013, with an 18% decline, compared to a 7% reduction in 2016. These findings highlight the disruptive consequences of labor shortages caused by migration, particularly when lost labor is not replaced through alternative means such as hired help or mechanization. This aligns with prior research documenting the adverse effects of migration on agricultural productivity through labor substitution and diminished household engagement in farming activities. Collectively, the evidence underscores the need for policy interventions that address rural labor constraints to protect agricultural productivity in the face of climate stresses [37–42].

Table 3. Two- Stage Tobit regression Results on the impact of RUM on the technical efficiency and farm productivity.

		SFA (Farm Productivity)				**Tobit(Technical Efficiency)**			
		1	2	3	4	5	6	7	8
		HNM	HWM	POOLED	POOLED	POOLED	2010	2013	2016
Log(farm size)	Ha	0.447***	0.078***	0.116**	0.136***	0.019***	0.003	0.024***	0.057***
		(16.39)	(13.20)	(3.29)	(3.70)	(5.18)	(0.46)	(3.65)	(9.38)
Log(seed)	Kg	0.178***	0.890***	0.083***	0.072***	0.032***	0.014***	0.019***	0.101***
		(12.19)	(25.08)	(38.96)	(19.99)	(15.02)	(4.83)	(4.12)	(17.65)
Log(labor)	Personal days	0.310***	0.216*	0.183**	0.186**	0.015*	0.011	0.013	−0.018
		(5.70)	(2.37)	(2.95)	(3.10)	(−2.14)	−0.84	(−1.05)	(−1.63)
Log(fertilizer)	Kg	0.208***	0.360***	0.361***	0.286***	0.006***	0.001	0.008**	0.006*
		(18.17)	(15.36)	(25.37)	(19.93)	(4.43)	(0.21)	(3.02)	(2.52)
Gender	Male = 1					0.029***	0.040*	0.025	0.017
						(3.75)	(2.57)	(1.77)	(1.46)
Age	Years					0.001	0.002	0.005*	0.002
						(0.66)	(0.94)	(2.25)	(1.83)
Age square	Years					−0.000	−0.000	−0.000	−0.000*
						(−0.77)	(−0.89)	(−1.79)	(−2.21)
Literacy	Yes = 1					0.01	0.024	0.019	0.042***
						(1.39)	(1.78)	(1.43)	(3.57)
Extension	Access = 1					0.012	0.01	0.058***	0.038***
						(1.90)	(0.80)	(4.77)	(3.29)
Rum	Yes = 1					−0.085***	−0.178***	−0.183***	−0.068**
						(−5.89)	(−4.96)	(−6.43)	(−2.97)
Rum*csa	Interaction					0.017***	0.047***	0.038***	0.009*
						(6.84)	(6.14)	(7.53)	(2.36)
Year	Number	−0.001***	−0.001***	−0.001***	−0.001***				
		(18.61)	(19.47)	(−33.33)	(−34.75)				
Gentle slope	Yes = 1				0.227***				
					(−3.45)				
Steep slope	Yes = 1				−0.016				
					(−0.15)				
Loamy soil	Yes = 1				0.090***				
					(14.32)				
Sandy soil	Yes = 1				−0.721***				
					(9.12)				
Fair soil type	Yes = 1				−0.451***				
					(−6.99)				
Poor soil type	Yes = 1				−0.487***				
					(−5.41)				
χ^2		1057.74***	471.61***	1922.12***	2672.14***	282.66***	30.02***	90.93***	622.70***
N		2533	1332	3865	3865	3827	1288	1266	1273

Note: t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The study reveals that although RUM alone exerts a negative effect on technical efficiency, which agrees with previous studies in Malawi [42–44], its interaction with CSA practices produces a positive and statistically significant impact on maize production efficiency. Specifically, households receiving remittances from migrated members who invest in CSA practices, such as soil and water conservation, drought-tolerant maize varieties, and agroforestry, are able to partially offset the labor losses associated with migration. The results indicate that this interaction between RUM and CSA adoption increases technical efficiency by an average of 2% across the study area, holding other factors constant. When disaggregated by year, the efficiency gains are 5% in 2010, 4% in 2013, and 1% in 2016. These findings suggest that remittances are being strategically redirected toward productivity-enhancing technologies and practices that help mitigate the adverse effects of weather variability. However, without such investments, CSA adoption may remain limited, particularly among HWM facing labor shortages due to the intensive labor demands of these practices. Additionally, constraints such as underdeveloped agricultural input markets in rural areas may hinder the effective use of remittances, thereby limiting the full potential of RUM as a climate adaptation mechanism [45,46] . These results corroborate earlier research highlighting that the productivity benefits of migration are contingent upon complementary agricultural investments [47–52].

3.4. Conclusion and Recommendations

Rural-urban migration (RUM) is increasingly employed by households as a strategic adaptation to cope with climate variability and weather-related shocks that threaten agricultural livelihoods. This migration strategy not only diversifies household income through remittance inflows but also facilitates the transfer of knowledge, skills, and innovations from migrants to their home communities. These remittances and innovations are often reinvested in agricultural inputs and climate-resilient farming practices, potentially enhancing productivity and strengthening resilience in smallholder farming systems. This study explores the interplay of RUM, CSA, and the technical efficiency of maize production by applying a two-staged stochastic frontier analysis (SFA) framework in rural Malawi. The findings reveal that, when considered independently, RUM exerts a negative influence on technical efficiency in maize cultivation. The primary driver of this adverse effect is the reduction in available household labor, which is critical for completing labor-intensive agronomic tasks such as timely weeding, fertilizer application, and organic manure use. These activities are essential to mitigating the detrimental effects of erratic weather and ensuring optimal crop performance.

The study's finding that rural-urban migration (RUM) reduces technical efficiency by an average of 9% carries significant policy implications. This decline highlights the need for policymakers to closely monitor and manage labor outmigration from rural areas. Importantly, the mitigating effect of Climate-Smart Agriculture (CSA) adoption on the productivity losses associated with RUM suggests that policy should not focus on restricting migration, often driven by economic necessity, but rather on developing balanced strategies that retain a portion of the rural workforce while enabling households to benefit from migration. Such strategies could involve investing in rural community labour markets, promoting mechanization, and supporting labor-saving technologies to address labor shortages. Simultaneously, policies should facilitate the productive use of remittances by enhancing financial literacy, expanding extension services, and incentivizing investment in CSA practices such as soil and water conservation, drought-resistant crop varieties, and agroforestry systems. Future research would, however, examine the effect of farm productivity on labour outmigration in rural communities.

Author Contributions

Conceptualization, I.P.-P.; methodology, I.P.-P. and E.M.; software, I.P.-P.; validation, I.P.-P. and E.M.; formal analysis, I.P.-P.; investigation, I.P.-P. and E.M.; resources, I.P.-P. and E.M.; data curation, I.P.-P. and E.M.; writing—original draft preparation, I.P.-P.; writing—review and editing, I.P.-P. and E.M.; visualization, I.P.-P.; supervision, E.M.; project administration, I.P.-P. and E.M.; funding acquisition, I.P.-P. and E.M. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

This was not applicable as study did not involve any human or animal samples.

Informed Consent Statement

Not applicable.

Data Availability Statement

This study used data from the National Statistical Office that is the Integrated Household Surveys, which can be obtained from the NSO microdata through https://microdata.worldbank.org/index.php/catalog/3819/get-microdata.

Conflicts of Interest

The authors declare no conflict of interest.

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