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Implications of climate variability on the technical efficiency of rice farmers in the western highlands of Cameroon

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ABSTRACT

Smallholder rice farming in the Western Highlands of Cameroon (WHC) is fundamentally threatened by escalating climate variability, including rising temperatures and altered precipitation patterns, which correlates with a drastic decline in national rice yields from 3 tons per hectare in 2000-2001 to a mere 1.22 tons per hectare in 2021. This predicament is compounded by low rates of technology, which prevent farmers from achieving the potential output of 6 tons per hectare and severely compromise their overall production efficiency. The study adopted a quantitative approach using cross-sectional data collected from a sample of 378 smallholder rice farmers across six rice-producing villages in the Ndop and Nun ecological zones of the Western Highlands of Cameroon. The Tobit regression results indicated that climate variability and selected socio-economic factors play differentiated roles in shaping rice production efficiency. Rainfall variability and high winds or storms showed no statistically significant effects across both model specifications, suggesting limited influence on efficiency, while temperature variability consistently exhibited a negative and highly significant impact, highlighting it as the most critical climatic constraint to rice production efficiency. Farmer experience displayed a non-linear pattern, with efficiency decreasing among those with 5–10 years of experience but increasing significantly for farmers with 16–20 years and 21 years or more, implying that long-term experience enhances productive efficiency. Educational attainment matters only at higher levels, as university education is positively associated with efficiency, whereas secondary and high school education were insignificant. Institutional factors further contribute, with farm association membership slightly improving efficiency, while farm training is associated with a small but significant reduction, possibly reflecting adjustment or relevance issues. Extension services and technology utilization did not show significant effects. The most pressing recommendation is to counteract the highly significant negative impact of temperature variability, for which current technology is not mediating. Given the failure of current technology to mitigate temperature stress, research and development efforts must be urgently channelled toward breeding and disseminating novel, heat-tolerant Improved Rice Varieties (IRV) suitable for the Western Highlands.

INTRODUCTION

The profound challenges presented by climate variability are significantly amplified by the rapid and continuing increase in global greenhouse gas (GHG) emissions. Counter intuitively, the agricultural sector itself is a leading source of these anthropogenic emissions, contributing a staggering 78.6% of nitrous oxide (N2O) and 39.1% of methane (CH4) emissions globally (IPCC, 2018; FAO, 2019). These potent GHGs primarily originate from soil management practices, livestock enteric fermentation, and manure management. Despite its contribution to emissions, agricultural practices are simultaneously highlighted as critical levers in the fight against climate change. By widely adopting sustainable agricultural practices such as improved soil management, agroforestry, and reduced use of nitrogen fertilizers, the sector can significantly reduce its emissions footprint. Furthermore, these practices can enhance soil carbon storage (sequestration) while contributing to increased resilience, thereby pursuing long-term climate mitigation and adaptation goals (Fuss *et al.,* 2020). Conversely, climate change is unleashing extreme weather events that severely outpace the ability of vulnerable populations and farming systems to adapt. Even slight increases in temperature and subtle shifts in rainfall patterns can precipitate severe crop failures and substantial yield losses for essential cereal crops (Babushkina *et al.,* 2018a). The long-term consequences of these biophysical changes are highly destructive, leading to chronically disrupted rainfall patterns, a pronounced decline in global food production, widespread food insecurity, and escalating water scarcity (Asante & Amuakwa-Mensah, 2015). Under various climate scenarios, individual crop production is projected to decline substantially, with estimates ranging from 10% to 38%. This significant range reflects the inherent uncertainty across differing climate models (Babushkina *et al.,* 2018a; Rolim *et al.,* 2017). Given this complexity and the scale of the threat, urgent and transformative action is essential. An effective response to this global crisis requires addressing the complex interplay of biophysical, social, and economic factors that constrain farmers' capacity to adapt and build resilience.

Climate variability poses an existential threat to African agriculture, a sector that is overwhelmingly rain-fed and

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forms the core of many national economies and rural livelihoods. The primary impacts stem from persistently rising temperatures and increasingly unpredictable changes in rainfall patterns, leading to severe socio-economic and environmental consequences across the continent. The vulnerability of the African continent is particularly pronounced, with the Intergovernmental Panel on Climate Change (IPCC, 2014) warning that Africa is warming at an alarming rate, projected between 0.2ºC and 0.5ºC per decade. Research indicates that even a modest temperature increase of 1ºC to 2ºC could lead to severe reductions in crop yields due to heightened evapotranspiration and significantly decreased soil moisture availability (Kolleh & Jones, 2018; Kurukulasuriya & Rosenthal, 2013). This hydrological stress disproportionately affects smallholder farmers who lack access to modern irrigation systems. The aggregated effect of these climatic changes is substantial. Staple crop yields in Sub-Saharan Africa are projected to decline by 10%–20% by 2050 under current climate trends, severely threatening regional food security (Gebrechorkos *et al.,* 2019). For instance, maize production in East Africa, a critical food source, could fall by up to 40% by the end of the century due to climate variability (Thornton *et al.,* 2018). Furthermore, the IPCC (2014) notes that irregular rainfall patterns and temperature increases are shortening the crop and fodder growing periods. Projections suggest an average 20% shortening of the growing season by 2050 in Western and Southern Africa, which is expected to cause a corresponding 40% decline in cereal yields. These losses underscore the urgent need for enhanced adaptive capacity and resilient agricultural systems across the continent.

In Cameroon, observed weather statistics confirm alarming climate trends (NOCC, 2021). Climate variability poses formidable challenges to agricultural production, particularly rice farming, which is crucial for food security and economic stability in many developing countries, including Cameroon. The Western Highlands region stands out as a vital hub for rice production, contributing a considerable share of the nation's overall output (MINADER, 2020). However, farmers in this region are increasingly struggling due to unpredictable weather patterns, including persistently rising temperatures and shifting rainfall (Kurukulasuriya & Rosenthal, 2013). Analysis of Cameroon's decadal rainfall trends from 1982 to 2020 indicates a notable decline in average rainfall patterns across the decades, despite a brief recovery period from 2002 to 2011 (NOCC, 2021). Conversely, recent analyses of decadal temperature trends from 1991 to 2020 demonstrate a significant and consistent increase in average temperatures (NOCC, 2021). This statistically significant climatic shift is increasingly influencing Cameroon, adversely affecting smallholder farmers, including those engaged in rice cultivation (Fongnzossie *et al.,* 2018). The Western Highlands region is particularly sensitive to shifting climatic patterns, as the agricultural sector is heavily dependent on natural and rain-fed systems (Awazi *et al.,* 2019a). These changes pose a substantial risk to agricultural productivity, threatening the livelihoods and food security of millions. Projections for Cameroon indicate that climate variability will continue to result in increased temperatures, altered precipitation patterns, and a heightened frequency of extreme weather events (Awazi *et al.,* 2019b). While Cameroon has significant potential to increase its rice output (FAO, 2020), the rice sector is highly susceptible to the repercussions of climate change. Rising temperatures and unpredictable rainfall threaten to disrupt growing seasons and reduce crop yields (Awazi *et al.,* 2019b). Moreover, increasingly frequent extreme weather events, including droughts and floods, further jeopardize the crop, thereby threatening national food security.

The climate trends in Cameroon are alarming, between 1960 and 2015, the country experienced a 2.2% annual decrease in rainfall and a 0.7°C rise in mean annual temperature, as highlighted by research from Amougou *et al.* (2015). These shifts have resulted in irregular rainfall and intensified extreme weather events, such as floods and droughts, which negatively affect agricultural productivity. Further studies by Awazi *et al.* (2020) confirm that temperature fluctuations in the western highlands became more extreme between 2004 and 2018, with below-average rainfall in 8 out of those 15 years. Despite considerable investment in agricultural research and extension aimed at developing and disseminating Climate-Resilient Agricultural Technologies (CRATs) including early-maturing and stress-tolerant rice varieties the rates of technology adoption and sustained utilization among smallholder farmers in Cameroon remain alarmingly low (Fani *et al.,* 2020; Gaston *et al.,* 2022). This low adoption and utilisation indicates a significant disconnects between expert recommendations and actual on-farm practices, preventing farmers from effectively mitigating climate risks (Arslan *et al.,* 2015). Gaston *et al.* (2022) indicate that rice farmers in the Western highlands region have adopted only 8 of the approximately 32 different farm technologies introduced, suggesting a markedly low level of technology utilisation. Furthermore, for the limited number of technologies implemented, yields have either stagnated or declined, contradicting the expectation that these innovations would lead to productivity enhancements.

The pathway to building resilience against climate change and enhancing food security lies in the strategic adoption of innovative technology that can significantly enhance production efficiency. The urgent adoption of climate-resilient technologies, such as drought-tolerant rice varieties, improved water management techniques, and precision agriculture systems, is essential for empowering smallholder farmers to effectively tackle the challenges of climate variability while enhancing productivity. By implementing strategies that increase agricultural output and improve the living standards of smallholder farmers, Cameroon and other developing nations can effectively address rising food demand and contribute significantly to several Sustainable Development Goals (SDGs), specifically; SDG1 (No Poverty), SDG2 (Zero Hunger), SDG12 (Responsible Consumption and Production) (FAO, 2018). Moreover, effectively addressing climate variability in agriculture aligns directly with SDG6 (Clean Water and Sanitation) through sustainable water resource management and SDG13 (Climate Action) aimed at combating climate change and its impacts. Advanced production methods and practices that drive agricultural output expansion are collectively known as agricultural technologies (Sennuga *et al.,* 2020a). The adoption of these climate-resilient technologies is crucial for enabling farmers to effectively adapt to shifting climate conditions. Leveraging technology is therefore not merely beneficial but essential for driving productivity growth and securing the livelihoods of smallholder farmers in many developing countries. To this end, this study sought to investigate the implications of climate variability on technical efficiency of rice farmers in the western highlands of Cameroon.

LITERATURE REVIEW

Adeosun *et al.* (2024) evaluated the effect of climate change vulnerability on farm technical efficiency in rural Cameroon. Employing a two-step approach, the researchers first calculated technical efficiency using the stochastic frontier approach with a Cobb–Douglas specification. Subsequently, they applied a Tobit model to investigate the effect of climate change on efficiency. Data were collected through a questionnaire survey of 419 randomly selected farmers. The findings revealed that the average level of technical efficiency was 62.9%, indicating potential for improvement if resources are used optimally. Moreover, increases in the climate change vulnerability index had statistically significant negative effects on technical efficiency. This negative relationship was attributed to the adverse influence of the exposure and sensitivity components of the climate change vulnerability index. The study provides insights into how climate change vulnerability affects farm efficiency and suggests means for improvement.

Joseph *et al.* (2021) assessed the effect of adopting climate change adaptation measures on the production efficiency of citrus farmers in the Limpopo province of South Africa. The study utilized a stochastic frontier production function with a Cobb–Douglas functional form to analyze the productivity of farmers in relation to adopted climate change strategies. The adaptation measures examined included planting drought-resistant varieties, rainwater harvesting, planting early maturing varieties, integrated pest management (IPM), changing fertilizer types, and applying drip irrigation. Data were collected through a semi-structured questionnaire administered to 235 production units across five district municipalities. The likelihood ratio tests for profit models indicated that farmers were profit efficient considering the identified adaptation strategies. However, the inefficiency model revealed that, besides changing fertilizer as an adaptation measure, the other strategies, including IPM, water harvesting, and planting drought-resistant varieties, did not significantly change the profit efficiency of farmers. Notably, the price of fertilizer ($p < 0.010$) and water cost ($p < 0.010$) were significant variables influencing profit efficiency. The study suggests that while certain adaptation strategies may not directly impact profit efficiency, citrus farmers can still adapt to climate change and maintain profitability.

Mbwambo *et al.* (2023) investigated the impact of climate variability and change adaptation strategies on the technical efficiency of sorghum production in Manyoni District, Tanzania. Using a cross-sectional research design, data were collected from 330 randomly selected household heads. A Cobb–Douglas stochastic frontier model was employed to determine the impact of adaptation strategies on technical efficiency. Farmers adopted various strategies, including drought-tolerant crops, conservation agriculture, drainage systems, and early maturing crops, use of hired labor, resistant livestock breeds, and membership in farmer organizations, access to extension services, and access to credit. The findings revealed that these adaptation strategies significantly improved the technical efficiency of sorghum production. The study highlights the importance of adopting climate change adaptation strategies to enhance agricultural productivity in the face of climate variability.

Atsiaya *et al.* (2023) assessed the composite effect of adaptation to climate variability, agro meteorological information, and socioeconomic and institutional factors on agricultural productivity in Kenya. A multi-stage sampling technique was used to obtain a sample size of 384 sorghum farmers. An endogenous switching regression model was applied to control for the selection problem arising from adaptation to climate variability on agricultural productivity. The results indicated that extension contacts and education level were positively significant among adapters of climate variability. Additionally, the proportion of income allocated for farming was positively significant among non-adapters. On the other hand, access to credit, gender, and age of decision-makers were negatively significant among adapters of climate variability. Similarly, age was negatively significant among non-adapters of climate variability. Overall, adapters to climate variability had higher sorghum output than non-adapters. The study recommends increasing extension contacts and promoting education to enhance adaptation to climate variability.

Ijachi *et al.* (2023) assessed the effects of climate variability on rice production and identified effective coping strategies used by rice farmers in Abuja, Nigeria. Data were collected using 200 well-structured questionnaires and multistage sampling techniques from two rural communities (Dobi and Dukpa). Analyses were carried out using descriptive statistics, and coping strategies were evaluated using a coping strategies index (CSI). The study found that climate variability adversely affected rice production. Farmers employed multiple coping strategies to mitigate these effects, with the most effective being the adjustment of the rice planting calendar based on the onset of the rain (55.7%) and the adoption of recommended improved rice production strategies (53.2%). Other strategies included the use of improved varieties, growing drought-resistant crop varieties, and constructing drainage systems. The study recommends training on soil and water management in rice production and the engagement of extension agents to teach climate-friendly practices. Additionally, it suggests that plant breeders develop rice varieties that can withstand higher floods, drought, pests, and diseases.

Ortiz-Bobea *et al.* (2020) conducted a comprehensive study to quantify the historical impact of anthropogenic climate change on global agricultural total factor productivity (TFP) from 1961 onwards. Employing a robust econometric model that integrates weather effects with counterfactual climate scenarios, the researchers aimed to isolate the influence of human-induced climate trends on agricultural productivity. Their findings revealed that anthropogenic climate change has led to a significant reduction in global agricultural TFP by approximately 21% since 1961, effectively erasing nearly nine years of productivity gains. The impact was notably more severe in warmer regions, with reductions of about 30-33% observed in Africa and Latin America. This study underscores the substantial hindrance that climate change poses to agricultural productivity, particularly in regions already vulnerable to food insecurity. The authors emphasize the urgency for targeted adaptation strategies to mitigate these adverse effects and enhance resilience in the agricultural sector.

Choudhary and Gupta (2024) investigated the impact of climate change on major crop production in India using a Panel Autoregressive Distributed Lag (ARDL) model. The study focused on assessing how variations in temperature, precipitation, and carbon dioxide emissions influence crop yields over time. The analysis revealed that in the long run, a 1% increase in maximum temperature led to a 0.13% reduction in crop production, indicating a negative correlation between rising temperatures and agricultural output. Conversely, carbon dioxide emissions had a positive effect, with a one-unit increase resulting in a 0.26-unit rise in crop production, suggesting a fertilization effect. In the short run, minimum temperature negatively impacted crop production by 0.23% per 1% increase, while area under cultivation and average precipitation positively influenced yields. These findings highlight the complex interplay between various climatic factors and their differential impacts on crop productivity, emphasizing the need for nuanced adaptation strategies in the agricultural sector.

Mekonnen and Kassa (2023) explored the contribution of smallholder farmers' climate change adaptation practices to crop production efficiency in southern Ethiopia. Utilizing stochastic frontier analysis, the study assessed how various adaptation strategies, such as the use of improved seed varieties, soil conservation techniques, and water management practices, influenced technical efficiency (TE) among smallholder farmers. The results indicated that adaptation practices significantly improved TE, with all inputs, except labor and oxen power in wheat and teff productions, being key determinants in crop production. The study suggests that scaling up climate-smart agricultural practices can enhance productivity and resilience to climate variability. It also highlights the need for policies that support the adoption of such practices to ensure sustainable agricultural development.

Mbonu (2025) investigated the effects of climate change on agricultural productivity in Nigeria from 2000 to 2023. Employing an ex post facto research design and analyzing data using linear regression with an Error Correction Model (ECM), the study aimed to assess how climatic variables such as temperature, rainfall, and humidity influenced agricultural output. The findings revealed that climate change had a negative impact on agricultural output in Nigeria during the examined period. The study concludes that the detrimental effects of climate change on Nigeria's agricultural sector highlight the need for immediate adaptive strategies. Key measures such as the adoption of climate-resilient crop varieties, enhanced irrigation systems, and sustainable farming practices are essential for building resilience and ensuring food security amid current environmental challenges.

Shirley *et al.* (2020) applied an empirical, data-driven approach to model the impact of weather on maize yields in the US Corn Belt from 1981 to 2014. Employing generative probabilistic models with parameters determined through Bayesian inference, the study aimed to characterize maize growth rates as a function of monthly temperature and precipitation. The models identified that temperature and precipitation had the largest impact on yield in the six months prior to harvest, aligning with the typical growing season for US maize. Optimal growth rates were observed at monthly mean temperatures of 18-19°C and monthly total precipitation of 115 mm. The study also projected that a temperature increase of 2°C, relative to 1981-2014, would result in an 8% decrease in mean yield and a threefold increase in yield variance, highlighting the potential risks of climate change on maize production.

Dontsi *et al.* (2023) analyse the impact of climate change on the technical efficiency of farms in the Adamawa, North, and West and South regions of Cameroon. The analysis of the study were carried out in two stages with the first stage estimation of the efficiency scores of a sample of 793 farms located in the above regions, using the DEA method. The Tobit-type regression model was used in the second stage to determine the influence of climate variables on the efficiency scores obtained. The technical efficiency score indicate that the technical efficiency of farms is relatively low in these regions. Furthermore, factors such as disruptions in the start dates of the rainy seasons and the increase in the average temperature during the rainy season have a negative and significant impact on the technical efficiency of farms. Also, adaptation of the agricultural calendar, adoption of improved irrigation techniques and intensive use of fertilizers can mitigate the effect of climate shocks on technical efficiency.

Makki *et al.* (2015) evaluate the impact of climate change on productivity and technical efficiency of paddy farms in tidal swamp land. The analysis showed Impact on productivity is negative. Technical efficiency analysis uses frontier production function. The analysis demonstrates that farmers in tidal swamp land have good efficiency, with an average technical efficiency score of 0.78. However, land use, fertilizer; labour and climate have a positive and significant effect on local paddy varieties production in tidal swamp land. The number of seeds had no significant effect while education has a significant influence on farmer's technical efficiency. Age and farm business experience had no real effect on productivity and efficiency.

Djido *et al.* (2021) evaluates the impacts of a pilot project that introduced weather and climate information services on technical efficiency and sorghum productivity in the Upper West Region of Ghana. The Stochastic Frontier model to measure the level of technical efficiency was used in the first stage. The model adopted a Cobb-Douglas functional form with the assumption of an exponential distribution for the identification of technical efficiency scores. Secondly, to measure the impact of the adoption of climate information services (CIS) on technical efficiency and productivity separately, a Control Function estimator was used. Their study also employs a Structural Equation System to deal with the simultaneous problems of the endogenous treatment of CIS into the dependent variables. The findings show that pilot project through the adoption of CIS has a substantial positive effect on improving technical efficiency and productivity in the study area. The empirical results consistently estimate approximately 6% increase in technical efficiency and 35% sorghum yield improvement among users.

Galushko and Gamtessa (2022), investigated the link between climate change, output, and inefficiency in Canadian crop production using provincial data for the period of 1972–2016. This study utilizes a unique climate dataset from station-level weather data and applies a panel stochastic frontier model to explore the effect of climatic conditions on crop production and inefficiency. According to the results, climatic variables are significant predictors of both the maximum potential output (frontier) and technical inefficiency. The combined effect of higher temperatures and lower precipitation as reflected in a lower index signifies a downward shift of the crop production frontier. While greater variability of daily temperatures during the growing season is found to have no statistically significant effect in the frontier equation, greater variation in rainfall results in a downward frontier shift. The results also show that weather shocks measured as a deviation from historical weather normal are significant predictors of technical inefficiency.

Diallo *et al.* (2019) evaluated farm household-level impacts of weather extreme events on Vietnamese rice technical efficiency. Vietnam is an agricultural economy and considered among the most vulnerable countries to climate change, and the Vietnamese economy is highly dependent on rice production that is strongly affected by climate change. A stochastic frontier analysis was applied with census panel data and weather data from 2010 to 2014 to estimate these impacts while controlling for both adaptation strategy and household characteristics. Also, this study combines these estimated marginal effects with future climate scenarios to anticipate the potential impact of hot temperatures in 2050 on rice technical efficiency. We find that weather shocks measured by the occurrence of floods, typhoons and droughts negatively affect technical efficiency. Also, additional days with a temperature above 31°C dampen technical efficiency and the negative effect is increasing with temperature.

Existing empirical studies provide strong evidence that climate change and climate variability adversely affect agricultural productivity and technical efficiency, mainly through increased temperature, rainfall variability, and extreme weather events. However, much of the literature either adopts a broad, aggregated approach or focuses on crops and regions outside the specific agro-ecological conditions of the Western Highlands of Cameroon. For instance, studies such as Adeosun *et al.* (2024) and Dontsi *et al.* (2023) examine climate change impacts on farm efficiency in Cameroon but do so at a national or multi-regional level, without isolating rice production systems or high-altitude, high-rainfall ecologies such as the Western Highlands. Similarly, several studies concentrate on sorghum (Mbwambo *et al.,* 2023; Atsiaya *et al.,* 2023; Djido *et al.,* 2021), citrus (Joseph *et al.,* 2021), maize (Shirley *et al.,* 2020), or general crop productivity (Ortiz-Bobea *et al.,* 2020; Choudhary & Gupta, 2024; Galushko & Gamtessa, 2022), thereby limiting their direct applicability to rice-based systems that are particularly sensitive to temperature and water dynamics. While Diallo *et al.* (2019) and Makki *et al.* (2015) focus on rice, their analyses are situated in Asian tidal swamp and Southeast Asian contexts, which differ markedly from the socio-economic, institutional, and climatic realities of Cameroon's Western Highlands.

Moreover, a significant gap persists in disentangling the specific effects of climate variability as opposed to long-term climate change or composite vulnerability indices on the technical efficiency of rice farmers, especially using micro-level farm data. Many studies emphasize adaptation strategies and productivity outcomes rather than explicitly modeling how variability in rainfall, temperature, and extreme events translates into efficiency losses or gains at the farm level (Ijachi *et al.,* 2023; Mekonnen & Kassa, 2023; Mbonu, 2025). Where efficiency is examined, the role of climate variability is often embedded within broader adaptation or vulnerability frameworks, making it difficult to isolate its independent effects. Consequently, there is limited empirical evidence that directly links climate variability indices to technical efficiency outcomes for rice farmers in the Western Highlands of Cameroon, while simultaneously accounting for farmer experience, education, and institutional factors. This study therefore fills an important gap by providing location-specific, crop-specific, and efficiency-focused evidence on how climate variability shapes rice production efficiency in one of Cameroon's most important but understudied rice-growing zones.

MATERIALS AND METHODS

The study area is the Western Highlands of Cameroon which covers part of the North West and West Regions of the country. The Western Highlands are located in northwestern Cameroon, bordering Nigeria to the west. The zone is home to the second-largest rice production basin in Cameroon and constitutes what is called the "Upper Nun Valley Area". These production zones cuts across both regions with a bigger production area in the North West Region. The highland covers 5 Divisions within the 2 regions namely, the Ngohketunjia, Mezam, and Bui in the North West Region and the Noun and Bamboutous Divisions in the West Region. In total, the Upper Nun Valley Area has about 16685 registered rice farmers (PRODERIP, 2021).

The western highland is characterised by a cool temperate-like climate and lies between latitudes 5°20' and 7° North and longitude 9°40' and 11°10' East of the Equator, with a surface area covering 1/6 of the country's land area (31,110 km2). The region is characterized by a rugged terrain, with elevations ranging from 300 to 3000 meters above sea level and average rainfall is about 1500-2400 mm, while temperature averages 23°C, ranging between 15°-32°C (Balgah *et al.,* 2016). The climate of the Western Highlands is humid subtropical, with two distinct seasons: a wet season that lasts from April to October, and a dry season that lasts from November to March.

Agriculture is the mainstay of the economy in the Western Highlands, with rice being one of the major crops grown in the region. The region's fertile soils, adequate rainfall, and favourable climate make it suitable for rice cultivation. The region is greatly blessed with extensive swamps that significantly favour rice production. However, the region is vulnerable to climate variability, with increasing temperatures, changing rainfall patterns, and increased frequency of extreme weather events posing significant challenges to rice farmers. The study focused on the following specific locations within the Western Highlands:

1. Ngohketunjia Division in the North West Region, and
2. Noun Division in the West Region

These divisions were selected based on their rice production potential and vulnerability to climate change. This study aimed at analysing the effect of climate change on economic and technical efficiencies of rice farmers in the western highlands of Cameroon. To achieve this objective, an econometric model known as the censored Tobit regression model is applied. This model is considered over other approaches because it gives consistent and unbiased results and the production efficiency scores (dependent variable) obtained are censored from below and above that is, between 0 and 1. The level of efficiency estimated using the stochastic frontier approach is used as the dependent variable. The efficiency scores are regressed on climate variables and controlled socioeconomic and institutional variables in order to estimate their effect on production efficiency.

The Tobit model for this analysis is given as follows

Where, β_0, β_n, δ_k and are the parameters to be estimated,

$$Y^* = \beta_0 + \sum_{n=1}^{m} \beta_n C_{ni} + \sum_{k=1}^{l} \delta_k Z_{ki} + \mu_i \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \mathbf{1}$$

C_{ni} represents the vector of independent climate variability variables which include rainfall, temperature, floods and drought. Z_{ki} represents vector of control variables for farm i and include, years of farming experience, level of education, farm size, availability of credit, extension visit and farm training. μ_i is the error term, which is defined as independently and normally distributed, that is, μ_i ~N(0,σ2). Y* Represent production efficiency. The table below shows the Tobit model variables and their expected signs

The generalized form is as follows

$$Y = \beta_0 + \beta_1 C_1 + \beta_2 C_2 + \beta_3 C_3 + \beta_4 C_4 + \beta_5 C_5 + \delta_1 YFT_6 + \delta_2 ELF_7 + \delta_3 FMS_8 + \delta_4 ATC_9 + \delta_5 AFT_{10} + \delta_6 EXTV_{11} + \mu_i \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \mathbf{2}$$

Where is the natural logarithm (i.e. logarithm to base β_k are parameters to be estimated (k = 1… 11). The subscript i indicates the ith household in the sample (. The parameters μ_i represent the stochastic and inefficiency components of the error term respectively. In this study, the half-normal distribution is assumed for the asymmetric technical inefficiency parameter. In the specified model, the parameters to be estimated, β_k represent the elasticity of output with respect to each ith input, which is the percentage change in output from a 1% change in the input. From the above equation, the output Y depends on the inputs X. When farmers combine the right inputs at the minimum level, which yield the maximum output, then the farmers are said to be producing at the efficiency level.

RESULTS AND DISCUSSIONS

Presentation

This section looks at the effects of climate variability on production efficiency of rice farmers in the western highlands of Cameroon. To do this, the censored Tobit regression model is employed

Table 1 demonstrate the summary Statistics of variables used in the Tobit regression of the effects of climate variability on production efficiency. The rain variability and temperature variability indices were captured using the aggregation and scaling approach of their indicators in question 10. High winds storm was captured as a dummy variable, since we had just one indicator. The table provides descriptive statistics for several variables

Table 1: Measurability of Variables used in the model

Parameters	Variables	Description Of Variables	Measurement Of Variables	Expected Signs
	Climate variables			
β1	C1	Increased Rainfall	Millimetres	Negative
β2	C2	Increased Temperature	Degree Celsius	Negative
β3	C3	Frequent Floods	Dummy	Negative
β4	C4	Frequent Drought	Dummy	Negative
β5	C5	Insect and disease development	Dummy	Negative
	Control variables			
δ1	YFT	Years of farming experience	Number of years	Positive
δ2	ELF	Education level of farmers	Years of schooling	Positive
δ3	FMS	farm size	Hectares	Positive
δ4	ATC	Access to credit	Dummy	Positive
δ5	AFT	Access to farm training	Dummy	Positive
δ5	EXTV	Extension visit	Dummy	Positive

used in a Tobit regression analysis. These variables include both continuous and categorical data, offering insights into the characteristics of the sample. The total number of observations varies slightly across variables, with most having 352 observations, and a few having 349, 351, or 328. The production efficiency of rice farmers is notably high, with a mean of 0.946. The variable exhibits a very low standard deviation of 0.00032, indicating a remarkable uniformity in efficiency across the surveyed farms. The values range from a minimum of 0.945 to a maximum of 0.947, reinforcing that all farms operate within a narrow, highly efficient band.

Table 2: Summary Statistics of Variables used in the Tobit Regression Model

Variable	Obs	Mean	Std. Dev.	Min	Max
Production efficiency(TEF)	328	.946	.00032	.945	.947
Rain variability index	352	2.606	.386	1.222	4.667
Temp variability index	352	2.292	.533	1	3.333
High winds storm	352	.545	.499	0	1
Long5 10yrs	352	.179	.384	0	1
Long11 15yrs	352	.372	.484	0	1
Long 16 20yrs	352	.151	.358	0	1
Long more21	352	.148	.355	0	1
Secondary educ	352	.281	.450	0	1
High educ	352	.128	.334	0	1
University educ	352	.151	.358	0	1
Farm association	349	.418	.494	0	1
Farm training	351	.479	.500	0	1
Extension service	351	.413	.493	0	1
Tech adoption	352	.702	.458	0	1

The Rain variability index has a mean of 2.606 and a standard deviation of 0.386, suggesting a moderate level of variation in rainfall. The values span from 1.222 to 4.667. The Temp variability index has a mean of 2.292 with a standard deviation of 0.533, indicating slightly more variability than the rain index. Its values range from 1 to 3.333. The variables for High winds storm, Long tenure, education, and farm/tech-related characteristics are all binary, with values of 0 or 1. The mean for these variables represents the proportion of the sample that possesses that characteristic. High winds storm mean is 0.545, indicating that slightly more than half of the observations reported experiencing a high-wind storm. A mean of 0.179 for Long 5-10yrs indicates a smaller proportion of farmers in this category, while a mean of 0.372 for Long 11-15yrs represents the largest group. Education means show the educational attainment of the farmers. For instance, the Secondary education variable

Table 3: Tobit Regression for the Effects of Climate Variability on Production Efficiency

	Coefficients	**Coefficients**
VARIABLES	Model (1)	Model (2)
Rain_variability_index	0.000049	0.000058
	(4.45e-05)	(4.56e-05)
Temp_variability_index	-0.000198***	-0.000215***
	(3.20e-05)	(3.32e-05)
High_winds_storm	0.000238	-0.000022
	(3.57e-05)	(3.78e-05)
Long5_10yrs		-0.0000964*
		(5.80e-05)
Long11_15yrs		0.0000091
		(5.28e-05)
Long_16_20yrs		0.000138**
		(6.47e-05)
Long_more21		0.000022
		(6.47e-05)
Secondary_educ		-0000278
		(4.23e-05)
High_educ		0.000348
		(5.78e-05)
University_educ		0.0000986*
		(5.32e-05)
Farm_asso		6.78e-05*
		(3.80e-05)
Farm_training		-0.000075*
		(3.92e-05)
Extension_service		0.000536
		(3.85e-05)
Tech_adopt		0.000040
		(3.62e-05)
Constant	0.946***	0.946***
	(0.000125)	(0.000145)
sigma	0.000302***	0.000288***
	(1.18e-05)	(1.13e-05)
Observations	328	326

Robust standard errors in parentheses
**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Source: Designed by Author Using Field Survey (2025)

has a mean of 0.281, suggesting a larger proportion of farmers with this level of education compared to those with High school education (mean 0.128) or University education (mean 0.151). A mean of 0.418 for Farm association and 0.413 for Extension service indicates a similar proportion of farmers in both categories. The mean of 0.479 for Farm training shows a slightly higher proportion, and the mean of 0.702 for Technology utilisation indicates that a substantial majority have adopted some form of technology.

Table 2 hosts the Tobit regression of the effects of climate variability on production efficiency. In model 1, we have only the climate variability variables and in model 2 we include control variables. This is to help ascertain for the stability of the climate variability variables and the model as a whole. In the model with control variables, like in that without, rain variability maintains a positive, but insignificant, effect on rice production efficiency. On the contrary, temperature variability has a negative and significant impact on rice production efficiency.

Table 4: Variance Inflation Factor

VARIABLES	VIF	1/VIF
Long11_15yrs	2.594	.386
Long More21	2.138	.468
Long5 10yrs	1.986	.504
Long 16 20yrs	1.732	.577
Farm Training	1.51	.662
University Educ	1.493	.67
Secondary Educ	1.44	.694
Extension Service	1.426	.701
High Winds Storm	1.396	.716
Farm Asso	1.389	.72
Temp Variability I~X	1.28	.781
Rain Variability I~X	1.269	.788
High Educ	1.259	.794
Tech Adopt	1.126	.888
Mean VIF	1.574	.

The coefficients from the Tobit regression show the estimated effect of each variable on production efficiency, with robust standard errors in parentheses. In line with Rainfall variability index, the coefficient is 0.000049 in Model (1) and 0.000058 in Model (2). This variable is not statistically significant in either model, suggesting that rainfall variability has no significant effect on production efficiency. Temperature variability index has a coefficient of -0.000198* in Model (1) and -0.000215* in Model (2). This negative and highly significant coefficient ($p<0.01$) indicates that increased temperature variability is associated with a decrease in production efficiency. High winds and storm has a coefficient of 0.000238 in Model (1) and -0.000022 in Model (2). This variable is not statistically significant in either model, suggesting no significant effect on production efficiency.

The coefficient for Longevity between 5_10yrs is -0.0000964*. This negative and significant coefficient ($p<0.1$) suggests that farmers with 5 to 10 years of experience have lower production efficiency. Longevity between 11_15yrs has a coefficient of 0.0000091 and not statistically significant, indicating no significant effect on efficiency. Longevity between 16_20yrs shows the coefficient 0.000138*. This positive and significant coefficient ($p<0.05$) indicates that farmers with 16 to 20 years of experience have higher production efficiency. Longevity of 21yrs and above has a coefficient of 0.000022* and statistically significant. The coefficient for secondary education is -0000278 and not statistically significant, suggesting no significant effect of secondary education on efficiency. The coefficient for high school education is 0.000348 and not statistically significant. University education has a coefficient of 0.0000986*. This positive and significant coefficient ($p<0.1$) suggests that a university education is associated with higher production efficiency.

Based on Farm association, the coefficient is 6.78e-05*. This positive and significant coefficient ($p<0.1$) suggests that being part of a farm association is associated with a slight increase in efficiency. The coefficient for farm training is -0.000075*. This negative and significant coefficient ($p<0.1$) suggests that farm training is associated with a slight decrease in production efficiency. Extension service has a coefficient of 0.000536 and not statistically significant. The coefficient for technology utilisation is 0.000040 and not statistically significant. The constant is 0.946* in both models, its positive and highly significant coefficient ($p<0.01$) represents the baseline production efficiency when all other variables are zero. The sigma coefficient is 0.000302* in Model (1) and 0.000288* in Model (2). This value is highly significant ($p<0.01$) in both models, confirming the validity of the Tobit regression.

Multicollinearity test

Multicollinearity is a statistical phenomenon where two or more predictor variables in a multiple regression model are highly correlated with each other. When multicollinearity exists, it becomes difficult for the model to accurately estimate the independent effect of each predictor on the dependent variable. This can lead to inflated standard errors, making the coefficients unstable and unreliable.

The Variance Inflation Factor (VIF) is a common diagnostic tool used to detect multicollinearity. It measures how much the variance of a regression coefficient is inflated due to multicollinearity. A VIF of 1 indicates no correlation between the predictor variable and any other predictor variables in the model. As the VIF increases, it suggests a higher degree of multicollinearity.

Table 5 shows the White's Test for Homoskedasticity. The provided results show the following for White's test:

1. Chi-Square(97) = 155.78
2. Prob > chi-square = 0.0001

Here, the degrees of freedom (df) are 97, and the test

Table 5: White's Test for Homoskedasticity

White's test for Ho: homoskedasticity	chi2(97) = 155.78 Prob > chi2 = 0.0001		
Cameron & Trivedi's decomposition of IM-test			
Source	Chi2	df	P-value
Heteroskedasticity	155.780	97	0.000
Skewness	24.080	14	0.045
Kurtosis	0.180	1	0.671
Total	180.040	112	0.000

statistic (chi-square) is 155.78. The p-value, or probability, is 0.0001 is less than the typical significance level of 0.05 or 5% ($p<0.05$). Consequently, the null hypothesis of homoskedasticity is rejected, suggesting that heteroskedasticity is present in the model. This indicates that the standard errors and confidence intervals in the initial regression analysis may be unreliable. To address this, a robust regression method, such as using heteroskedasticity-robust standard errors, should be applied to correct the model's output. The results of the White's test indicate a statistically significant presence of heteroskedasticity. This is a common issue in regression analysis and must be addressed to ensure the validity of the model's coefficients and standard errors. The Tobit regression of the effects of climate variability on production efficiency was run with robust standard errors to control for the presence of heteroskedasticity.

Discussion

The results of a Tobit regression analysis, which investigates the effects of climate variability and other factors on the production efficiency of rice farmers in the western highlands of Cameroon. This methodology, employing a Tobit model in a second stage after efficiency calculation, aligns with approaches used in other agricultural efficiency studies, such as the work by Adeosun, Bitting, and Tabi (2024) and Dontsi *et al.* (2023) in Cameroon. Climate variability has no significant effect on technical efficiency of rice farmers in the western highlands of Cameroon. The results indicate a significant effect of at least one climate variability index, suggesting rejection of the null hypothesis. The temperature variable has a highly significant negative effect on production efficiency in both models (1 and 2) ($p < 0.01$). This means that as the variability in temperature increases, the production efficiency of rice farmers decreases. This finding is consistent with literature that links adverse climatic conditions to reduced efficiency. Specifically, Dontsi *et al.* (2023) found that an increase in average temperature during the rainy season had a negative and significant impact on farm technical efficiency in other regions of Cameroon. Similarly, Diallo *et al.* (2019) found that additional days with rising temperatures dampen rice technical efficiency in Vietnam, and Choudhary and Gupta (2024) noted a negative correlation between rising maximum temperatures and crop production in India.

Rain Variability Index is not statistically significant in either model. While greater variation in rainfall was found to result in a downward shift of the crop production frontier in Canadian crop production by Galushko and Gamtessa (2022), in this specific context, the change in the rain variability index does not appear to significantly affect the rice farmers' efficiency. High Winds Storm variable is not statistically significant in either model. However, the broader literature on weather extremes has shown negative impacts; for example, Diallo *et al.* (2019) found that weather shocks like floods and typhoons negatively affect technical efficiency.

The farmer's experience, proxied by the length of farming years in the area shows mixed effects in Model (2) of the above table. Longevity of 16-20yrs has a significant positive effect on efficiency ($p < 0.05$). Farmers with 16 to 20 years of experience are likely more efficient, perhaps due to accumulated knowledge and better management practices. Longevity in rice farming of 5-10yrs has a weakly significant negative effect on efficiency ($p < 0.1$). This mid-level experience group might still be in a learning phase and facing greater barriers to adapting to climate shocks compared to the most experienced group. Generally, more years of farming experience have a significant effect on production efficiency. The study results, showing a negative effect for the mid-level experience group (5-10 years) and a positive effect for the high-experience group (16-20 years), strongly suggest a non-linear relationship between years of experience and efficiency. Many studies hypothesize and find an inverted U-shaped relationship where efficiency initially increases with age/experience, peaks at an intermediate point (often around a farmer's mid-career), and then declines for older, more experienced farmers. Longevity of 16-20 years group aligns with the ascending part of this curve, where the accumulation of knowledge, farming-specific skills, and tacit knowledge of local conditions translates directly into higher Technical Efficiency (TE) and better resource management. Positive and Significant (16-20 years) experience reduces technical inefficiency because it enhances managerial capability, resource allocation skills, and adaptability to local climate or market shocks. The results are consistent with the study of Adebayo and Okunlola (2020) on rice farmers in Nigeria.

The negative or weakly significant effect of the 5-10 year farming experience group reflects the challenge of moving beyond basic farming. They may have abandoned old methods but still lack the depth of experience needed to fully optimize new technologies, a period sometimes referred to as the "learning phase". The negative relationship often means more experienced farmers are less willing to adopt modern, high-yielding technology compared to younger farmers, or that the quality of experience has plateaued before reaching peak efficiency. Ogundari and Sylvester (2005) on food crop farmers in Nigeria, where experience was found to increase technical inefficiency. Sheng *et al.* (2011) on rice production and marketing in China, where experience had a non-significant or weakly negative impact for younger farmers. While the inverted U-shape is common, some studies find a continuous decrease in efficiency with age in certain regions, often attributed to the negative factors of aging (e.g., reduced physical labour, reluctance to adopt modern technology) outweighing the positive factors of experience. The findings of this study emphasize the positive aspect of accumulated experience. The findings that the 5-10 year group faces greater barriers in adapting to climate shocks are a key factor. Highly experienced farmers (16-20 years) have endured multiple seasons, allowing them to accumulate a deep reserve of local ecological knowledge for managing extreme weather events, a form of resilience that newer farmers lack.

The variable University Education has a weakly significant positive effect on efficiency ($p < 0.1$). This suggests that higher education may improve the adoption of complex, efficient farming strategies as well as the understanding of climate information, supporting the findings of Atsiaya *et al.* (2023) in Kenya that education level was positively significant among farmers adapting to climate variability. Makki *et al.* (2015) also found that education has a significant influence on a farmer's technical efficiency. Membership in a farm association has a weakly significant positive effect on efficiency ($p < 0.1$). This likely reflects the benefits of collective action, shared knowledge, and easier access to resources, aligning with Mbwambo *et al.* (2023), who found that membership in farmer organizations, was one of the adaptation strategies that significantly improved technical efficiency of sorghum production in Tanzania. The variable Farm Training variable shows a weakly significant negative effect on efficiency ($p < 0.1$). This unexpected result might suggest issues with the quality, relevance, or timely application of the training provided, or that the training is primarily targeted at less efficient farmers. This finding is contrary to the general recommendation in literature for increasing training and extension contacts to enhance adaptation and efficiency.

CONCLUSION

To conclude, the Tobit regression results indicate that climate variability and selected socio-economic factors play differentiated roles in shaping rice production efficiency. Rainfall variability and high winds or storms show no statistically significant effects across both model specifications, suggesting limited influence on efficiency, while temperature variability consistently exhibits a negative and highly significant impact, highlighting it as the most critical climatic constraint to rice production efficiency. Farmer experience displays a non-linear pattern, with efficiency decreasing among those with 5–10 years of experience but increasing significantly for farmers with 16–20 years and 21 years or more, implying that long-term experience enhances productive efficiency. Educational attainment matters only at higher levels, as university education is positively associated with efficiency, whereas secondary and high school education are insignificant. Institutional factors further contribute, with farm association membership slightly improving efficiency, while farm training is associated with a small but significant reduction, possibly reflecting adjustment or relevance issues. Extension services and technology utilization do not show significant effects. The positive and highly significant constant term suggests a high baseline efficiency, and the significant sigma coefficients confirm the validity and robustness of the Tobit model.

The most pressing recommendation is to counteract the highly significant negative impact of temperature variability, for which current technology is not mediating. Given the failure of current technology to mitigate temperature stress, research and development efforts must be urgently channelled toward breeding and disseminating novel, heat-tolerant Improved Rice Varieties (IRV) suitable for the Western Highlands. These varieties should be the cornerstone of the temperature adaptation strategy. Government and agricultural research institutes should introduce and train farmers on specialized practices to manage high-temperature risks, such as: Altering planting times to avoid critical reproductive stages (e.g., flowering) coinciding with peak temperature periods, using mulching or maintaining deeper water levels to cool the micro-environment. Given that the Rain Variability Index effect is partially mediated by technology, continue to promote and refine technologies like Irrigation Management Systems (IRS) and Farm Diversification (FD) as these are effective in managing water-related climate risks.

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