DETERMINANTS OF TECHNICAL EFFICIENCY IN MAIZE FARMING IN TRANS-NZOIA COUNTY, KENYA

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A RESEARCH PROJECT SUBMITTED TO THE DEPARTMENT OF ECONOMIC THEORY IN THE SCHOOL OF BUSINESS, ECONOMICS, AND TOURISM IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF DEGREE OF MASTER OF ECONOMICS (ECONOMETRICS) OF KENYATTA UNIVERSITY

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DECLARATION

This project is my original work and has not been presented for a degree award in any other university or any other award.

Signature………………………………… Date: ……………………….………..…

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I confirm that the work reported in this project was carried out by the candidate under my supervision.

Signature……………………………… Date: ……………..………………..……

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DEDICATION

To my parents, Mr. and Mrs. Marcellinus Serem, I dedicate this thesis.

ACKNOWLEDGMENTS

I want to sincerely thank the Almighty God for giving me life and excellent health, which have supported me during my academic career. None of this could have happened without His grace and direction.

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ABBREVIATIONS AND ACRONYMS

AE	-	Allocative Efficiency
ASTGS	-	Agriculture Sector Transformation and Growth Strategy
AU	-	African Union
CRS	-	Constant Return to Scale
DEA	-	Data Envelopment Analysis
DEAP	-	Data Envelopment Analysis Program
EE	-	Economic Efficiency
FAO	-	Food and Agriculture Organization
GDP	-	Gross Domestic Product
KNBS	-	Kenya National Bureau of Statistics
MPP	-	Marginal Physical Product
MT	-	Million per Tonne
NACOSTI	-	National Commission for Science, Technology and Innovation
NCPB	-	National Cereals and Produce Board
RTS	-	Return to Scale
SE	-	Scale Efficiency
SFA	-	Stochastic Frontier Approach
TE	-	Technical Efficiency
VRS	-	Variable Returns to Scale

OPERATIONAL DEFINITION OF TERMS

Data Envelopment Analysis:	It's a method used in determining production frontiers in economics and operation research.
Efficiency:	It refers to the ability to achieve a desired outcome with minimal waste of resources such as time, effort, or energy.
Stochastic Frontier Analysis:	It is a technique used in economics that considers the inefficiency of companies explicitly when estimating production and cost function
Technical Efficiency:	It refers to the effectiveness with which a system or process uses inputs to produce outputs without any waste.

ABSTRACT

This study examines the factors influencing the technical efficiency of maize farming in Trans-Nzoia County, Kenya, with a focus on farm size and seed quantity as significant determinants. The specific objective was to identify and evaluate the socio-economic and farm-level factors affecting technical efficiency and to quantify the levels of technical efficiency in maize farming in Trans-Nzoia County, Kenya. The socio-economic factors were Level of Education, age, gender and household size and access to credit while the farm-level factors were quantity of seeds and farm size. For this study secondary data from Kenya Integrated Household Budgetary Survey, 2015 – 16 was used and Seventy-Seven (77) maize farmers in Trans-Nzoia County were the response rate which was analyzed. The Data Envelopment Analysis (DEA) was employed to estimate the technical efficiency scores of maize farming, while Tobit regression model was used to identify the factors influencing technical efficiency. Using empirical analysis, the study finds that larger farm sizes contribute positively to efficiency by enabling economies of scale, while excessive seed use negatively affects productivity due to overcrowding and competition for resources. Specifically, for each additional unit increase in seed quantity, technical efficiency is expected to decrease by approximately 0.62% (-0.0062), whereas for each additional unit increase in farm size, technical efficiency is expected to increase by approximately 9.94% (0.0994), holding other variables constant. Based on these findings, the study concludes that optimizing farm size and improving seed management are critical to enhancing technical efficiency in maize farming. The positive impact of farm size suggests that policies should focus on land consolidation, cooperative farming, and improved land utilization strategies to maximize productivity. Conversely, the negative impact of excessive seed use highlights the need for proper seed spacing and planting techniques to prevent overcrowding and inefficiencies. To address these issues, the study recommends targeted interventions, including farmer education on optimal seed application rates, increased access to improved and certified seed varieties, and enhanced agricultural extension services to promote best planting practices. Additionally, policies that facilitate land expansion through leasing or cooperative farming models should be encouraged to enable smallholder farmers to achieve economies of scale. Implementing these recommendations can significantly improve maize productivity, enhance farmer incomes, and contribute to food security in the region.

CHAPTER ONE

INTRODUCTION

1.1 Background

According to the World Bank (2025), agricultural development has been widely recognized as a powerful tool to combat extreme poverty. It is estimated that by 2050, the agriculture sector will contribute to the global economy's growth and feed a population of around 9.7 billion (The World Bank, 2020). Four percent of the world's gross domestic product (GDP) is made up of this sector. It is considered the largest industry in the world since it generates food worth about $1.3 trillion annually and is estimated to employ around one billion.

According to the African Union. (2014), agriculture is the backbone of most African communities, and its importance is evidenced by the multiple declarations such as Maputo and Malabo and the 2030 Agenda for Sustainable Development. Through a program, the Maputo Declaration aids in improving food security while the Malabo Declaration aims to accelerate agricultural growth and improve the nutrition of African communities. In addition to the two declarations above, the 2030 Agenda strives to end hunger and promote sustainable agriculture.

The primary economic sector in Kenya is agriculture and can potentially reduce poverty by almost 2.5 times (The World Bank, 2017). It is the most effective way to reduce poverty in sub-Saharan Africa (Farm Africa, 2019). Increased productivity of agriculture raises farm income, food supply increases, the prices of food reduce and creates employment opportunities thus reducing poverty. In 2014, African states committed to improving agricultural productivity to boost growth and eradicate poverty which was referred to as the Malabo declaration. Notably, African countries agreed to allocate a minimum of 10 percent of the public expenditure to agriculture.

In Kenya, according to FAO (2025), agriculture plays a pivotal role in Kenya's economy, directly accounting for 33% of the Gross Domestic Product (GDP) and contributing an additional 27% indirectly through its interactions with other sectors.

The agricultural sector provides employment for over 40% of the total population and supports more than 70% of the rural population. It is a diverse and intricate sector, involving public institutions, parastatals, non-governmental organizations, and private entities. Also, the sector plays a major role in the export market accounting for approximately 65 percent of the total exports (The World Bank, 2019). The significance of agriculture in Kenya has been emphasized in some policy documents key among them being Vision 2030, its implementation strategy-the Medium-Term Plan III, and Agenda Four which seeks to achieve 100 percent food and nutritional security.

In 2019, growth in Agriculture Value Added decelerated to 3.6 percent from 6.0 percent recorded in 2018. The performance of crops and livestock production declined due to unfavorable weather conditions. (KNBS, 2020).

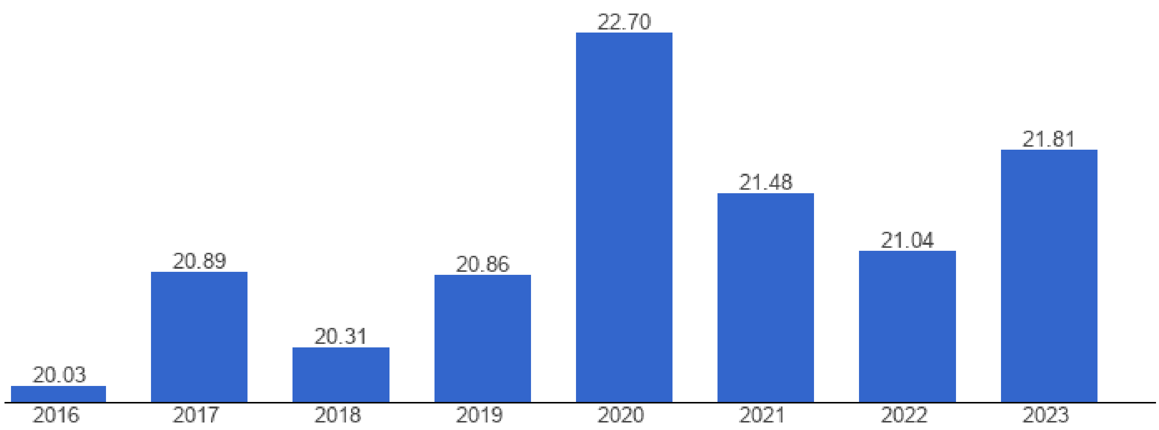


Figure 1.1: Value added in the agricultural sector as percent of GDP

Source: Global Economy, 2025:
(https://www.theglobaleconomy.com/Kenya/Share_of_agriculture/)

The value added in the agricultural sector as a percentage of GDP has shown notable fluctuations between 2016 and 2023. In 2016, the contribution stood at 20.03%, increasing slightly to 20.89% in 2017. However, 2018 saw a marginal dip to 20.31%. This decline was followed by a recovery in 2019, where the figure rose to 20.86%, and further increased to 22.70% in 2020, marking the highest value during the observed period. Subsequently, the contribution began to decline, reaching 21.48% in 2021 and continuing downward to 21.04% in 2022. The trend reversed slightly in 2023, with the sector rebounding to a contribution of 21.81%. These variations reflect a combination of factors, such as changing economic priorities, climatic impacts, COVID-19 Pandemic, shifts in agricultural productivity and policies, which influence the sector's role in the broader economy.

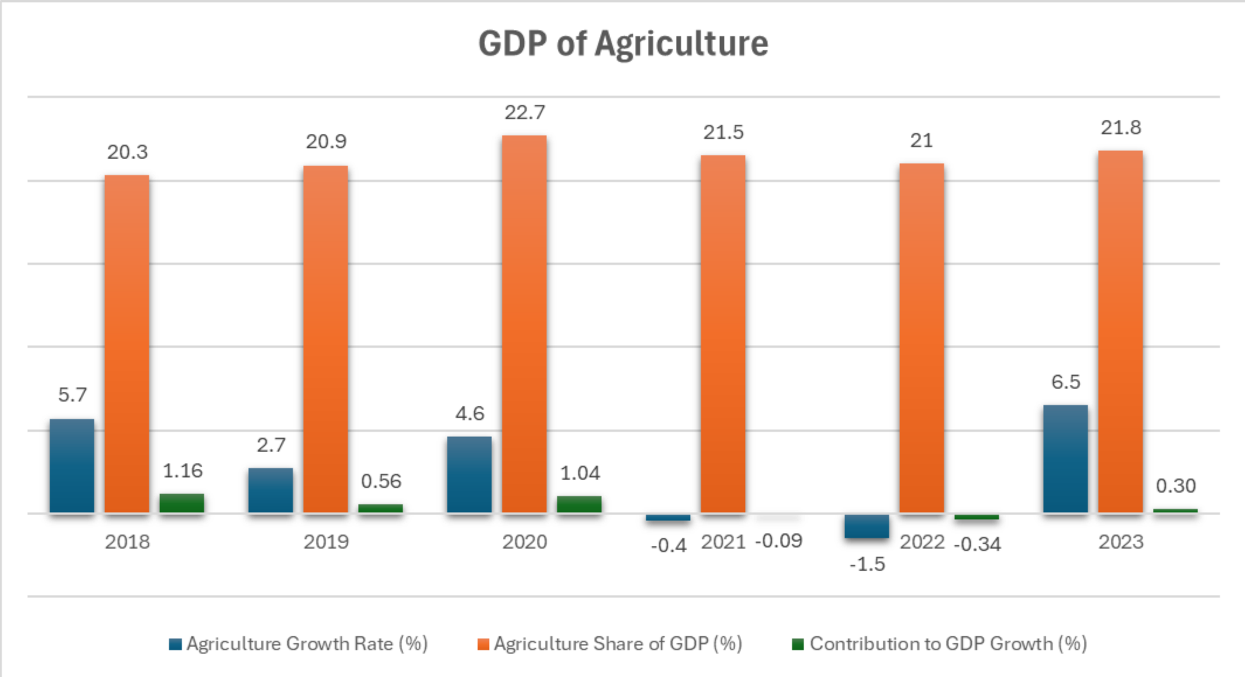


Figure 1. 2: Agriculture Performance of Kenya in GDP (2018-2023)

Source: KNBS,2024: (https://www.knbs.or.ke/reports/2024-economic-survey/)

Figure 1.2 shows the growth rate was positive in 2018 (5.7%) and 2019 (2.7%), spiked again in 2020 (4.6%), but turned negative in 2021 (-0.4%) and 2022 (-1.5%), signaling contractions likely caused by adverse weather conditions or sector-specific challenges. However, the growth rebounded strongly in 2023, reaching 6.5%, showcasing remarkable recovery and resilience. Agriculture Share of GDP (%) remained relatively stable, averaging around 21% throughout the period. It peaked in 2020 at 22.7%, likely reflecting the sector's critical role during the COVID-19 pandemic, and then settled back to 21.8% by 2023. Contribution to GDP Growth (%) highlights how the agriculture sector influenced overall economic growth. Positive contributions were seen in 2018 (1.16%), 2019 (0.56%), and 2020 (1.04%). However, negative contributions emerged in 2021 (-0.09%) and 2022 (-0.34%) due to contractions in the sector. The trend reversed in 2023, with agriculture contributing 0.30%, aligning with its recovered growth rate.

According to Khan et. al., (2021), enhancing agricultural productivity is essential for fostering economic growth and alleviating poverty. While the introduction of new technologies has historically been a primary focus, recent studies emphasize that optimizing the efficiency of existing technologies is equally critical. Efficient utilization of resources and factor inputs can significantly boost output, demonstrating that growth is achievable through both innovation and improved operational practices, (Khan et. al., 2021).

1.1.1 Kenya Maize Production

World Bank (2025), maize remains a cornerstone of Kenya's agricultural landscape, cultivated on two-thirds of farms across diverse agro-ecological zones. As the nation's most vital cereal grain, it is grown by approximately 90% of rural households. Statistica (2023) explains that small-scale farmers contribute 75% of the total maize production, primarily for subsistence, retaining around 58% for household consumption. Large-scale farmers account for the remaining 25% of production. In 2023, the country produced approximately 4.38 million metric tons of dry maize, marking a significant increase from 2022, which saw 3.34 million metric tons. Sciatica (2024), states that this growth can be attributed to factors such as improved maize yields, subsidized fertilizers, and favorable rainfall conditions. Additionally, the total area under maize cultivation expanded by 18% between 2022 and 2024, reflecting the sector's adaptability and importance in Kenya's agricultural economy.

Due to favorable weather in the areas where maize is grown, maize production increased by 26.0 percent from 35.4 million bags in 2017 to 44.6 million bags in 2018 (KNBS, 2019). The total maize productivity in Kenya for the period 1960 to 2019 has fluctuated over the years which may be because of climate shocks, inefficient use of technologies, policy-related constraints, and pests and diseases invasion. According to Njeru, (2019), 40 million bags has been the annual production target of Kenya. The average maize production for most years has been well below 40 million bags. However, the average production of Maize in 2012, 2013, 2015, and 2018 was above

40 million bags. This is because the maize-growing regions experienced favorable weather and minimal disease and pest prevalence was reported. (Njeru, 2019).

The Agriculture Development Policy of 2006 emphasizes the need to boost maize production to achieve self-sufficiency and food security in Kenya. With a growing population, the demand for maize has steadily increased, surpassing 50 million bags in 2019 and projected to reach 60 million bags by 2025 (Njeru, 2019). However, the high cost of production remains a significant challenge, driven by limited access to affordable credit, high input prices, inadequate extension services, and inefficient information flow. Addressing these barriers is critical to enhancing productivity and meeting the rising demand.

Research by Aguk et. al., (2021) underscores that improving technical efficiency in maize farming could mitigate production losses caused by inefficiencies, particularly among smallholder farmers. Additionally, the adoption of modern farming technologies, such as drought-resistant maize varieties and precision agriculture, has been identified as a pathway to enhance productivity and resilience against climate variability (KIPPRA, 2022). Quantifying technical efficiency levels remains essential for identifying and addressing inefficiencies, ultimately contributing to sustainable agricultural growth.

1.1.2 Technical Efficiency in Agriculture

Technical efficiency (TE) in agriculture is a critical metric for understanding productivity differences and optimizing resource utilization. Globally, TE has been recognized as a cornerstone for improving agricultural efficiency across diverse farming systems. For instance, Zhu and Lansink (2020) demonstrated that TE improvements in European farms led to significant reductions in input wastage while maintaining high yield levels. Similarly, Chavas et al. (2021) highlighted TE as a determinant of smallholder farmers' ability to cope with economic pressures and climate change in Asia and Latin America. These studies underscore the importance of TE in achieving sustainable agricultural productivity, particularly in resource-constrained environments.

Regionally, in Africa, TE has been a focal point for addressing agricultural inefficiencies. Geffersa et al. (2024) investigated TE in maize production in Ethiopia, revealing that adopting improved maize varieties increased TE by 33.82%, showcasing the potential for technology-driven efficiency gains. Additionally, Suri et al. (2024) emphasized the stagnation in agricultural technology adoption across Africa, attributing it to heterogeneity in returns and challenges in scaling innovations. These findings highlight the need for targeted interventions to enhance TE and bridge the productivity gap in African agriculture.

Locally, in Kenya, TE is particularly relevant due to its significant role in economic development and food security. Agriculture contributes a substantial share of Kenya's GDP, yet productivity remains low due to inefficiencies in resource utilization, climate-related challenges, and financial constraints. Mutoko et al. (2024) demonstrated that integrated soil fertility management practices increased TE by 26% among smallholder maize farmers in Kenya, emphasizing the importance of sustainable farming practices. Similarly, Mutiso et al. (2023) noted that enhancing TE in maize farming could streamline operations, minimize resource wastage, and reduce production costs, making it a vital strategy for achieving economic sustainability amid rising input prices and climate challenges.

Given the global, regional, and local emphasis on TE as a driver of agricultural efficiency, this study focuses on Kenya to examine context-specific challenges and opportunities. Kenya's smallholder-dominated farming structure, climate variability, and resource limitations make TE a particularly relevant metric for evaluating and improving agricultural productivity. By analyzing TE within the Kenyan context, this study aims to provide actionable insights that align with global best practices while addressing local inefficiencies.

1.1.3 Maize production in Trans –Nzoia County

Maize production is undeniably the backbone of Trans-Nzoia County's economy, aligning with its vision "to be an outstanding agro-industrialized county with a high quality of life for residents" (Trans-Nzoia County Integrated Development Plan, 2018). Both small-scale and large-scale farming contribute to the county's annual maize yield of approximately 5,000 metric tons. Farm sizes range from 0.816 hectares for small-scale farmers to 22.55 hectares for large-scale operations (County Annual Development

Plan of Trans-Nzoia, 2019/20). Notably, about 90% of farmers in the county grow maize for commercial purposes, underscoring its economic significance (Soko Directory, 2015).

The county contributes approximately 40% of Kenya's annual maize requirement of 41 million bags, producing about 5 million bags annually from over 107,000 hectares of land dedicated to maize farming (County of Trans-Nzoia, Department of Agriculture, 2017). The land under maize cultivation increased from 103,876 hectares to 107,000 hectares in 2017, reflecting the county's commitment to enhancing agricultural productivity. Table 1.1 below provides updated projections for maize productivity, production, and land area under cultivation for the period 2022/23 to 2026/27.

Table 1.1: County Indicators Projection (2022/23 - 2026/27)

Output	Indicator	2022/23	2023/24	2024/25	2025/26	2026/27
Increased maize productivity	**Yield/acre (Bags)**	18	19	20	21	22
Increased maize production	**Bags (Millions)**	5.5	5.6	5.7	5.9	6
Increased land under maize	**Area (Hectares)**	170,000	170,000	180,000	190,000	200,000

Source: Trans-Nzoia County Integrated Development Plan

Recent studies have highlighted several factors influencing maize production in Trans-Nzoia County. According to Njogu (2019), small-scale farmers face challenges such as limited access to credit, high input costs, and inadequate extension services, which hinder productivity. Additionally, climate variability has emerged as a critical factor affecting maize yields. Kimani (2022) found that changes in rainfall patterns and temperature significantly impact maize production, necessitating adaptive strategies such as drought-resistant maize varieties and improved agronomic practices.

Soil fertility has also been identified as a key determinant of maize productivity. Nzomo (2022) reported that overuse of specific fertilizers has led to soil nutrient imbalances, reducing yields. To address this, the county has initiated soil testing programs and promoted the use of balanced fertilizers tailored to specific soil needs. Furthermore, Kipkulei et al. (2022) emphasized the importance of adopting modern agricultural technologies, such as precision farming and optimized sowing dates, to enhance productivity and resilience against climatic challenges.

The focus on maize production in Trans-Nzoia County is driven by its pivotal role in ensuring food security and economic stability. By addressing the challenges of soil fertility, climate variability, and resource constraints, the county can unlock its full agricultural potential and contribute significantly to national food security.

1.2 The Statement of the Problem

Maize production remains vital to Kenya's food security and economic stability, serving as a staple food and a major contributor to agricultural GDP. Despite its importance, Kenya consistently falls short of the annual maize production target of 40 million bags, largely due to challenges such as erratic weather patterns, pest and disease outbreaks, and the inefficient use of farming technologies. Notably, while 2019 saw a record production of 46 million bags due to favorable weather, population growth continues to drive demand beyond current production levels. By 2025, this demand is expected to reach 60 million bags annually, creating a widening supply gap (Njeru, 2019; Statista, 2023).

Although studies on technical efficiency (TE) in agriculture are abundant at the national level, like those by Mutiso et al. (2023) and Fan et al. (2024), there is limited county-level focus, which is crucial given the regional disparities in agricultural conditions and practices. For example, Kiprop et al. (2015) analyzed TE among smallholder farmers in Kisii County, while Hugo P.K. (2016) assessed maize production efficiency in Busia County. However, Trans-Nzoia County, which contributes approximately 40% of Kenya's maize supply and serves as a maize production hub, remains underexplored despite its potential for modeling best practices in TE.

Understanding TE in Trans-Nzoia County is vital not only for improving maize productivity locally but also for informing policy and practices that can be replicated in other countries. Given the devolved nature of Kenya's agricultural sector and the unique challenges faced by each county, this study aims to address the gap by examining the determinants of TE in Trans-Nzoia County. By investigating context-specific factors such as access to credit, farm size, and education levels, this research will provide targeted recommendations for enhancing efficiency and scaling productivity to address Kenya's growing food security needs.

1.3 Objectives of the study

1.3.1 General Objectives

The general objective of this study is to determine the factors influencing the technical efficiency (TE) of maize farming. This study aims to assess how various independent variables contribute to variations in TE and provide recommendations for improving efficiency in maize production.

1.3.2 Specific objectives

This study aims to assess the technical efficiency levels among maize farmers and identify the key socio-economic and farm-level factors that contribute to variations in efficiency.

i. To quantify the levels of technical efficiency in maize farming in Trans-Nzoia County, Kenya.
ii. To identify and evaluate the socio-economic and farm-level factors affecting technical efficiency in maize farming in Trans-Nzoia County, Kenya.

1.3.3 Research questions

The following questions were the focus of the study:

i. What is the current extent of technical efficiency in maize farming in Trans-Nzoia County, Kenya?
ii. What are the key factors influencing the technical efficiency of maize farming in Trans-Nzoia County, Kenya?

1.4 Significance of the study

This study provides valuable insights for improving the technical efficiency of maize farming in Trans-Nzoia County, which serves as a critical agricultural hub in Kenya. The findings will inform the County Government and other policymakers on the determinants of technical efficiency, offering a basis for targeted interventions to enhance productivity and sustainability. Given that maize farming is the backbone of the Country's economy, understanding these determinants will help address persistent inefficiencies and maximize the economic benefits of maize production.

The study highlights the importance of reducing production inefficiencies, which are often linked to high costs and suboptimal resource utilization. By identifying key drivers of technical efficiency, such as education, farm size, and access to resources, the research presents opportunities to equip farmers with the knowledge and tools necessary to increase their output without incurring additional costs. Addressing technical inefficiency will also contribute to lowering production costs, improving household incomes, and promoting sustainable farming practices.

Furthermore, the study adds to the academic discourse on technical efficiency, particularly within the context of county-level agricultural analysis. By focusing on Trans-Nzoia County, it addresses the gap in localized research, recognizing the diverse conditions faced by Kenyan counties. The results will provide evidence-based recommendations for policymakers and development agencies seeking to enhance maize production efficiency, which can be adapted and scaled in other countries. Additionally, the findings will enrich academic literature, serving as a reference point for future studies on maize farming and agricultural efficiency.

Ultimately, this study aims to support Kenya’s broader goal of achieving food security and economic growth by aligning its insights with national policy frameworks, such as Vision 2030 and the Big Four Agenda. The practical implications of the research will empower farmers, improve productivity, and contribute to meeting the growing demand for maize in Kenya.

1.5 Scope of the study

This study examines the technical efficiency of maize farming in Trans-Nzoia County, Kenya. It focuses on estimating the technical efficiency scores of maize farmers and identifying the factors that influence these efficiency levels. The research is geographically confined to Trans-Nzoia County due to its critical role as Kenya's leading maize-producing region. The temporal scope is limited to data extracted from the Kenya Integrated Household Budgetary Survey (KIHBS) 2019/20, ensuring the findings are based on recent and reliable secondary data.

The analysis is centered on maize farming as it forms the backbone of the county's economy and plays a pivotal role in national food security. Specifically, the study targets smallholder and large-scale maize farmers within the region, with the aim of providing insights into their productivity and operational efficiency. Methodologically, the study employs the Data Envelopment Analysis (DEA) program to estimate efficiency scores and the Tobit regression model to identify determinants of technical efficiency.

The study is limited to key variables such as education level, farm size, household size, gender, age, and source of credit, reflecting the most significant factors influencing technical efficiency. Additionally, it includes one input—quantity of maize seeds—and one output—maize yield—to streamline the analysis. By narrowing its scope, the research aims to provide precise, actionable insights that address both policy gaps and practical challenges in maize farming within Trans-Nzoia County.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews existing literature to provide a theoretical and empirical foundation for the study. It examines key concepts, theories, and previous research on technical efficiency in agriculture, with a particular focus on maize farming. By exploring global, regional, and local perspectives, this chapter identifies gaps in the literature that this study seeks to address. The review begins with theoretical frameworks relevant to productivity and efficiency, followed by an analysis of empirical studies highlighting determinants of technical efficiency in agriculture. Finally, the chapter provides an overview of existing knowledge while aligning it with the unique context of maize farming in Trans-Nzoia County, Kenya.

2.2 Theoretical Framework

2.2.1 Production Theory

Production theory forms the backbone of agricultural productivity analysis, providing a framework for understanding how inputs are transformed into outputs under varying conditions. It emphasizes the efficient utilization of resources to achieve maximum productivity while minimizing costs. According to Antle and Capalbo (2015), recent developments in production theory have enhanced its application in agricultural contexts, allowing researchers to better quantify productivity and identify areas for optimization. The theory is rooted in the relationship between inputs, such as land, labor, and capital, and outputs, which are the resulting agricultural products. This relationship is often represented through production functions, such as the Cobb-Douglas and translog functions, which model the contribution of each input to overall output levels.

One of the critical advancements highlighted by Antle and Capalbo (2015) is the integration of environmental and technological variables into production functions. This approach enables a more comprehensive analysis of agricultural productivity, accounting for the impact of climate variability, soil quality, and technological innovation. For instance, Nugroho et al. (2022) demonstrated how applying production theory in the MENA region improved agricultural value-added by incorporating Diamond Porter's theory, which emphasizes competitive advantages through technology and resource efficiency. Their findings underline the necessity of adapting production theory to specific regional conditions to address unique agricultural challenges effectively.

Additionally, production theory intersects with behavioral frameworks to understand decision-making processes among farmers. Senger, Borges, and Machado (2017) explored this relationship by applying the theory of planned behavior to analyze farmers' intentions to diversify their agricultural practices. They found that production theory provides a structural basis for evaluating how resource allocation decisions influence diversification outcomes. This interplay highlights the value of production theory in shaping agricultural policies that encourage sustainable practices while enhancing efficiency.

The theory also plays a vital role in addressing climate change impacts on agricultural production. Zhang et al. (2020) compared the predictive power of production theory against the Value-Belief-Norm Theory to assess farmers' adaptation and mitigation behaviors. They concluded that production theory is particularly effective in quantifying resource adjustments needed to maintain productivity under changing climatic conditions. This capability makes it an invaluable tool for guiding adaptive strategies and promoting resilience in agricultural systems.

Figure 2.1 below explains the properties of a production function $q = f(x)$ where x represents the input variable which are resources used in the production process, such as seeds, land, labor, or capital. Concavity property is violated in region 0D while monotonicity property is violated in region GR. However, an economically feasible region of production is shown between D and G where the production function is consistent with all properties. Point E is known as the point of optimal scale of operations where the average product is being maximized.

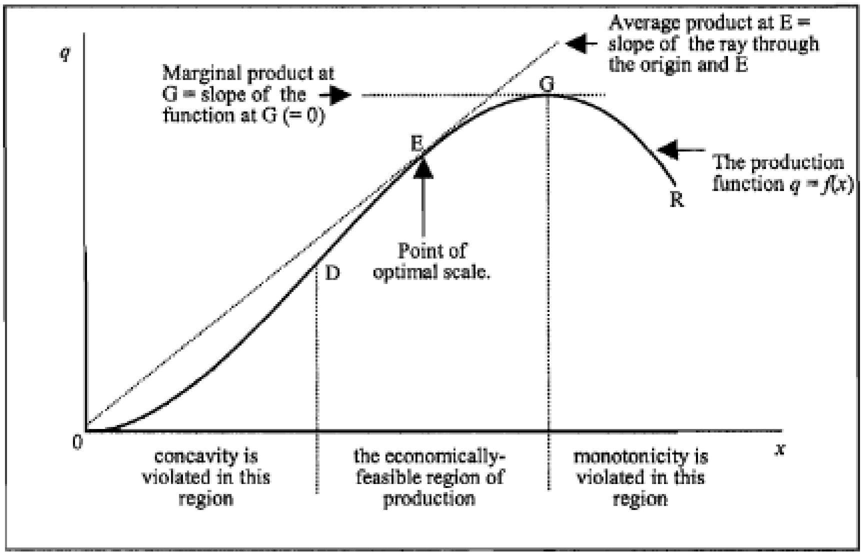


Figure 2. 1: Single Input function of production

Source:*(Coelli, PrasadoRao, O'Donnell & Battese. (2005). An introduction to efficiency and productivity analysis, second edition (Figure 2.1) page 14.*

Figure 2.2 below shows a production function which deals with the relationship between input usage and output levels. The graph represents isoquants, which depict different combinations of two inputs, x1 and x2, that produce the same level of output. er illustrate the concept of the Marginal Rate of Technical Substitution (MRTS) the rate at which one input can be substituted for another while maintaining the same level of output. higher isoquants correspond to greater levels of output, implying that producing more output ($q^2 > q^1 > q^0$) requires more input. The slope of the isoquant at point F represents the MRTS, indicating the trade-off between inputs. Output isoquants are the curves shown in figure 2.2. The curves are known as output isoquants, they are convex to the origin and don't intersect, therefore satisfying the properties of the production function. The Marginal Rate of Technical Substitution (MRTS) is the slope of the isoquants.

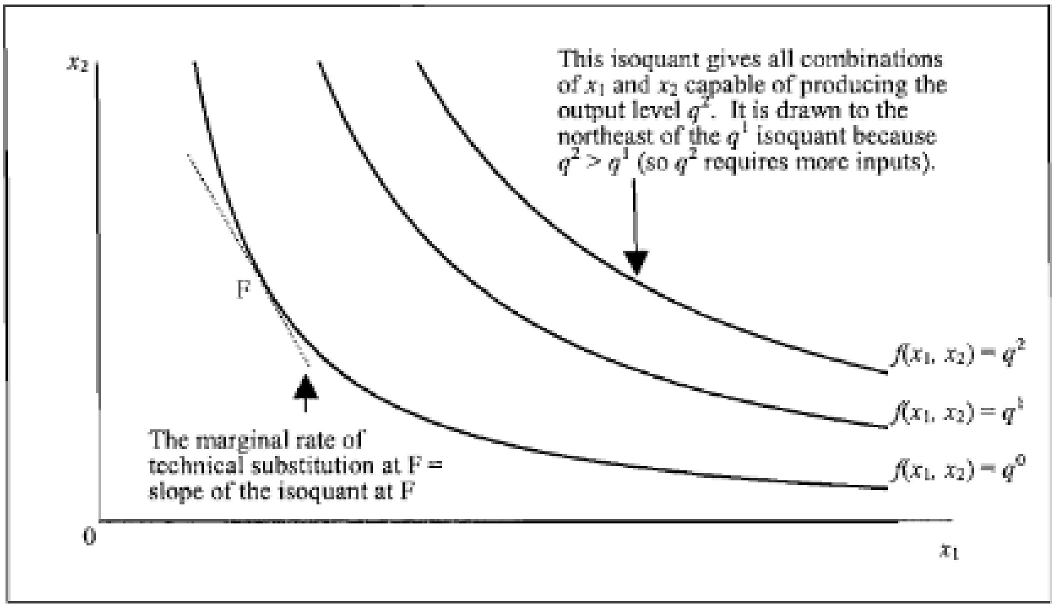


Figure 2. 2: Output Isoquants

Source:*(Coelli, PrasadoRao, O'Donnell & Battese. (2005). An introduction to efficiency and productivity analysis, second edition (Figure 2.2) page 15.*

2.2.2 Returns to Scale

Return to Scale (RTS) is a fundamental concept in production theory, describing the relationship between the proportional increase in input use and the resulting proportional change in output levels. The theory categorizes this relationship into three forms: increasing returns to scale (IRS), where output increases by a greater proportion than inputs; constant returns to scale (CRS), where inputs and outputs increase proportionally; and decreasing returns to scale (DRS), where output increases by a lesser proportion than inputs. These categories help elucidate the dynamics of production efficiency across varying scales of operation.

Sheng et al. (2015) reinvestigated RTS in Australian agriculture, illustrating that smaller farms often exhibit IRS due to their capacity to optimize labor and specialized inputs, whereas larger farms might transition toward DRS due to inefficiencies associated with operational complexity. Their findings emphasize the importance of identifying the optimal farm size, where CRS typically occurs, as a critical step toward achieving maximum productivity without unnecessary resource wastage.

The interplay between economies of scale and economies of scope further enriches the understanding of RTS in agriculture. De Roest et al. (2018) explored agricultural development pathways, highlighting that specialization in production systems may lead to economies of scale, enhancing efficiency. On the other hand, diversified systems benefit from economies of scope, where the combined use of inputs across multiple outputs drives efficiency gains. This nuanced perspective suggests that RTS may vary based on the production strategy employed—whether specialized or diversified farming.

Martinho (2019) extended the discussion of RTS by examining the socioeconomic impacts of forest fires on agriculture and forestry sectors in Portugal. His analysis revealed that larger operations under DRS are particularly vulnerable to external shocks, such as climate events, given their reliance on extensive resource bases. Smaller farms under IRS displayed greater adaptability, demonstrating the potential for scale-related resilience in agriculture. Such findings underscore the importance of considering spatial and environmental factors when assessing RTS.

The spatial dimensions of RTS have also been explored in regions like Nepal and Greece. Wagle (2016) applied the Cobb-Douglas production function to Nepal's agricultural sector, empirically analyzing RTS across varying farm sizes. His results demonstrated that IRS was prevalent in smaller-scale operations, promoting growth and efficiency. Conversely, Koutridi et al. (2023) examined the spatial effect of "smartness" on agriculture in Greece, revealing that farms leveraging technological advancements tend to operate closer to CRS due to the balance between input optimization and output maximization.

2.2.3 Production Efficiency Theory (Production Frontier Theory)

The Production Frontier Theory is used to analyze the efficiency of production systems by measuring how well farmers convert inputs education, age, gender, household size, farm size and seeds into outputs (maize yield). Productivity is an absolute term concerned with the outputs-to-inputs ratio, whereas efficiency is a concept concerned with the observed vector of outputs to inputs with the ideal outputs and inputs ratio (Coelli et.al, 2005). Efficiency measurement is attributed to Koopmans & Debreu (1951) and Farrell (1957) said efficiency is the observed production to the desired (potential) productions. A firm's output is maximized if it has the least amount of inputs but produces the most output. Farrell (1957) argues that the efficiency of a farm is divided into either technical or allocative efficiency. The concept of TE is minimizing factor inputs to achieve a particular output level.This theory suggests that investment in human capital (such as education and training) improves farmers' skills, leading to better resource allocation and higher technical efficiency, (Koopmans and Debreu, 1951).

The overall efficiency refers to the ratio of outputs to inputs. It can be expressed as the sum of the inputs and outputs. Farrell (1957) distinguished between two types of efficiency: efficiency based on input and one based on output. The former illustrates how a company can produce a certain output while reducing its inputs. In efficiency based on output, a company can increase output at a given level of input.

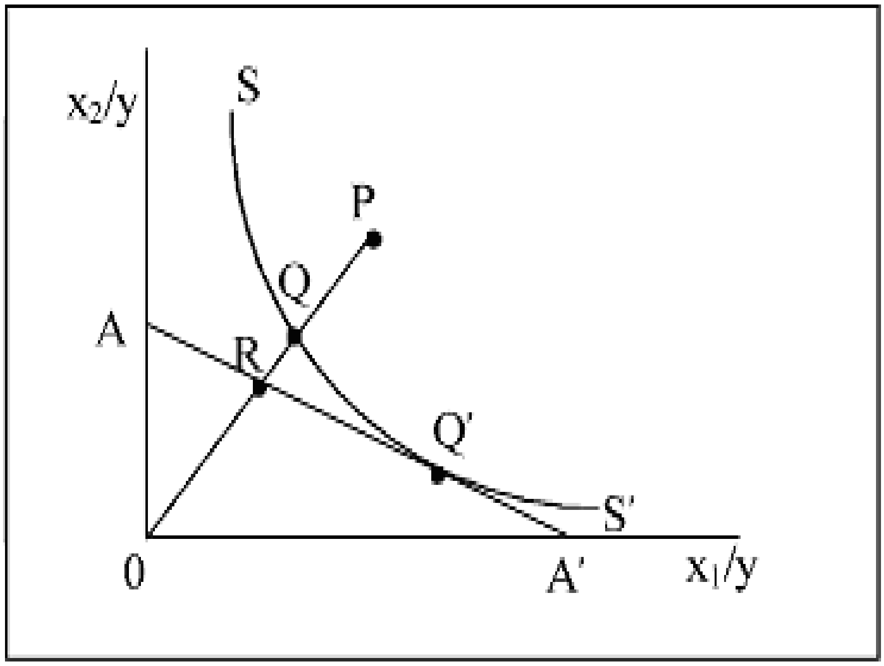


Figure 2. 3: Technical and allocative efficiencies

Farrell, M. J. (1957). The Measurement of Productive Efficiency. Journal of Royal Statistical Society Series A 120, Page 254. Diagram 1.

Farrell (1957) argues that a firm that employs two-factor inputs (X_1 X_2) under constant returns to scale is said to be technically efficient if it is operating at point SS (see figure

2.3.). For any firm that uses factor inputs, given at point P, to produce a given level of output, then the firm is said to be technically inefficient, and the inefficiency is given by the distance QP. The distance represents the number of factor inputs that can proportionally be reduced to produce the optimal output. In percentage terms, the amount required to reduce inputs without reducing output is given as QP/0P.
The technical efficiency score is given by one minus the QP/0P. An efficient firm has a score of one. A score of less than one implies the firm is technically inefficient and some improvements can be made to make the firm efficient.

Point AA is the allocative efficiency, and it represents the factor input prices. A firm operating at point P implies that the firm can cut costs if it is allocative efficient. As a result, the ratio 0R/0Q represents the allocative efficiency. RQ is the distance in terms of costs that must be reduced for the company to be technically and allocatively efficient at point Q'. The product of technical and allocative efficiency is known as economic efficiency. Efficiency is classified as either a parametric or non-parametric frontier (Coelli, 1995; Farrel, 1957).

The parametric assumes a prior production function taking account of disturbances whenever they arise while the non-parametric does assume a specific production function and disturbances are not considered (Coelli, 2005). The commonly used parametric frontier is the Stochastic Frontier Analysis (SFA) while the non-parametric frontier is the data envelopment analysis (DEA). There are two methods of estimating technical efficiency: the DEA or SFA.

2.3 Empirical literature

Education plays a critical role in influencing farmers' decision-making, resource allocation, and adoption of modern agricultural techniques. Studies by Wamuyu et al. (2022) found that higher education levels among maize farmers correlate positively with TE due to better knowledge of improved farming practices, efficient use of inputs, and access to market information. Similarly, Makokha et al. (2024) reported that formal education enhances farmers' ability to interpret extension services and technological innovations, leading to increased maize productivity in Kenya.

Education also facilitates better farm management, including crop rotation, timely planting, and pest control. Farmers with higher education levels tend to be more open to adopting climate-smart agricultural practices that contribute to sustainability and efficiency. Moreover, training programs and workshops enhance knowledge transfer, ensuring that even less formally educated farmers can access relevant information on improving their productivity. Boundeth et.al. (2012) in their study, established TE of Laos maize farmers. From the study, 35 percent of the farmers were efficient. 30 percent of the farmers scored higher than 80 percent on technical efficiency. Maize experience was positively associated with increased technical efficiency. Using the DEA, Abdulai et al. (2013) investigated the TE of maize farmers in Ghana. The study found that the average TE was 77 percent. The study found that mechanization and education negatively affected technical efficiency, while extension services had a positive effect on technical efficiency. According to the study, non-formal education significantly contributes to maize farmers increased technical efficiency.

Kibaara (2005) estimated the TE of Maize farmers in Kenya. Cross-sectional data of rural households and SFA was used. It was found that the mean TE was 49 percent with intra and inter-regional disparities. Years of schooling, age, and tractor use all contributed to increased technical efficiency. Extra years of education enhanced technical efficiency by 0.84 percent, although at a decreasing rate. The study showed that elementary schooling (5 years of schooling) was sufficient for a farmer to be technically efficient. Hybrid seeds increased efficiency by 36 percent while the use of tractors increased efficiency by 26 percent.

Age has been observed to have a mixed impact on TE. According to Wamuyu et al. (2022), younger farmers are more likely to adopt new farming technologies and optimize resource utilization, thereby improving efficiency. Conversely, Okoror and Areal (2020) suggest that older farmers have accumulated farming experience, which can also enhance efficiency, although they may be less receptive to innovation. The balance between experience and adaptability determines the overall effect of age on maize farming efficiency.

A study by Ogada et al. (2014) revealed that younger farmers often experiment with new maize varieties and conservation agriculture practices, which can lead to improved yield and efficiency. However, aging farmers may exhibit risk aversion, preferring traditional farming methods over modern alternatives, which can sometimes hinder efficiency gains. Debebe et al. (2024) employed a panel stochastic frontier model to assess the impact of various agricultural technologies on crop production efficiency in Ethiopia. Their findings indicate that factors such as the education level of the household head, access to extension services, and the use of improved seeds and fertilizers significantly enhance technical efficiency. However, the study did not account for potential non-linear relationships, such as including an age-squared term, which could provide deeper insights into how farmers' age influences efficiency. Additionally, the research highlights that while certain inputs like labor and cultivated area positively affect crop output, the use of capital and local seed varieties had negative impacts, suggesting the need for targeted interventions to improve resource utilization among smallholder farmers in Ethiopia.

Gender differences in agricultural productivity have been widely studied, with Okoror and Areal (2020) demonstrating that female farmers often face more constraints in accessing land, credit, and extension services compared to their male counterparts. However, Wamuyu et al. (2022) found that when given equal access to resources, female farmers can achieve similar levels of TE as male farmers. Gender-responsive policies are therefore crucial in improving efficiency in maize farming. Gender disparities in land ownership, decision-making, and labor allocation often result in variations in TE. Women frequently engage in labor-intensive farming tasks yet lack control over financial and land resources, limiting their ability to invest in productivity-enhancing inputs such as fertilizers and irrigation systems. Addressing these disparities through financial inclusion initiatives, gender-sensitive extension services, and policy reforms can significantly enhance TE.

Household size significantly affects labor availability and overall, TE. A study by Okoror and Areal (2020) showed that larger households tend to have more labor resources, which can reduce reliance on hired labor and enhance farm efficiency. However, Makokha et al. (2024) highlighted that large household sizes may also lead to increased consumption needs, potentially diverting resources away from productive farming investments. Household composition also plays a crucial role, as families with more working-age members can allocate labor efficiently, whereas those with dependent members may experience labor shortages, (Okoror and Areal, 2020).

Efficient labor allocation through training and mechanization can help mitigate potential inefficiencies associated with large households.

Bempomaa and Acquah (2014) estimated technical efficiency using the SFA method. The study discovered that land, labor, and fertilizer all contributed to a farm's efficiency. Seeds and agrochemicals had a negative effect on TE. The factors that negatively affected TE include age, gender, and off-farm work. Farm size is a crucial determinant of TE, with empirical evidence from Ogada et al. (2014) indicating that larger farms benefit from economies of scale, improved mechanization, and better input utilization. Conversely, Wamuyu et al. (2022) found that smallholder farmers, despite their land constraints, often achieve high levels of efficiency due to intensive land use and labor optimization. Farm fragmentation remains a challenge in maize production, as it often leads to inefficient resource allocation and increased production costs. Policy interventions that promote land consolidation and cooperative farming models can help improve efficiency among smallholder farmers.

Credit accessibility enables farmers to invest in improved seeds, fertilizers, and modern farming technologies. Studies by Wamuyu et al. (2022) have shown that farmers with access to credit exhibit higher TE compared to those who rely solely on personal savings. However, high-interest rates and stringent lending conditions remain barriers to credit access for many maize farmers in Kenya. Financial institutions and microfinance services have increasingly played a role in bridging the credit gap by offering tailored agricultural loans. Digital financial services, such as mobile banking and agricultural insurance, have also facilitated better credit access, enhancing farm investments and efficiency. Memon et.al (2016) in their study of estimating TE of maize production in Sindh province found that the average efficiency was 0.48 with the majority of the farmers operating below 0.5 technical efficiency score. The low technical efficiency emanated from soil quality, inadequate water, lack of robust extension services such as modern technology and credit access, and pests. The study concluded that improving these factors could significantly improve the TE of the maize farmers.

The choice of maize seeds significantly impacts TE, as high-quality seeds contribute to better yields and resistance to pests and diseases. Studies have shown that hybrid and genetically improved seeds lead to higher TE compared to traditional seed varieties.

Wamuyu et al. (2022) observed that farmers who adopted certified hybrid maize seeds experienced a 20–30% increase in productivity compared to those using traditional seeds. Access to improved seeds is often hindered by high costs, limited awareness, and inadequate distribution networks. Government programs and private-sector initiatives aimed at improving seed accessibility can enhance TE by ensuring that farmers use high-yielding and climate-resilient maize varieties. Additionally, seed-saving practices and local seed banks have been suggested as alternative approaches to improving seed availability for smallholder farmers. Blanca (2017) investigated the attitudes and opinions of farmers toward the adoption of better seeds, as well as the factors influencing maize crop improvement decisions. Improved seeds, land size, and labor are all key factors impacting maize efficiency and yield, according to Gaspard (2017). Issa, Kagbu, and Abdulkadir (2016) state that the main elements influencing the adoption of improved maize production practices are seed dressing, manual weeding, and land preparation.

2.4 Summary of Literature and Research Gaps

The concept of productive efficiency is presented in the literature. This idea is linked to the concept of production, which refers to the output that can be obtained through a variety of methods. Technical efficiency (TE) and allocative efficiency (AE) are two components of efficiency, according to a review of the literature (Koopmans, 1951). Total economic efficiency can be expressed either as an output-input ratio or an input - output ratio. The output - input concept aims at how a firm can reduce inputs while still generating a particular level of production. The input -output approach indicates that given a set of inputs, the firm can raise its outputs. A firm's technical efficiency is determined by how it allocates its inputs to produce as much as possible. The production corresponds with the true production frontier at that level.

The conflicting evidence coming from the empirical studies points to the fact that economies are unlikely to produce a similar relationship between farm size, land fragmentation, crop variety, and other technical efficiency variables. TE of maize production could be calculated using SFA or DEA. The efficiency scores would indicate how efficient farmers are at growing maize. The literature review backs up the selection of variables in this study. Most studies have used stochastic frontier analysis at the country level to address the TE of the production of maize. As a result, the study closed this gap by utilizing data envelopment analysis in Kenya's Trans-Nzoia County.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter outlines the research methodology used to investigate the socio-economic, environmental, and farm-level factors affecting technical efficiency in maize farming in Trans-Nzoia County, Kenya. It details the research design, study area, target population, sampling techniques, data collection methods, and analytical approaches employed in the study. The methodology is structured to ensure the reliability and validity of the findings, aligning with the study's objectives. Quantitative and qualitative techniques are integrated to provide a comprehensive understanding of the determinants of technical efficiency among maize farmers.

3.2 Research design

The study employed a non-experimental research design, specifically utilizing a cross-sectional approach. While non-experimental designs can be categorized into time series, cross-sectional, or panel designs, this research focused on a cross-sectional analysis. It relied on secondary data obtained from the Trans-Nzoia County segment of the Kenya Integrated Household Budgetary Survey (2019/20). To evaluate maize production factors and technical efficiency, the study applied the Data Envelopment Analysis (DEA) and Tobit regression model.

3.3 Theoretical Framework

The farmer produces output from a set of given inputs. The production function specified in equation 3.1 expresses the relationship between the inputs and outputs.

$$Q = f(x) \qquad \text{(equation 3.1)}$$

Where x is a vector of inputs such as capital, labor, seeds, and land, and Q is the output level. Adam Smith created the first theory of production in 1776, demonstrating that output is dependent on labor, land, and capital. The firm's production function in equation 3.1 can be re-written to consist of the inputs presented as;

$$Q = f(K, L, M, \ldots) \qquad \text{(equation 3.2)}$$

From the equation above, the output is represented by Q over a given period, capital (K), labor (L), and raw materials (M), with the notations representing additional input variables that affect the production process. Equation 3.2 represents any potential set of inputs, as well as how they might be merged to produce outputs (Cobb & Douglas, 1928).

According to Battese (1992), the production frontier model examines three sub-sections: deterministic frontiers, panel data models, and stochastic frontiers. The dependent variable, indicated by Y, is the initial outcome of the production process, and it is stated as a product of vector x, which represents the production inputs, and a function of random variables and stochastic errors.

The model stated below is defined by:

$$Y_i = f.exp\ (V_i - U_i) \qquad i = 1,2,\dots,N \qquad \text{(equation 3.3)}$$

Given that:

Y_i is the probable production level for the ith sample firm;

$f(x_i;\beta)$ is a function of the vector x_i of inputs for the ith firm and a vector β of unknown parameters;

V_i is the random error term that accounts for factors outside the study

U_i is a positive random variable; and

N represents the firms' number.

The existence of the non-negative random variable U_i is linked with the inefficiency of the firm and means that the random variable $exp(-U_i)$ has values with a range of zero and one. As a result, the feasible production, Y_i is bounded above by the non-stochastic quantity, $f(x_i\,;\beta)$ (Battese, 1992). Thus, the stochastic frontier model accounts for both random noise (Vi) and inefficiency (Ui), offering a realistic approach to measuring production efficiency.

The factor that causes the level of production to be less than frontier output is the technical efficiency of a firm. The frontier output for the ith firm is $Y_i^* = f(x_i\,;\beta)$ and so the technical efficiency of the ith firm, denoted by TE_i is given as;

$$TE_i = \frac{Y_i}{Y_i^*}$$

$$= \frac{f(x_i\,;\beta).\,exp\,(-U_i)}{f(x_i\,;\beta)}$$

$$=exp\ exp\ (-U_i)$$

Based on previously acquired data, DEA users can select the input or output orientation analysis (Coelli et al., 2005). Farmers have greater control over their inputs than they do over their outputs, thus input orientation was preferable. The efficiency based on the input DEA model assumes a Constant Return to Scale (CRS). The CRS assumption, according to Coelli et al. (1998), is for farms operating at an optimal scale. However, only a small percentage of farms operate under this principle. Variable returns to scale (VRS) were suggested by Banker et al. as a solution to this challenge (1984). As a result, we used the DEA with the CRS and VRS, as recommended by Boubacar et al (2016). By reducing the number of inputs used, an ideal level of production is hoped to be achieved. Using the DEA, the technical efficiency is specified as follows:

Max $u, v\ \left(\frac{u'\ y_i}{v' x_i}\right)$ (equation 3.4)

$u\ and\ v$ are vectors of the weights of output and input respectively

Subject to

$\frac{u' y_j}{v' x_j} \leq 1$ (equation 3.5)

where $j = 1,2,3, \ldots.$

$u\ and\ v\ \geq 0$

A ratio formulation that results in many infinite solutions is implied in the above specification. To address the issue, we employ Charnes-Cooper's (1962) transformation but impose the following constraint.

$v' x_i = 1$, thus, now we have

Max $u, v(u' y_i)$ (equation 3.6)

Subject to

$\frac{u' y_j}{v' x_j} \leq 1$ (equation 3.7)

where $j = 1,2,3, \ldots.$

$u\ and\ v\ \geq 0$

The duality problem for linear programming is specified as follows:

Min $\theta,$

Subject to

$-y_i + Y \geq 0,$ (equation 3.8)

$X_i - X_I \geq 0,$ (equation 3.9)

$Y \geq 0,$ (equation 3.10)

Where ⌊ is the multiplier (vector of I*1), \ is the TE CRS of i[th] firms. When \ = 1, the firm is technically efficient since it is producing along the production curve. On the other hand, if \ < 1: technically inefficient.

3.4 Determinants of Technical Efficiency

Given the efficiency scores generated in DEA are intervals 0 and 1, then the dependent variable is censored, thus a necessary and sufficient condition to estimate the Tobit regression (Wooldridge, 2002; Semykina 2010; Greene, 2018). The Tobit model is widely used since the efficiency is bound between zero and one.

The Tobit model is represented as follows:

$$y_i^* = x_i'\beta + \varepsilon_i$$

Where

ε_i is N $(0,\sigma^2)$

$y_i = 0$ if $y_i^* \leq 0,$

$y_i = y_i^*$ if $y_i^* > 0.$

Y_i is the latent variable, X_i is a vector of independent variables, β represents parameters to be estimated, and ε_i is the error term.

Tobit regression was applied in this study is specified as:

$$Y_i = \beta_0 + \beta_1 education + \beta_2 Age + \beta_3 Gnd + \beta_4 hhsize + \beta_5\, farm\ size + \beta_6\, Cred + \beta_7\, SD\ \ \varepsilon_i$$

Where Y_i (dependent variable) is the quantity of maize harvested per farmer, X_i (independent variables) from X_1 to X_6 include: $Education$ = Years of the school attended by the farmer, Age= age of the farmer, Gnd= Gender of the farmer, $hhsize$= Household size, $farm\ size$= the farm size of the farmer and $Cred$= source of credit β_0 is y-intercept. $\beta_1, \beta_2, \ldots \beta_6$ are the parameter estimates of the model and ε_i represents the error term.

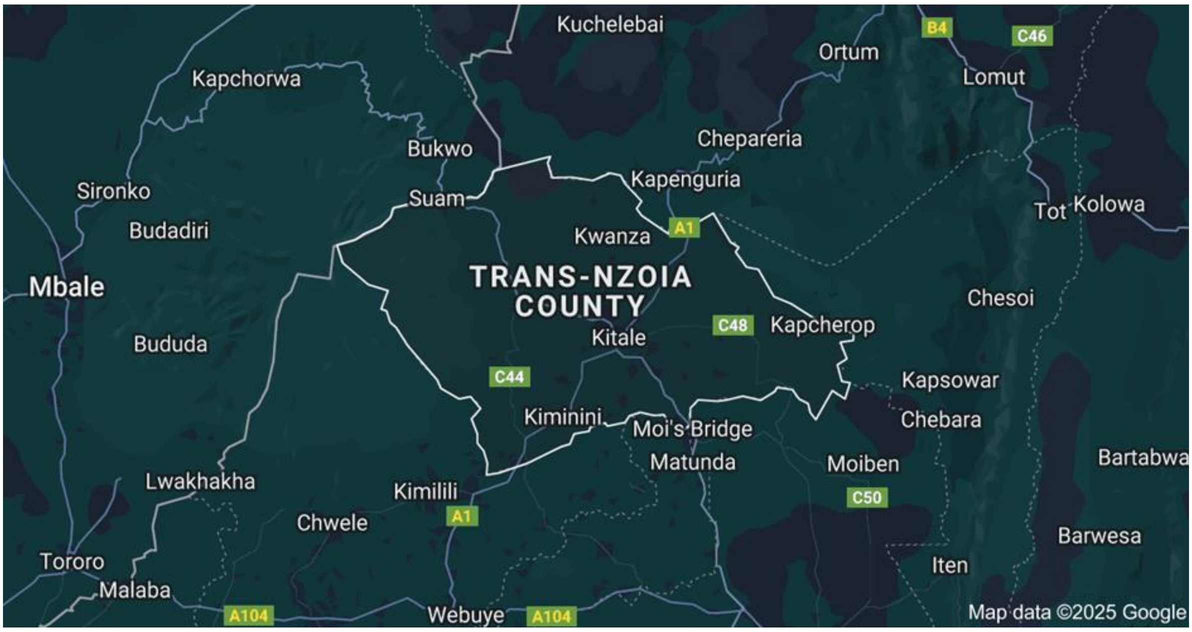
3.5 Definition and measurement of Variables

Table 3.1: Definition and measurement of Variables

SN	Variables	Definition	Measurement
1.	Maize yield (Y)	Quantity of maize harvested per farmer	In Kilograms
2.	Education (Education)	Years of the school attended by the farmer	Years
3.	Age (Age)	Age of the farmer	Years
4.	Gender (Gnd)	Farmer's gender	Dummy variable (1 = male, 0 = female)
5.	Household size (hhsize)	Number of members living in a household	Their number
6.	Farm size (F size)	Number of acres under maize plantation	Acres
7.	Credit (Cred)	Source of credit services	Dummy variable (1=Informal, 0 = Former)
8	Seeds(SD)	Quantity of seeds used per farmer	In Kilograms

3.6 Study area and population target

The study focused on Trans Nzoia County. As of the 2019 Census, 990,341 people were living in the County. There were 489,107 men, 501,206 women, and 28 intersex people among them. (2019, KNBS).



Map of Trans-Nzoia County.Source (Trans-Nzoia County https://g.co/kgs/RYjY6kp)

3.7 Data Type, Sources, and collection

After obtaining an introduction letter from the University, which was approved on December 8, 2022, secondary data from the Kenya Integrated Household Budgetary Survey (KIHBS) 2019–2020 was used. On August 16, 2023, an official permit to carry out this study in Kenya was obtained from the National Commission for Science, Technology, and Innovation (NACOSTI).

3.8 Data processing and analysis

The source of the agriculture dataset was KIHBS. After filtering the 40,283-piece dataset to only include information relevant to Trans-Nzoia County's maize farming, 77 maize farmers were found in Trans-Nzoia. The Data Envelopment Analysis Program (DEAP) was used to evaluate data associated with the first objective and produce technical efficiency scores. After that, Tobit regression analysis was performed to determine the factors affecting maize growing in the county. The analysis was conducted using STATA software, with data variables presented and compared through tables.

CHAPTER FOUR

RESEARCH FINDINGS

4.1 Introduction

This chapter presents the results of the analysis of efficiency scores. The sample size used in this study comprised 77 maize farmers from Trans-Nzoia County. This number was drawn from the Kenya Integrated Household Budget Survey (KIHBS) conducted in 2015/2016, which remains the most recent nationally representative dataset available at the time of this study. The KIHBS captured responses from a total of 40,243 individuals across the country, out of which 1,037 respondents were from Trans-Nzoia County. Among these, only 77 individuals were identified as maize farmers, and thus formed the basis of the sample for this analysis. While the sample may appear small, it is representative of the population of maize farmers in the county as captured in the KIHBS dataset. It is also important to note that a new KIHBS is scheduled to be conducted in 2025, which may provide a larger and more recent sample for future studies.

Section 4.2 presents descriptive statistics, technical efficiency indices are presented and discussed in section 4.3, which addresses objective one, and Tobit regression results which focus on objective two are included in section 4.4.

4.2 Descriptive Statistics

Descriptive statistics (mean, standard deviation, minimum, maximum, and sum) for the study's variables are presented in this part to aid in making sense of the sample data and pave the way for data analysis. Table 4.1 presents the summary data that were used to assist in achieving the study's objectives.

Table 4.1: Descriptive Statistics for the inputs and outputs

Variable	Measurement	Mean	Std. dev.	Min	Max
Quality of seeds (Input)	KGS	33.58442	40.24574	2	150
Maize Yield (Output)	KGS	4466.104	5802.861	450	22500

From the above table, the average quantity of seeds used by a farmer was 33.5 kgs with a minimum of 2 kgs and a maximum of 150 kgs. The maximum amount of maize produced was 22,500 kgs and a minimum of 450 kgs, the mean of the maize yield was 4466.1 kgs.

Table 4. 2: Descriptive Statistics for continuous variables used in regression analysis.

Variable	Measurement	Mean	Std. dev.	Min	Max
Years of Education	YEARS	12.03896	3.729123	5	20
Age	YEARS	32.31169	13.94751	15	67
Household Size	HH	5.987013	2.118176	1	9
Farm Size	ACRES	2.792208	2.611955	.3	10

Table 4.2 above shows that the mean age of maize farmers in Trans-Nzoia County was 32 years, with the oldest farmer being 67 years. The average age suggests that there is a mix of younger and older farmers, with some maize farmers being younger than 32 and some being older. The distribution is skewed towards the younger as shown in the histogram below meaning the younger people are in the agriculture sector more so in the maize farming.

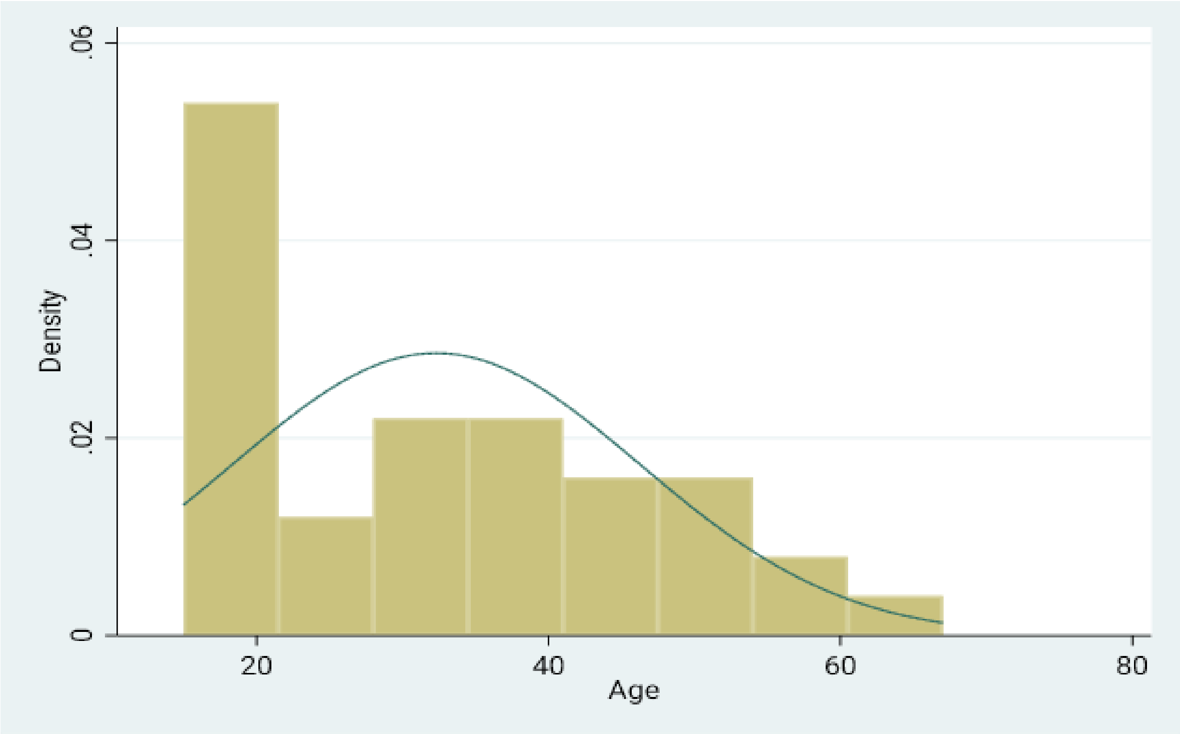


Figure 4.1: Age Distribution

The maximum household size was size 9 and the minimum was only 1 with an average of 5.9.

All the seventy-seven (77) farmers had gone through school. Twenty-nine (29) farmers had primary education as the highest education level, twenty-five (25) had secondary as the highest educational level, ten (10) completed school in college, twelve (12) had undergraduate as the highest, and only one (1) farmer had a postgraduate degree. The study calculated the years of education of each of the seventy-seven farmers depending on the number of years spent in school. The table below shows how years of education were tabulated

Table 4.3: Tabulation of years of education

DMU	**Education levels in years**	**Total number of years of education**
DMU 1	2 years in pre-primary and 3 years in primary	5
DMU 2	2 years pre-primary 8 years in primary 4 years in secondary 1 year in undergraduate	15
DMU 30	2 years pre-primary 8 years in primary 4 years in secondary 4 years in undergraduate 2 years in post graduate	20
DMU 37	2 years pre-primary 8 years in primary 4 years in secondary 2 years in college	16

The average years of education of a maize farmer was 12 years, the minimum being 5 years and the maximum being 20 years. From the findings, it's evident that the average level of education among farmers is at the secondary school level. This suggests that farmers with advanced education levels could potentially excel in integrating new technologies, grasping market dynamics, and implementing sustainable agricultural methods. Moreover, the educational background of farmers significantly impacts their access to crucial resources like information, financial services, and agricultural extension services. Those with higher education levels tend to have better access to these resources, thereby enhancing their maize productivity and overall profitability.

Table 4.4: Descriptive Statistics for Categorical Variables used in tobit regression analysis.

Variable	Categories	%	Total
Gender (Dummy Variable, Male = 1 and Female = 0)	Male	58.44	45
	Female	41.56	32
	Total	**100**	**77**
Source of Credit (Dummy Variable, Formal = 1 and Informal = 0)	Formal	51.95	40
	Informal	48.05	37
	Total	**100**	**77**

From the above table, the male farmers represented 58.44% while the female was 41.56%. The gender imbalance between male and female maize farmers was 16.88% suggesting that maize farming is primarily undertaken by men in Trans-Nzoia County, while women play a comparatively smaller role.

The source of credit showed that the formal sector took the majority with 51.95% and the informal sector 48.05%. The formal sector here includes commercial banks, micro finance, government funds, and SACCOs while the informal sector is composed of mobile platforms, self-help, relatives, shops, and religious institutions. The relatively balanced distribution of credit sources between the formal and informal sectors suggested that both sectors were playing significant roles in providing financial support to maize farmers in Trans-Nzoia County. It also implied that the farmers have diverse access options depending on their needs, preferences, and circumstances, the farmers can navigate between the formal and informal depending on the availability and Trans-Nzoia County had an inclusive financial landscape for the maize farmers.

The study focused on one input (quantity of seeds) and one output (maize yield) as it gives the best results statistically. Other inputs such as the use of fertilizer and the type of cropping system were also tested but the results were not statistically fit.

4.3 Technical Efficiency Scores

When a maize farm obtains a score of 1, it is considered fully technically efficient. A score of less than one for technical efficiency suggests that the farm is not operating at maximum technical efficiency. The difference between the technical efficiency score of 1 and the achieved technical efficiency score is the level of inefficiency. When a maize farm operates at its ideal size, any changes to that size will make the unit less efficient. This is known as scale efficiency. A scale efficiency score of 1 implies that the farm in question is operating at optimal scale or size. If the scale efficiency is less than 1, the farm is either too small or too big relative to its optimal size.

The analysis of data to obtain efficiency scores was executed using the DEAP Program Coelli, T(1996). Without making any assumptions about the distribution of the data, DEA enables the simultaneous consideration of multiple inputs and outputs. Efficiency is expressed as a proportionate change in inputs or outputs in each scenario. The DEA model is categorized into two: an output-oriented model that maximizes outputs without requiring more of any of the observed input values, and an input-oriented model that minimizes inputs while satisfying at least the specified output levels.

This study employs the **i**nput-oriented DEA model, as stated in the methodology. The input-oriented approach focuses on minimizing the use of inputs, such as seeds, while ensuring that at least the specified levels of output (maize yield) are achieved. This choice is appropriate because, in the context of smallholder farmers, inputs are typically more controllable than outputs, which are influenced by external factors like weather and pests. Additionally, the study specifically mentions that the Variable Returns to Scale (VRS) input-oriented DEA model was applied to analyze technical efficiency. This model allows for flexibility in capturing variations in scale efficiency, making it suitable for the study's objectives. The mean technical and scale efficiency scores for the maize farm are summarized in table 4.5 below.

Table 4.5: Mean Technical Efficiency of maize firms.

	Mean	**Std. Err**	**95% conf. interval**	
CRSTE	0.1723896	0.0173434	0.1378471	0.2069321
VRSTE	0.4761976	0.0320812	0.4123023	0.5400928
SCALE	0.4180199	0.0345025	0.3493022	0.4867376

Note:

CRSTE = Constant Return to Scale Technical Efficiency

VRSTE= Variable Return to Scale Technical Efficiency

SCALE = Scale Efficiency = CRSTE/VRSTE

The study focused on the VRS Input-Oriented Single stage DEA model as the model allows for variations in returns to scale, providing a more flexible approach to efficiency evaluation. Under the assumption of a variable return-to-scale input-oriented model, the study found that the mean Variable Return-to-Scale (VRS) Technical Efficiency score was 0.476. This implied that farmers were operating at a level of efficiency that was significantly below the production frontier. This score suggested that the farmers were producing only about 47.6% of the maximum possible maize yield given the quantity of seeds used as an input. Out of the 77 DMUs, only 1 was found to have a technical efficiency score of 1 which implies that DMU 48 utilized well its input to produce the output. Further, 7 DMUs had a scale efficiency score of 1 indicating that the farmers operated at the optimal scale size, achieving the highest level of efficiency possible given its scale of operations. 70 DMUs had a score of less than 1 suggesting inefficiency related to scale. The scale efficiency score of 0.418 implied that the farmers were not operating at the most productive scale size. This meant that the farmers could increase their productivity by adjusting their scale of operation, either by increasing or decreasing their input usage.

To put these scores into perspective, Boris et al (2014) conducted a study in Masaiti District, Zambia, and found that more than 90% of the maize farmers had technical efficiency scores above 70%, with a mean technical efficiency of 79.6%. Another study by Wassie 2014 in Western Ethiopia found a mean technical efficiency of 76% among improved maize producers. In his research in the Guji Zone of Ethiopia, Belete, A.S. 2020 used a stochastic frontier model to examine the technical efficiency of maize production and discovered that there is a chance to increase the study area's maize output per hectare by 30.07%. In order to increase technical efficiency, the study suggested making better seed and fertilizer more accessible, as well as loans, agricultural technology, and short-term training. A study by Kibaara in 2005 on Kenya's maize production using Stochastic Frontier Analysis (SFA) found that most farmers had varying levels of technical efficiency scores.

In conclusion, the mean VRS Technical Efficiency score of 0.476 and scale efficiency score of 0.418 in maize farming indicated significant inefficiencies in farming practices and the need to adjust the scale of operation to improve productivity. Comparing these scores with other studies highlights the potential for improvement in maize yield through better utilization of inputs and adoption of improved farming practices.

The study also established that 9.09% (7) DMUs i.e. DMU 48, 58, 63,64,65, 66, and 67 were efficient and operated at their optimal level of production, meaning that if they were to increase their inputs proportionally, their output would increase at the same rate without any change in their cost per unit of output. Some of the common characteristics of the efficient farmers were that they all used inorganic fertilizer, and certified seeds, and only used an average of 6kgs of the certified seeds to produce the 630 kgs of maize. Interestingly, all of them had secondary education as their highest level of education.

Most of the DMUs 81.82% (63) operated at a decreasing return to scale meaning as they increased their inputs, their output increased at a decreasing rate. The DMUs that their firms increased their inputs as their output increased by a greater proportion were also 9.09% (7). The table below shows the statistics on the same.

Table 4.6: Return to Scale

RTS	**Frequency**	**Percentage (%)**
-	7	9.09
DRS	63	81.82
IRS	7	9.09
Total	**77**	**100**

Note:

- = Efficient firms

DRS = Decreasing Return to Scale

IRS = Increasing Return to Scale

The summary of the efficiency Scores of individual DMUs is shown in the table below. The following DMUs are depicted as operating at optimum: 48, 58, 63,64,65, 66 and 67.

Table 4.7: Efficiency Scores

DMU	CRS_TE	VRS_TE	SCALE	RTS
1	0.372747	0.906893	0.411015	DRS
2	0.372747	0.906893	0.411015	DRS
3	0.096906	0.280848	0.345048	DRS
4	0.113199	0.415288	0.27258	DRS
5	0.101633	0.394807	0.257423	DRS
6	0.20676	0.750129	0.275633	DRS
7	0.219208	0.47952	0.45714	DRS
8	0.219208	0.47952	0.45714	DRS
9	0.219208	0.47952	0.45714	DRS
10	0.219208	0.47952	0.45714	DRS
11	0.098062	0.342847	0.286023	DRS
12	0.098062	0.342847	0.286023	DRS
13	0.098062	0.342847	0.286023	DRS
14	0.254081	0.987018	0.257423	DRS
15	0.27956	0.680169	0.411015	DRS
16	0.07874	0.371429	0.211991	DRS
17	0.031094	1	0.031094	DRS
18	0.031094	1	0.031094	DRS
19	0.031094	1	0.031094	DRS
20	0.031094	1	0.031094	DRS
21	0.031094	1	0.031094	DRS
22	0.031094	1	0.031094	DRS
23	0.076336	0.336447	0.226888	DRS
24	0.076336	0.336447	0.226888	DRS
25	0.076336	0.336447	0.226888	DRS
26	0.091722	0.250584	0.366033	DRS
27	0.028685	0.407092	0.070463	DRS
28	0.211991	1	0.211991	DRS
29	0.119749	0.387396	0.309112	DRS
30	0.119749	0.387396	0.309112	DRS
31	0.119749	0.387396	0.309112	DRS
32	0.119749	0.387396	0.309112	DRS
33	0.119749	0.387396	0.309112	DRS

34	0.119749	0.387396	0.309112	DRS
35	0.124519	0.456817	0.27258	DRS
36	0.091195	0.42362	0.215277	DRS
37	0.018373	0.086667	0.211991	DRS
38	0.018373	0.086667	0.211991	DRS
39	0.018373	0.086667	0.211991	DRS
40	0.018373	0.086667	0.211991	DRS
41	0.018373	0.086667	0.211991	DRS
42	0.095293	0.302544	0.314971	DRS
43	0.095293	0.302544	0.314971	DRS
44	0.095293	0.302544	0.314971	DRS
45	0.095293	0.302544	0.314971	DRS
46	0.519495	0.783696	0.662878	DRS
47	0.519495	0.783696	0.662878	DRS
48	1	1	1	-
49	0.068048	0.086765	0.784278	DRS
50	0.107658	0.482497	0.223127	DRS
51	0.081718	0.285706	0.286023	DRS
52	0.081718	0.285706	0.286023	DRS
53	0.390434	0.4	0.976085	IRS
54	0.390434	0.4	0.976085	IRS
55	0.390434	0.4	0.976085	IRS
56	0.048028	0.732646	0.065555	DRS
57	0.116287	0.337018	0.345048	DRS
58	0.333333	0.333333	1	-
59	0.074573	0.310793	0.239944	DRS
60	0.156211	0.579202	0.269701	DRS
61	0.156211	0.579202	0.269701	DRS
62	0.127041	0.493509	0.257423	DRS
63	0.333333	0.333333	1	-
64	0.333333	0.333333	1	-
65	0.333333	0.333333	1	-
66	0.25	0.25	1	-
67	0.25	0.25	1	-
68	0.207798	0.313478	0.662878	DRS

69	0.207798	0.313478	0.662878	DRS
70	0.116287	0.337018	0.345048	DRS
71	0.18956	0.2	0.947799	IRS
72	0.254081	0.987018	0.257423	DRS
73	0.254081	0.987018	0.257423	DRS
74	0.211991	1	0.211991	DRS
75	0.18956	0.2	0.947799	IRS
76	0.18956	0.2	0.947799	IRS
77	0.18956	0.2	0.947799	IRS

4.4 Diagnostic test results

A few diagnostic tests were conducted on the estimated model to assess its statistical soundness. The results of the various diagnostic tests that were performed are shown in the following section.

4.4.1 Test for heteroskedasticity

To determine whether heteroskedasticity tests are employed. present, the Breusch-Pagan If the variance of the residuals is not constant, heteroscedasticity arises. Table 4.8 displays the results of the Breusch-Pagan test.

Table 4.8: Heteroskedasticity test

Breusch–Pagan/Cook–Weisberg test for heteroskedasticity Variable: Fitted values of VRS_TE	
Assumption: Normal error terms	
H0: Constant variance	
chi2(1)	1.39
Prob > chi2	0.2379

The test's p-value is higher than 0.05, and the Chi-square is relatively small. The null hypothesis, which is predicated on "constant variance," is therefore not rejected. According to the outcome, heteroskedasticity was not an issue.

4.4.2 Normality test

The normal distribution was tested using the Shapiro-Wilk Method. The study results were assessed at a 5% significance level using the Shapiro-Wilk Approach. Smaller values of t less than 0.05 showed non-normality, and values larger than 0.05 indicated normalcy. The outcomes are shown below in Table 4.9.

Table 4.9: Shapiro-Wilks normality test

Variable	Obs	W	V	z	Prob>z
Quantity of seeds	77	0.68419	21.009	6.657	0.00000
Maize yield	77	0.64720	23.469	6.900	0.00000
Source of credit	77	0.99848	0.101	-5.004	1.00000
years of edu~n	77	0.97613	1.588	1.011	0.15595
farm size	77	0.71431	19.005	6.438	0.00000
hhsize	77	0.96572	2.280	1.802	0.03575
Age	77	0.92508	4.984	3.512	0.00022
Male	77	0.99702	0.198	-3.538	0.99980

The Shapiro-Wilk normality test assesses whether a dataset follows a normal distribution. In this test, the W statistic (closer to 1 indicates normality) and the p-value (Prob > z) help determine normality. A p-value below 0.05 suggests the variable significantly deviates from normality. In the given results, the quantity of seeds (p = 0.000), maize yield (p = 0.000), farm size (p = 0.000), and age (p = 0.00022) show strong evidence against normality. Household size (p = 0.03575) is also non-normally distributed but with a weaker deviation. Conversely, years of education (p = 0.15595), informal (p = 1.000), and male (p = 0.99980) do not show significant deviations from normality, suggesting they may follow a normal distribution.

4.5 Econometric Analysis

In the second stage, regression analysis was used to identify the determinants of the technical efficiency of maize farming in Trans-Nzoia County. When the observations are clustered at the constraint and the dependent variable is bounded, the Tobit model is employed (Dougherty, 2002). Technical efficiency scores, the dependent variable, are bounded between 0 and 1, hence the Tobit model is estimated.

4.5.1 Determinants of Technical Efficiency

Table 4.7 presents the Tobit regression results on the determinants of VRSTE of maize farming in Trans-Nzoia County. The variables used were gender, age, source of credit, household size, farm size, and years of education. The gender and source of credit were dummy variables, taking the value 1 for males and 0 for females and 1 for formal sources and 0 for informal respectively.

Table 4.10: Tobit regression results

Log-likelihood = -5.6444034
Number of obs = 77
LR chi2(6) = 11.01
Prob > chi2 = 0.0000
Pseudo R2 = 1.4597

VRS _TE	**Coefficient**	**Std.err.**	**t**	**P>t**	**[95% conf. Interval**	
Quantity of seeds	-.0061973	.0012431	-4.99	0.000	-.0086765	-.0037181
Source of credit	.0361208	.066762	0.54	0.590	-.0970317	.1692733
Years of education	.011247	.0077901	1.44	0.153	-.0042899	.0267839
Farm size	.0993562	.0174086	5.71	0.000	.0646359	.1340765
Household size	.007913	.0147712	0.54	0.594	-.0215472	.0373731
Age	.001001	.0019466	0.51	0.609	-.0028814	.0048835
Male	-.0239012	.0570441	-0.42	0.677	-.1376721	.0898697
_cons	.2082627	.1592657	1.31	0.195	-.1093827	.5259081

The findings of the Tobit regression model showed that age had a positive coefficient (.001001) with technical efficiency but was statistically not significant since p-value is 0.609 > 0.05. However, the statistical insignificance of the age coefficient implied that the impact of age on technical efficiency was negligible compared to the influence of other factors included in the model. In comparison, a study by Battese and Coelli 1995 on Indian farmers was consistent with the study and found that age had a positive and significant effect on technical efficiency. They argued that older farmers tend to have more experience and are more likely to adopt efficient farming practices. In contrast, a study by Wadud and White 2000 on Bangladeshi rice farmers found that age had a negative and significant impact on technical efficiency. They attributed this to the potential physical limitations and resistance to change that may come with advanced age. The positive coefficient implied that as individuals get older, their technical efficiency tends to improve slightly. This could be due to factors such as increased experience, knowledge accumulation, and better decision-making skills that come with age.

Household size has a positive coefficient (0.007913) with technical coefficient but is statistically not significant since p-value is 0.594 > 0.05. The study found that household size had a negative and statistically insignificant relationship with technical efficiency in maize farming. The positive coefficient (0.007913) indicated that an increase in household size is linked to lower levels of technical efficiency. Specifically, for each additional member added to the household, technical efficiency was expected to decrease by an average of 0.0154501 units, with other variables held constant. Consistent with this finding, other studies explored the relationship between household size and technical efficiency in maize farming. One such study by Abdulaleem et al. (2019) in Southwest Nigeria found that household size negatively impacted technical efficiency. Similarly, a study by Kuwornu et al. (2013) in the eastern Terai of Nepal observed that larger households were more efficient in hybrid maize production due to the availability of more resources and labor for farm activities. In contrast, research by Anang (2022) et al. in Ghana suggested that larger households were less technically efficient in maize production, contrary to the findings in Southwest Nigeria and Nepal. Years of education has a positive coefficient (0 .011247) with technical coefficient but is statistically not significant since p-value is 0.153 > 0.05. The finding that years of education were positively related to technical efficiency in maize farming in Trans-

Nzoia County was supported by various studies. Specifically, the increase in formal education enhanced farmers' efficiency in utilizing input resources effectively. Consistent with this, the study by Koduo, *et.al* 2022 on the technical efficiency of maize farmers in the Central African Republic and the analysis of technical efficiency in maize production in the Guji Zone by Belete 2020 both highlighted the positive impact of education on technical efficiency. These studies emphasized the significant influence of socio-economic factors, environmental factors, and physical and technical factors on maize production, underscoring the importance of education in enhancing efficiency. On the contrary, some studies have shown contrasting results regarding the relationship between education and technical efficiency. For instance, Onu *et al.* (202) found no significant relationship between education and technical efficiency.

Source of credit has a positive coefficient (0.0361208) with technical coefficient but is statistically not significant since p-value is $0.590 > 0.05$. Quantity of seed has a negative coefficient (-0.0061973) with technical coefficient and statistically significant since p-value is $0.677 > 0.05$. The analysis of the impact of credit on maize farming technical efficiency revealed that accessing credit from informal sources was associated with lower levels of technical efficiency compared to accessing credit from formal sources. This finding was supported by a negative coefficient of 0.0361208, indicating that farmers who relied on informal sources of credit had, on average, a technical efficiency that was 0.0361208 units higher than farmers who accessed credit from formal sources. Consistent with this finding, Aminou (2021) in his study in Benin found that access to informal credit had a negative and significant effect on the level of technical efficiency of farmers. This suggested that informal credit sources may not provide the same level of support for farmers as formal credit sources, leading to lower technical efficiency. On the other hand, Bekele (2020) found that access to credit, regardless of whether it is formal or informal, had a positive effect on technical efficiency in Ethiopia. This contrasted with the finding that informal sources of credit were associated with lower technical efficiency. The study further suggested that access to credit in general improved technical efficiency, whereas the finding in this analysis suggested that the source of credit (formal or informal) may play a role in the level of technical efficiency achieved.

Farm size has a positive coefficient (0.0993562) with technical coefficient and statistically significant since p-value is 0.000 < 0.05. Farm size was found to be positively related to technical efficiency, with larger farms exhibiting higher levels of efficiency. Specifically, for each additional acre increase in farm size, technical efficiency was expected to increase by an average of 9.9%, holding other variables constant. This implied that larger farms tend to be more efficient in converting inputs into outputs compared to smaller farms. Consistent with this finding, other studies have also explored the relationship between farm size and technical efficiency in maize farming. One such study by Abdulai, Nkegbe, and Donkoh in 2013 focused on the technical efficiency of maize production in Northern Ghana. Additionally, Alvares and Arias in 2024 conducted a study on technical efficiency and farm size, providing insights into the conditional analysis of this relationship. These studies, like the one in question, contributed to understanding how farm size impacts positively technical efficiency in maize farming. Contrastingly, Bagi in 2022 examined the relationship between farm size and technical efficiency in West Tennessee agriculture, offering a different perspective on this topic. The study suggested that farm size had a negative relationship with technical efficiency.

Gender has a negative coefficient (-0.0239012) with technical coefficient but is statistically not significant p-value is 0.000 < 0.05. Specifically, male farmers had a 2.39% lower level of technical efficiency compared to female farmers. This finding was consistent with other studies that have examined the relationship between gender and technical efficiency in maize farming. First, Male maize farmers were found to be significantly more technically skilled than female farmers in Mussa's 2017 study. The authors contended that the fact that female farmers in developing nations do not have the same inheritance rights as male farmers may serve as a deterrent to hard work.. Secondly, Amondo 2019 using stochastic frontier analysis found that male-managed farms had slightly higher technical efficiency compared to female-managed farms, though the difference was not statistically significant. In contrast, Belete 2020 found that the gender of the household head being male had a negative impact on farm inefficiency, indicating that male-headed households had higher technical efficiency compared to female-headed households. The authors attributed this to the fact that agriculture is mainly practiced by males in the study area. Interestingly, Marinda, *et. al*

2006 in their study in West Pokot Kenya found that both male and female-managed farms had similar levels of technical efficiency in maize production.

Quantity of seeds has a negative coefficient (-0.0061973) with technical efficiency and is statistically significant since the p-value is $0.000 < 0.05$. This indicates that an increase in the quantity of seeds used in maize farming is associated with a decrease in technical efficiency. Specifically, for each additional unit increase in seed quantity, technical efficiency is expected to decrease by an average of 0.62%, holding other variables constant. This suggests that excessive seed use may lead to overcrowding, competition for nutrients, and inefficient input utilization, ultimately reducing productivity. Consistent with this finding, several studies have examined the relationship between seed quantity and technical efficiency in maize farming. For instance, Kibaara et al. (2016) explored maize farming efficiency in Kenya and found that overuse of seeds negatively impacted yields due to poor spacing and resource competition. Similarly, a study by Danso-Abbeam et al. (2020) in Ghana concluded that optimal seed application rates significantly improved maize productivity and efficiency. In contrast, a study by Musumba and Nyikal (2023) in Uganda suggested that higher seed use could enhance efficiency when combined with improved agronomic practices such as precision planting and fertilizer application. These contrasting perspectives highlight the importance of proper seed management and the need for farmers to adopt recommended planting densities to maximize efficiency.

CHAPTER FIVE

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

5.1 Introduction

An overview of the study's findings, conclusions, and policy implications is given in this chapter. It also makes recommendations for more research areas.

5.2 Summary

This study examined the technical efficiency of maize farming in Trans-Nzoia County, Kenya using secondary data extracted from the Kenya Integrated Household Budgetary Survey (KIHBS) 2015/16. The specific objective of this study was: To investigate whether maize production in Kenya's Trans-Nzoia County is technically efficient to establish which factors determine the efficiency of maize farming in Trans-Nzoia County; and make conclusions about how to increase the technical effectiveness of maize farming. The study estimated the technical efficiency of maize farming using a Data Envelopment Analysis (DEA) program. One input and one output were used in the DEA analysis. The input was the quantity of seeds in kgs and the output was the maize yield in Kgs.

The efficiency scores under CRS, VRS, and Scale efficiency revealed that, on average, seventy (70) farmers were not operating at their best. The study examined seventy-seven (77) maize farmers. The analysis yielded mean technical efficiency scores of 17.2 percent for CRS, 47.6 percent for VRS, and 41.8 percent for scale efficiency.

The Tobit regression model was used to regress the technical efficiency scores against six variables, namely gender, age, years of education, source of credit, farm size, and household size, in order to determine the factors that are likely to impact the technical efficiency of maize farming in Trans-Nzoia County. Age, gender, farm size, and years of education were found to have a positive relationship with technical efficiency while source of credit and household size had a negative relationship with technical efficiency. Only years of farm size and quantity of seeds were found to be statistically significant.

5.3 Conclusion

The purpose of having technically efficient maize farming is to increase productivity, reduce costs, and improve the overall sustainability of the farming process. Following an in-depth assessment of the technical efficiency of maize farming in Trans-Nzoia County, the findings of this study provide valuable insights into the factors influencing farmers' productivity levels and operational performance. With a sample size of seventy-seven maize farmers analyzed, the study revealed that a substantial majority, comprising approximately ninety-one percent, were not operating at optimal efficiency levels. This indicates a significant scope for improvement in agricultural practices within the region. One of the key contributions of this study lies in identifying the determinants of technical efficiency among maize farmers in Trans-Nzoia County.

The findings of this study highlight the significant impact of farm size and quantity of seeds on the technical efficiency of maize farming in Trans-Nzoia County, Kenya. The results indicate that farm size ($p = 0.000$, coefficient = 0.0994) has a positive and significant effect on technical efficiency, suggesting that larger farms benefit from economies of scale, improved resource allocation, and higher productivity. Similarly, quantity of seeds ($p = 0.000$, coefficient = -0.0062) has a significant but negative relationship with technical efficiency, indicating that excessive seed usage may lead to diminishing returns, likely due to overcrowding or improper spacing. These findings emphasize the need for optimal land utilization strategies and seed management practices to enhance efficiency in maize production. Future policies and interventions should focus on promoting efficient farm expansion while ensuring farmers are educated on appropriate seed application rates to maximize productivity. On the other hand, the study also uncovered factors that exerted negative influences on technical efficiency. Notably, the informal source of credit was found to have adverse effects on farmers' productivity levels. Possible reasons for this negative association might include higher interest rates, less favorable loan terms, limited access to financial services, and potentially lower investment in productive inputs among farmers relying on informal credit. This emphasizes the importance of access to formal credit.

These findings carry significant implications for policymakers, agricultural extension services, and other stakeholders involved in promoting agricultural development and food security in Trans-Nzoia County. Strategies aimed at improving technical efficiency should prioritize interventions targeting the identified determinants. Initiatives to enhance access to agricultural credit, provide training and extension services tailored to farmers' needs, and promote sustainable land management practices could yield substantial improvements in productivity and overall agricultural performance.

Furthermore, addressing gender disparities in access to resources and decision-making processes within farming households is crucial for fostering inclusive and equitable agricultural development. By recognizing and addressing the diverse socio-economic factors influencing technical efficiency, policymakers and stakeholders can design more targeted and effective interventions to support maize farmers in Trans-Nzoia County and contribute to the region's agricultural sustainability and economic prosperity. In conclusion, this study sheds light on the multifaceted nature of technical efficiency in maize farming, highlighting the importance of considering various socio-economic factors in agricultural development strategies. Moving forward, concerted efforts from all stakeholders will be essential to implement tailored interventions that address the identified challenges and capitalize on opportunities to enhance maize farming productivity and livelihoods in Trans-Nzoia County.

5.4 Policy recommendations

Based on the findings of this study, which identified farm size and quantity of seeds as significant factors affecting the technical efficiency of maize farming in Trans-Nzoia County, several policy and practical recommendations can be proposed to enhance productivity and efficiency in the region. These recommendations focus on optimizing land use, improving seed management, strengthening extension services, and fostering institutional support to create a more sustainable and productive maize farming system. The study results indicate that farm size has a positive and significant impact on technical efficiency. Larger farms tend to experience better economies of scale, allowing for more efficient use of inputs such as labor, machinery, and agrochemicals. Given this, policies should aim to support land consolidation and discourage excessive land fragmentation, which often reduces efficiency.

One way to achieve this is through land leasing and cooperative farming models. The government and private sector stakeholders should facilitate affordable and accessible land leasing opportunities for smallholder farmers, enabling them to increase their farm sizes without the need for land ownership. Additionally, promoting cooperative farming, where small-scale farmers can pool their land and resources, would enhance efficiency by reducing per-unit production costs and enabling shared use of modern agricultural equipment. Furthermore, land tenure security should be strengthened to encourage long-term investments in farming. Farmers who have guaranteed ownership or long-term leases on their land are more likely to invest in soil fertility management, irrigation infrastructure, and modern farming techniques, all of which contribute to improved technical efficiency.

The study found that the quantity of seeds used had a negative and significant effect on technical efficiency, implying that excessive seed use may lead to overcrowding and reduced productivity. This indicates that many farmers may not be following recommended seed spacing and planting densities, which can result in competition for nutrients, sunlight, and water, ultimately lowering yields. To address this, there is a need for farmer education and training programs focused on appropriate seed application rates. Agricultural extension services should emphasize the importance of proper seed spacing to avoid overcrowding. Demonstration farms and farmer field schools should be established to illustrate the best planting techniques that optimize seed use while ensuring high yields.

Additionally, there should be greater promotion of improved seed varieties. The use of hybrid and drought-resistant maize varieties can significantly enhance yield potential while requiring fewer seeds per hectare. Farmers should be educated on the benefits of certified seeds, including their higher germination rates, disease resistance, and ability to withstand climatic variability. One of the major barriers to improving technical efficiency is the limited access to knowledge and training on modern agricultural practices. Strengthening extension services can bridge this gap by providing farmers with up-to-date information on seed management, soil fertility, pest control, and other crucial aspects of maize farming.

Governments and agricultural stakeholders should increase the number of extension officers available to farmers, ensuring that training and support reach even the most remote areas. Additionally, modern technologies such as mobile-based advisory services and digital farming platforms should be leveraged to disseminate real-time farming tips, weather forecasts, and market prices. Encouraging peer learning and farmer-to-farmer knowledge exchange programs can also be highly effective. Experienced farmers who have successfully adopted efficient farming techniques can serve as mentors to others in the community, promoting the widespread adoption of best practices. While this study found that farm size and seed quantity were the most significant variables affecting efficiency, other factors such as access to credit and extension services play a crucial indirect role. Limited access to financial resources often prevents farmers from investing in improved seeds, fertilizers, and mechanization, which are essential for enhancing productivity.

To overcome this challenge, financial institutions and the government should develop farmer-friendly credit schemes with low interest rates and flexible repayment terms. Special emphasis should be placed on providing loans to smallholder farmers, who often struggle to secure funding due to a lack of collateral. Additionally, subsidized input programs for certified seeds and fertilizers should be expanded to ensure that farmers can afford high-quality inputs that contribute to increased efficiency. The promotion of public-private partnerships (PPPs) in the agricultural sector can also help improve farmers' access to inputs. Collaborations between seed companies, financial institutions, and agricultural extension agencies create a more integrated support system for maize farmers, ensuring they have access to the necessary resources and knowledge.

5.5 Areas of further research

While this study has provided valuable insights into the factors affecting technical efficiency in maize farming, several areas warrant further investigation. Future research should explore the long-term impacts of climate change on maize productivity, the effect of emerging digital technologies in precision farming, and the role of diversified cropping systems in enhancing food security and resilience. Additionally, further studies should examine the socio-economic and policy-driven constraints that limit farm expansion, as well as the effectiveness of different financial instruments in improving access to agricultural credit for smallholder farmers.

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APPENDICES

Appendix I: National Commission for Science, Technology and Innovation (NACOSTI), Research Permit

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