EXPLORING THE DRIVERS OF PRODUCTIVITY AND TECHNICAL EFFICIENCY IN RICE PRODUCTION IN THE MWEA IRRIGATION SCHEME OF KENYA

MUIGAI WAINAINA

K96/CTY/27921/2014

A THESIS SUBMITTED TO THE SCHOOL OF BUSINESS, ECONOMICS AND TOURISM IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF DOCTOR OF PHILOSOPHY IN ECONOMICS OF KENYATTA UNIVERSITY

OCTOBER, 2024

DECLARATION

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

Signature………………………………….. Date………………….

Muigai Wainaina

B.A. Economics

M.A. Economics

K96/CTY/27921/2014

This thesis has been submitted with our approval as university supervisors.

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

Professor Martin Etyang

School of Business, Economics & Tourism

Kenyatta University

Nairobi, Kenya.

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

Dr. Dianah Ngui Muchai

School of Business, Economics & Tourism

Kenyatta University

Nairobi, Kenya.

DEDICATION

This thesis is dedicated to my loving family.

ACKNOWLEDGEMENTS

I wish to express my sincere gratitude to the Almighty God for the opportunity He gave me to pursue a Doctor of Philosophy degree in the School of Business, Economics, and Tourism at Kenyatta University. My deep appreciation goes to my esteemed research supervisors, Professor Martin Etyang and Dr. Dianah Ngui Muchai, whose exceptional guidance and support have been invaluable throughout my thesis journey. Their expertise has significantly shaped my research. I would also like to extend heartfelt thanks to my wife Nyambura and my daughters, whose unwavering support and encouragement have been crucial during the writing and research phases of this thesis. Finally, I acknowledge my classmates and colleagues for their continuous support and motivation, which have greatly contributed to my academic success.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS AND ACRONYMS

DEA: Data Envelopment Analysis

FAO: Food and Agriculture Organization

IRRI: International Rice Research Institute

LBDA: Lake Basin Development Authority

MLE: Maximum Likelihood Estimation

MMRGC - Mwea Multi - Purpose Rice Growers Cooperative Society

NIB: National Irrigation board

OLS: Ordinary Least Squares

SFA: Stochastic Frontier Analysis

SRI - System of Rice Intensification

SSA: Sub Saharan Africa

TARDA - Tana River Development Authority

TE: Technical Efficiency

WARDA: West Africa Rice Development Authority

WKRM - Western Kenya Rice Mills

WRUA - Water Resources Users Association

OPERATIONAL DEFINITION OF TERMS

Allocative Efficiency: This is a metric that gauges out the farmer's ability on the use of farm inputs in their best proportions with respect to their prices. It arises at the production level where the price equals the marginal cost

Technical Efficiency: This measures the effectiveness of how a given set of inputs can be used to produce a given output. A firm becomes technically efficient when maximum production is attained given minimum inputs such as capital, labour and technology. It is a ratio of actual output from a given input to the highest potential output. A firm is said to be highly technically efficient when a value close to one is attained.

Economic Efficiency: It is a product of both allocative and technical efficiency.

Production Efficiency- This is concerned with producing goods and services with the optimal combination of inputs to produce the highest output at the lowest cost.

ABSTRACT

Rice has been classified as the third most vital food crop in Kenya after Maize and wheat. In the country, over 80 per cent of rice consumed is imported from other countries like Egypt, Tanzania, Thailand, among others at a cost of over Ksh.30 billion per year. Annual rice production and consumption in the country between 1990 and 2020 averaged 47 and 383 thousand tons per year, respectively. This implies an average shortage of 336 thousand tons, which was imported. In an attempt to increase rice production to cope up with increasing demand in the country, The Ministry of Agriculture, Fishing and Forestry developed the National Rice Development Strategy in 2008 to increase production and reduce deficit from 227 thousand tons in 2008 to 175 thousand tons by 2020. Introduction of this strategy would lead the country into a path of self-sustenance on food and drastically reduce the food imports. This was not successful. Instead, the deficit continued to increase and hit 650 thousand tons in 2020. There is therefore a need to understand the constraints facing rice production levels in the country. The purpose of the study was: to determine the factors that affect rice production; to measure technical efficiency of rice farmers in Mwea Tebere Irrigation Scheme and to establish the determinants of rice technical efficiencies in the scheme. Data was collected from a sample of 313 farmers in five rice growing regions of Mwea Tebere Irrigation Scheme through structured questionnaire. The study used multiple regression to measure the factors that affect rice production, a stochastic frontier analysis to measure the level technical efficiency and a Tobit model to measure the determinants of technical efficiency in Mwea Irrigation Scheme. From the findings, rice yield is determined by the amount of labour used, amount of fertilizer applied, machine use, water availability and total seeds planted. Technical Efficiency levels stood at 80 percent with a median of 81 percent. These are a bit low compared to other studies in the other regions. The study found that the main determinant of technical efficiency in Mwea Irrigation Scheme was the education of the farmer. Other determinants were gender, total land size, water availability and extension services. More technically efficient farmers were also found to use more fertilizer and were more experienced compared to the less efficient ones. Based on these findings, this study makes several recommendations. These include advising farmers to invest in and adopt more efficient and labour cost saving technologies like the use of equipment and machines, the board to liaise with the government to provide various subsidies to the farmers, manufacture of cheap and quality fertilizers in the country, manufacture cheaper rice farming machines locally, incorporate public private partnerships in water management systems, introduce fast growing and quality varieties that mature in shorter periods (drought resistant seeds) and improve farmers skills through seminars, shows, exhibitions and other outlets.

CHAPTER ONE

BACKGROUND

1.1 Introduction

1.1.1 Overview of Rice Farming in the World

Oryza sativa (rice), is the second most important crop for food production in the world after maize, according to a 2014 study by (Muthayya, Sugimoto, Montgomery and Maberly). Rice is grown in over 150 million acres of land throughout the world with an annual output of more than 20 billion metric tons per year. More than one hundred countries throughout the globe cultivate the crop. Rice is a staple food crop to around 3.5 billion people- about half of the global population. China and India produce and consume half of this amount (Muthayya *et al*., 2014). 29 per cent of all the land under agricultural grain crops in the world is planted with rice, with Africa producing 10 to 13 per cent of all the rice produced globally (Atera, Onyancha and Majiwa, 2018). Rice demand has been increasing steadily in the world, with production increasing from 16 billion tons in 1990 to around 20 billion tons in 2016 (FAOSTAT, 2018). This has been attributed to the application of modern cultivation techniques, including mechanization (Erhie *et al*., 2018).

Globally, for rice production to yield significant contribution in agricultural growth, it will mainly depend on the farm inputs, level of technology, and level of efficiency that is available (Kumbhakar and Lovell, 2003). The ability to generate a specified yield, given the current level of technology, with the least amount of inputs is referred to as the technical efficiency. It results from research and development. It is affected by infrastructures such as roads, dams, irrigation and drainage, electricity and communication, information flow, credit availability and farmer's ability to make decisions (Chandio *et al.*, 2019).

Many developing countries in the world use their available resources inefficiently in agricultural production. Several studies on technical and economic efficiency have identified yield gap or inefficiency in agricultural produce especially in developing countries (Villano, 2005; Kouser, Mushtaq and Abedullah, 2007). As a consequence of such inefficiencies, it is feasible to enhance rice output via higher productivity, without increasing the available inputs or upgrading the technology. Many farmers prioritize the profitability of their produce, which is significantly influenced by the efficiency of resource utilization.

As noted above, Asia has been the leading producer of rice in the globe. Percentage share of rice from Asia is as shown in figure 1.1, while the percentage of rice produced in other continents is as shown in figure 1.2.

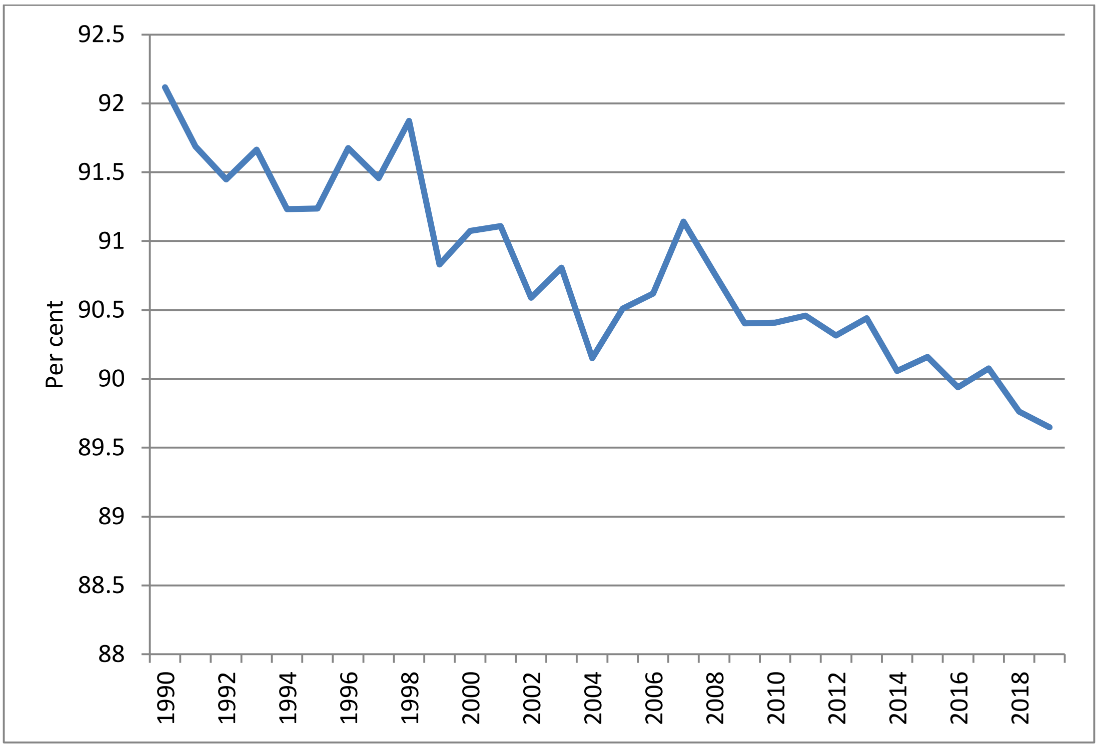


Figure 1.1: Share of rice production in Asia compared to the world production: 1990-2019

Source: FAO Corporate Statistical Database (FAOSTAT) (2021)

Figure 1.1 shows that although rice production has been falling in Asia, the continent still remains the worlds' biggest producer of rice between 1990 and 2018. During this 29-year period, there has been a discernible downward trend, with Asia's proportion of rice production consistently falling, punctuated by occasional slight increases, such as in 1996 and 2004. The peak of this share was recorded in 1990, above 92%, while the lowest was in 2018, when the share of rice produced by the continent declined by three per cent to reach 89.6 per cent. The main factors leading to declining rice production in the continent are urbanization, crop diversification and industrialization especially in India and China. In China, for example, the acreage under rice production declined from 37 to 31 million hectares between 1986 and 1996 (FAO, 2021). To reverse this decline, some of the measures that the countries in the continent (for example Thailand, Pakistan and Vietnam) have put in place is to plant short maturing varieties, planting new hybrid varieties, better fertilizer usage, increase in the use of irrigation services, supportive institutions (to provide agricultural inputs), integrated crop management, research and extension services and reduce post-harvest losses among others (FAO, 2020).

Figure 1.2 gives the comparison of rice produced in the other continents (excluding Asia) from 1990 to 2019.

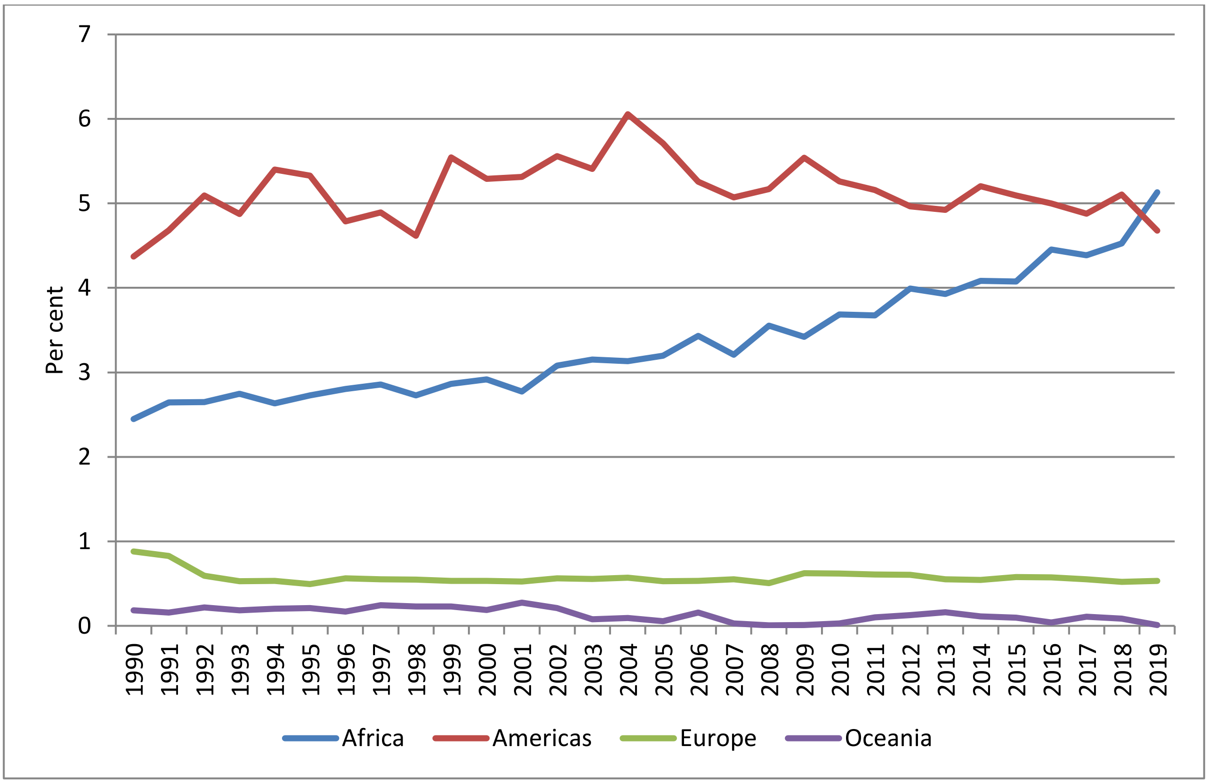


Figure 1.2: Share of rice produced in the world major regions (excluding Asia)

Note: Americas include both North and South America.

Source: FAO Corporate Statistical Database (FAOSTAT, 2021).

Figure 1.2 reveals that the Americas was leading in rice production outside Asia upto 2018, starting with over 4% in 1990 and showing an upward trend, particularly from the early 2000s when the share stabilizes at or above 6%. In contrast, Africa, beginning at 2.4%, sees a modest but consistent increase, reaching 5.1% by 2019. This is mainly as a result of productivity improvement which led to increased production in Madagascar, Nigeria and Egypt (FAOSTAT, 2021). Nevertheless, this high production growth in Africa has been outpaced by consumption and Africa (and the world in general) continues to face rice production deficits. Europe and Oceania maintain minimal and stable contributions, with Europe barely surpassing 0.5% and Oceania remaining under 0.5%, both exhibiting flat trends throughout the period. Across the regions, the Americas emerge as the dominant rice-producing region, with Africa showing incremental growth, while Europe and Oceania's shares remain negligible. Despite some fluctuations, the trend for the Americas and Africa ascends slightly, while Europe and Oceania show stability with no significant change in their rice production shares, highlighting the global rice production landscape's disparities outside of Asia.

1.1.2 Overview of Rice Farming in Africa

In Africa, rice is the fourth most significant crop, preceded by maize, sorghum, and millet. More than 75% of African countries produce the crop, and 800 million Africans depend on it as their major source of food (Atera, Onyancha, & Majiwa, 2018). Small-scale farmers produce much of the Africa's rice. These farmers face various challenges such as limited market access, use of simple tools and machinery and inefficient use of inputs (Toure, Bamba & Diagne, 2008). The average rice production in the continent is 1.4 tonnes per acre compared with 4 tons in Asia and 6 tons in China. The amount of land under rice cultivation in the continent amounts to ten percent of the total land under farming (8.5 million hectares), and accounts for fifteen percent of the total cereals produced. According to FAOSTAT (2019), Nigeria and Madagascar produce sixty (60) percent of all the rice grown in Africa.

Sub-Saharan Africa (SSA) saw a 150% rise in rice production between 1980 and 2006 to reach 2 billion tons (From 800 million in 1980 to 2 billion tons in 2006). It was the fastest growing staple food in the region within the period (FAO, 2007). This increase was associated with productivity improvement, shift in customer preferences towards rice, urbanization, land expansion, income growth and population growth (4 per cent per annum) (Africa Rice Centre, 2008). However, in contrast to the other continents, the rate of mechanisation in Africa has been slow and insufficient to increase rice production.

Between 1960 and 2019, rice demand increased in Africa more than any other continent, leading to increased imports. Saito et.al (2020) show that between 1960 and 2020, rice consumption in Africa increased tenfold, with rice self-sufficiency in the continent being 48% only. At the same time, Africa imported 0.5 million tons of rice in 1961 compared with 11.8 million tons in 2011. Nakano *et al.* (2011) argue that in 2011 alone, Africa spent US 4.3 billion dollars on rice importation. Figure 1.3 shows the trends in rice production in Africa (as a share of total production, by region) from 1990 to 2019.

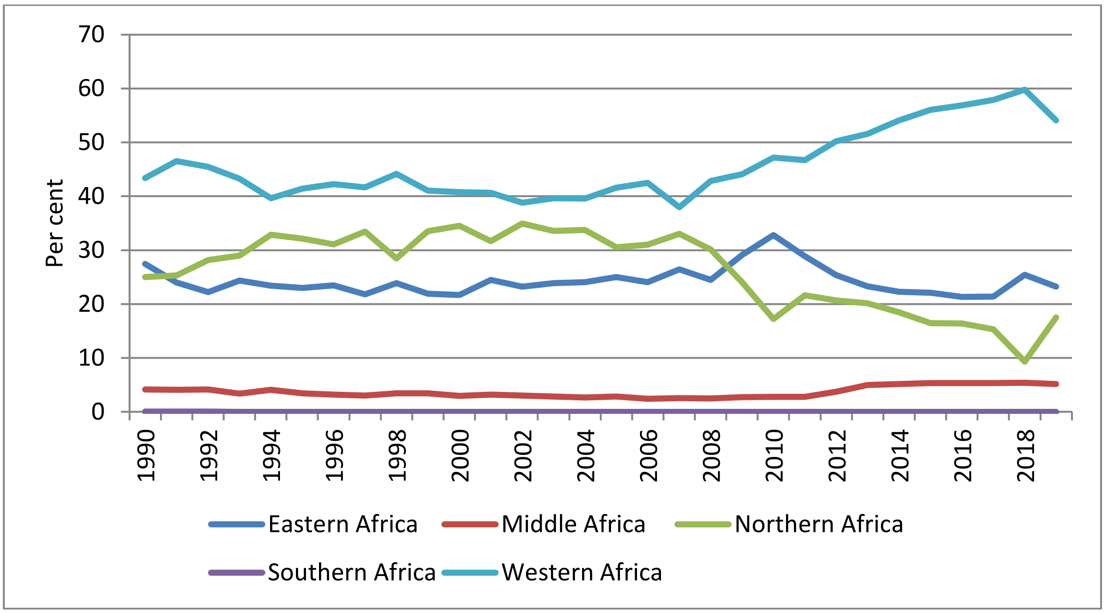


Figure 1.3: Share of rice production by African regions

Note: Middle Africa refers to central Africa
Source: FAO Corporate Statistical Database (FAOSTAT) (2021).

Figure 1.3 shows that the share of rice production was more or less stable between 1990 and 2008. However, after the 2008-09 global economic crises, the dynamics changed and the production in Northern and East Africa has been declining while that of Western Africa has been increasing. Production by Middle Africa has also risen slightly. Starting in 1990 with a share of 4%, Middle Africa sees a slight rise in rice production, achieving the highest regional share of about 5% by 2019. Eastern Africa begins just below 30%, experiencing minor fluctuations and a gentle decline to 23% over the same duration. Northern Africa, with the initial share of 25%, displays a slight upward shift between 1994 up to 2007 and thereafter slows down to 17% at the end of the period. Southern Africa's share, also beginning low at 0.04% portrays a dismal performance over the period to end at 0.01% at the end of the period. Western Africa's trajectory shows a modest increase from 43% at the beginning of the period under review, experiences an almost constant growth up to 2007, increases steadily to 59% in 2018 before slowing slightly down to 54% at the end of the period in 2019.

1.1.3 Overview of Rice Farming in Kenya

Rice growing in Kenya dates back to 1907 when it was first cultivated in the Country. It is believed to have originated from the continent of Asia. After maize and wheat, it is the country's third most important crop for food production. According to the Ministry of Agriculture (2008), irrigated rice farming accounts for eighty percent (80%) of Kenya's rice production, while the remaining twenty percent (20%) relies on natural rainfall. It is grown in four main areas including Western, Coast, Central and Nyanza. Kenya's coastal counties of Kwale, Kilifi, and Tana River, as well as the western counties of Bunyala and Teso, are the primary producers of rain-dependent rice. In addition, rice is cultivated using well-established government irrigation systems governed by the National Irrigation Board (NIB). According to Onyango (2014), these irrigation projects include Bunyala, Ahero, West Kano and Mwea Tebere. Rice is cultivated by more than 300,000 farmers for both food and commercial use.

Rice milling is done by both government and privately owned mills. The country has four major government owned rice mills with varying production capacities. These include the Lake Basin Development Authority (LBDA), Western Kenya Rice Mills (WKRM), NIB-Mwea, and TARDA rice mills. Mwea Tebere's National Irrigation Board (NIB) is the largest mill capable of producing 24 tons of rice in an hour. LBDA, Western Kenya Rice Mills and Tana Delta have milling capacities of 3.5, 3.0 and 3.0 tons per hour, respectively.

In addition, there are a number of other privately owned mills including Capwell, Dominion Farms Mill, Nice Rice Millers, and other small rice millers, most of which are located in the Mwea Area and western Kenya. These mills have an output of around 2.0 to 2.5 metric tons per hour on average. It is remarkable that rice millers have been able to attain competitiveness despite the fact that they often encounter machine breakdowns, make small investments in contemporary mills, face intense competition from imported low-cost rice, and rely on unstable sources of electricity for milling (Atera *et al.*, 2018).

The rate of production and consumption of rice has both increased rapidly in recent years. Toure *et al* (2008) report that rice is a staple food for the vast majority of Kenyans residing in urban areas. Over the last several years, its' consumption in Kenya has been growing at a rate of 12% annually. This is impressive compared with the annual figures for wheat and maize, which stands at four and one per cent, respectively. This is as a result of continuous change in eating habits, increased population growth rate, increased income level, along with increased rural urban immigration (Muthayya *et al*., 2014).

Similarly, rice production in Kenya has been increasing, but at a lower rate compared with consumption. This increase can be attributed to rise in irrigable land in the country. However, compared to other African countries which are major rice producers in Africa, Kenya's production is still low. The average production of milled rice in Kenya between 2000 and 2005 was 32,490 tons. Similar values for Nigeria, Madagascar and Tanzania were 2,103,400 tons, 1,942,520 tons and 456,970 tons, respectively (Toure *et al* 2008). High level of rice production in Madagascar's has been attributed to increased application of system of rice intensification (SRI). The system ensures maximum output at the lowest possible input of water and fertilizer (De Laulanie, 2011).

Annual rice production and consumption in the country between 1990 and 2018 averaged 45 and 351 thousand tons, respectively. This implies an average shortage of 306 thousand tons, which was met through imports. Therefore, increasing rise production in the country is paramount. Increased production will lead to increased farmer's income, increased food security, reduced rice import expenditure and create employment (USDA, 2018).

Rice production in Kenya, according to Onyango (2014), is plagued by a number of obstacles, including: high prices for farm inputs; high costs of electricity for pumping water; farmers are often excluded from NIB lending schemes; informal fragmentation of land; high cost of leasing land; and deprived access to extension services, amongst others. Rice production in Kenya is significantly hindered by various challenges, particularly for small-scale farmers operating under irrigation projects managed by the National Irrigation Board (NIB). Rice output in the nation might be significantly increased if interventions to handle the challenges highlighted above are brought on board.

Rice produced in Kenya only meets 20 per cent of the demand[1] with the difference being imported. For the country to fully address its rice demand, production should be increased by 9.3 per cent annually (Ministry of Agriculture, 2008). To achieve this, the Government of Kenya took several steps. First, it doubled the land under irrigation to 48,000 acres at Mwea Irrigation Scheme. Secondly, it improved infrastructure such as roads in the rice growing areas, provided irrigation water for rice growers, fixed the drainage channels to control flooding, and provided electricity and communication

---

[1] The average annual rice production in Kenya in 2015 was 150, 000 metric tonnes per year while the demand was 550,000 metric tons (Republic of Kenya, 2016).

channels in Western Kenya for small scale holders. Finally, it planned to build a fertilizer production plant in Eldoret to reduce fertiliser costs and thus bring down the rice input costs.

It is essential for policymakers in Kenya to understand the issues that rice farmers face across its value chain. This includes the stages of cultivation, harvesting, milling, and storage processes, if improvement in rice productivity in the country is to be achieved. In addition, farmers must increase the amount of area planted with rice, employ more inputs, and implement cutting-edge production technology in order to enhance rice yield. However, this is offset by the fact that land for cultivation is limited, population growth is increasing, materials are expensive, and the available technology is also expensive. The best alternative is to increase rice productivity through effective use of available resources subject to the available technology. Furthermore, as Lema, et.al. (2017) observes, introduction of new technology is not cost effective if available inputs and technologies are not used optimally. Efficient use of available resources may include improvements in infrastructure such as roads, dams, irrigation and drainage, electricity and communication, farmer's skills through training, and providing extension system, among others (Ali and Chaudhury, 1990; Bravo–Ureta & Pinheiro, 1997; Galawat & Yabe, 2012; Li, Kea & Pich, 2016). If farmers are already technically efficient, increasing the amount of farm inputs being used will not raise output. New inputs and technology will be needed to increase output.

1.1.4 Trends in Rice Production and Consumption in Kenya (1990 – 2020)

Since independence, Kenya has never produced enough rice to meet its demand. Rice production in Kenya shot by 196% between the years 1990 and 2020, while the country's consumption increased by 595 % over the same time period. This implies an average growth of 6.5 and 19.8 per cent per year for both production and consumption respectively. These statistics indicate that the growth rate of rice consumption is thrice that of production (WARDA, 2017). The growth in the area under rice farming has also increased minimally, by a meagre 4.7 per cent per year. Notably, production reduced between 1999 and 2001 due to draught that affected the country leading to fall in water levels for major rivers that supply water to rice irrigation schemes in Kenya, for example Mwea and Nyamindi (Republic of Kenya, 2002).

Figure 1.4 shows rice production, consumption and the deficit in Kenya between 1990 and 2020.

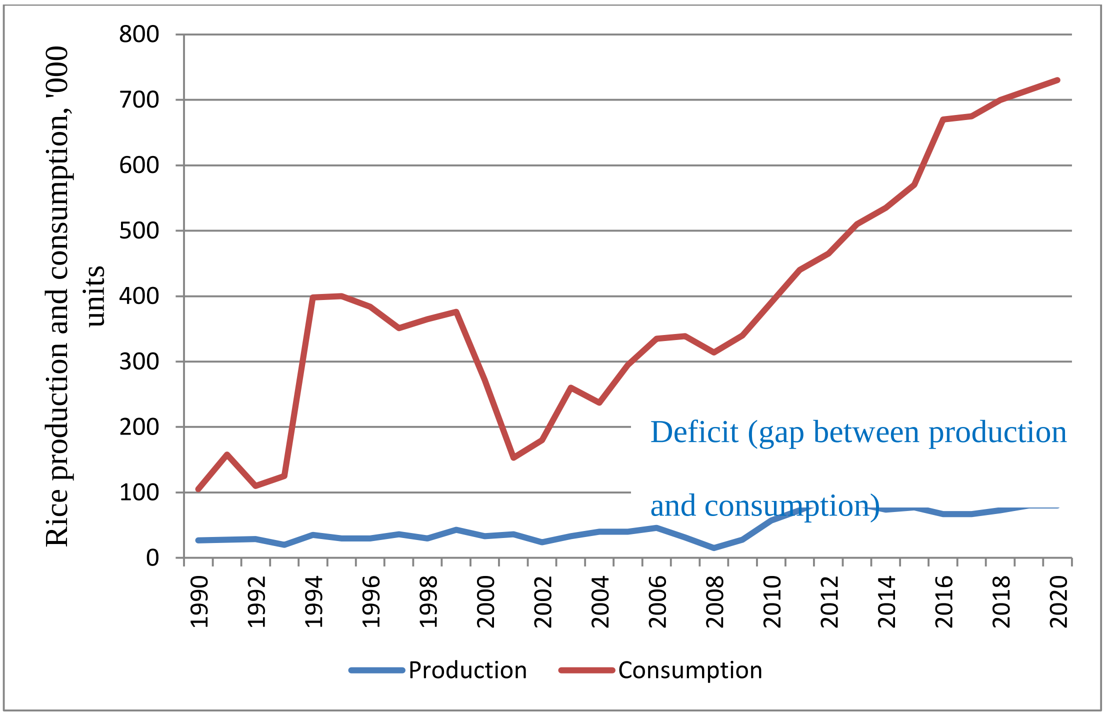


Figure 1.4: Trends in Rice Production and Consumption in Kenya between 1990 and 2020

Source: National Rice Development Strategy (2008) and United States Department of Agriculture (USDA) (2018).

In can be inferred from the figure above that rice production and consumption in the country was growing at a faster rate from 2001 to 2020 compared to 1990 and 2000. The increase in rice consumption has outpaced its production courtesy of increasing demand with increasing population, high incomes, changing tastes and preferences, increased consumption of rice-based value-added products (for example rice pasta, rice flakes, crackers and breakfast cereals) and urbanization (Muthayya *et al.*, 2014). The increasing demand saw the retail price of rice per kilogram increase by 38 per cent in 2018 compared with 2017 (Shawiza, 2018).

Rice production in Kenya rose from 27 thousand tonnes in 1990 to 80 thousand tonnes in 2020. An almost constant growth is observed between 1990 and 2008. Thereafter a slight increase is seen after the implementation of the National Rice Development Strategy (NRDS, 2008) in 2008 which raises output from 27 thousand tonnes up to 91 thousand tonnes in 2012 after which it relaxes and begins to fall. According to Atera *et al.* (2018), this record gain in output is connected with an increase in the amount of irrigable land in Kenya. Nevertheless, rice production in rain dependent areas remained low, averaging one ton per acre. This is due to persistent draught, crop diseases, depletion of essential nutrients and inefficiency of storage facilities for the farmers. Despite this achievement, the growth rate of consumption has been outstripping production.

Rice consumption on the other hand shows some astronomical increases from 105 thousand tonnes in 1990 to 730 tonnes in 2020. A sharp increase is noticed from 1990 up to 1994 hitting 398 tonnes mark and later slows down to 153 thousand tonnes in 2001. A sharp rise thereafter follows up to 730 thousand tonnes in 2020 showing no signs of abatement.

In the year 2008, the Ministry of Agriculture developed the National Rice Development Strategy (NRDS) with the goal of ensuring that the nation would enhance its rice output in accordance with the government's policy towards food sufficiency. The overarching objective of the plan was to boost rice farming and enhance marketing with the end goal of increasing farmers' incomes and ensuring the country grew enough food to sustain its growing population. To eliminate rice deficit by 2030, the Ministry targeted an annual increase in rice production of 9.3 per cent. This was however not achieved since the deficit continued to rise as shown in the Figure 1.5.

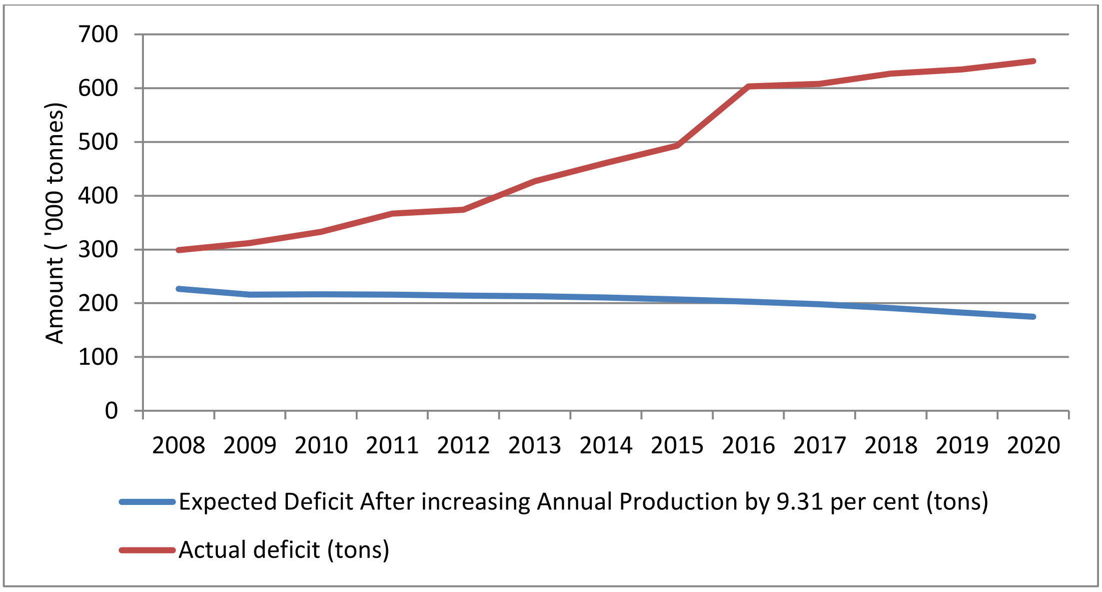


Figure 1.5: Annual expected and actual rice production deficit in Kenya between 2008 and 2020.

Source: National Rice Development Strategy (2008) and United States Department of Agriculture (USDA) (2018).

Figure 1.5 presents a comparison between the expected and actual rice production deficits in Kenya from 2008 to 2020. The blue line represents the expected deficit assuming an annual increase in production of 9.3 percent, while the red line depicts the actual deficit in tons. From 2008, the expected deficit would have been as shown with the blue line, if production had increased by 9.3 percent annually. The deficit would have remained relatively stable, showing only a slight decrease over the 12-year period. In contrast, the actual deficit, illustrated by the red line, shows a different scenario. Starting at approximately the same level as the expected deficit, the actual deficit increases significantly over time, rising steadily to a peak in 2020 that is over three times higher than the initial amount. This stark divergence indicates that the actual production did not keep pace with the expected growth rate of 9.3 percent. The increasing actual deficit suggests that despite the anticipated growth, factors such as lower yield, inadequate farming practices, or policy shortcomings might have contributed to the shortfall in meeting the rice output in the country.

In summary, Figure 1.5 shows that the goals have not been realized so far. There exists a widening gap between rice production and consumption in the country. For instance, the strategy targeted a deficit of 213 thousand metric tons of rice by 2013 and 175 thousand metric tons by 2020, respectively (Ministry of Agriculture, 2008). However, these goals were not attained and the deficit was recorded at 427 thousand tons and 650 thousand tons, respectively (USDA, 2020). The narrowing of this gap will help ease pressure on foreign exchange, ensure food security, create employment and reduce poverty. Some of the measures that need to be taken into account to increase production are to increase the irrigable land, improve production technology, avail inputs at affordable prices to the farmers, improve infrastructure such as roads, dams, irrigation and drainage, electricity and communication and ensure efficient use of resources by the farmers.

1.1.5 Overview of Rice Farming in Mwea Tebere Irrigation Scheme

The Mwea Tebere scheme lies about one hundred kilometres to the north-east of Nairobi metropolis. Since 1956, rice has been the main crop grown at Mwea Tebere irrigation scheme. The scheme’s 48,000 acres under rice have been modified and placed under the irrigation program. Before 1998, the program was controlled by a number of different government bodies. The administration of the scheme was transferred to the Mwea Multi - Purpose Rice Growers Cooperative Society (MMRGC) after 1998. However, MMRGC was unable to oversee the running of the system due to financial challenges, lack of trained employees, and equipment required to maintain the scheme. In the year 2003, the government once again started to run the scheme. The NIB was founded in 1966 with the purpose of facilitating the development, control, and improvement of irrigation projects in Kenya. Currently, NIB and several farmer's associations are managing the scheme. The Water Users Association, sometimes known simply as WUA, is the most influential farmers' group in the scheme. While the NIB is responsible for the infrastructural part of the project, (WUA) the water user’s association is manages the scheme’s water. Marketing of rice is fully left to the decision of the farmers.

1.1.6 Trends in Rice Production in Different Irrigation Schemes in Kenya (1990 – 2016)

Paddy rice output in the country has historically been very low. Annual production of all other irrigation schemes apart from Mwea has remained below 10 thousand tons per year. Figure 1.6 below depicts the trends in rice output in different irrigation schemes in Kenya.

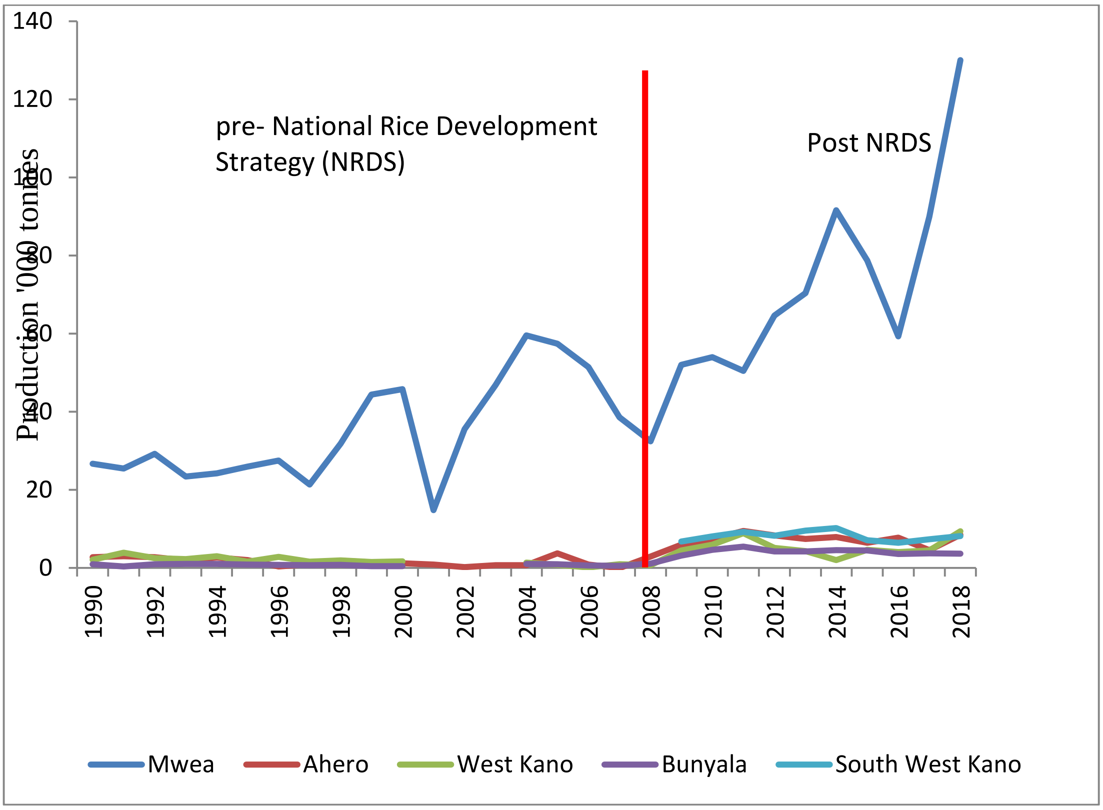


Figure 1.6: Rice Production in different Irrigation Schemes in Kenya between 1990/91 – 2018/19.

Source: Economic surveys (various issues)

Figure 1.6 displays the rice production levels across various irrigation schemes in Kenya from the 1990/91 to 2018/19 growing seasons. It also marks the division between the periods before and after the implementation of the NRDS with a vertical red line. Mwea, shows a noticeable variability in production but generally exhibits a significant increase post-NRDS, with production levels peaking at about 120,000 tonnes towards the end of the observed period. Improvement in Mwea irrigation scheme was impressive between 2008 and 2014. Production declined to 59, 000 tonnes in 2016 but the trend reversed between 2016 and 2018.

This suggests that Mwea has been the most productive scheme, especially following the NRDS's implementation. In contrast, the other schemes, Ahero, West Kano, Bunyala, and South West Kano, show much lower production levels throughout the same period.

These schemes have remained relatively flat with minor fluctuations over the years, and their production has stayed consistently below 10,000 tonnes. The introduction of the NRDS had a considerable positive impact on rice production in the Mwea scheme, highlighting its effectiveness or the influence of other factors enhancing productivity there. However, the other schemes do not show a similar level of improvement post-NRDS, indicating that the strategy's influence or other beneficial developments may not have been as pronounced or evenly distributed across all areas. Although an addition of 18,279 acres were planted with rice between 2014 and 2019, output only increased by 44,111 tones (an increase of 37.87 per cent) (Republic of Kenya, 2018). This drop can be attributed to inefficiency in rice farming.

1.2 Statement of the Problem

Rice production in the country remains insufficient despite being the third most important food crop in Kenya. The country incurs in excess of Ksh 30 billion annually, to import over 80% of the rice consumed in the country from countries such as Egypt, Tanzania, and Thailand (Knoema, 2021). Annual rice production and consumption in the country between 1990 and 2020 averaged 46.97 thousand tons and 383.77 thousand tons, respectively. This implies an average shortage of 336.8 thousand tons, which was met through imports. The Ministry of Agriculture' through the NRDS advocated for an annual production increase of 9.3 percent in order to reduce the deficit. However, this was not achieved. Rice imports in Kenya increased by 87.18 per cent from 2010 to reach 730 thousand tonnes in 2020.

The NRDS was developed in 2008 by the government in response to the nationwide rice production challenges. The overarching aim of the plan was to boost rice output and decrease the deficit gap from 227 thousand tons in 2008 to 175 thousand tons in 2020. However, the deficit continued to increase and hit 650 thousand tons in 2020 (USDA, 2020). Thus, the deficit has raised several questions to both policy makers and researchers. For instance, what are the factors that explain country's rice deficit? Fundamental to this question could be due to farmer's efficiencies in the course of rice production in the country. Notably, despite the declining production and the rise in rice imports, none of the reviewed studies have lately carried out research to investigate this problem.

Various studies have examined rice production in Kenya in the past. These include Kuria *et al.* (2003), and Omondi and Shikuku (2010), and Mwatete *et al*. (2015). This study, however, is different from the earlier research in four respects.

To begin, the study is being conducted more than 10 years after the 2008 National Rice Development Strategy was put into effect. No other study has been carried out in this post-NRDS period to evaluate the success in rice production, following its implementation. The current study seeks to fulfil this gap. Secondly, a small sample size bias was present in the research conducted by Kuria et al. (2003), Omondi and Shikuku (2010), and Mwatete et al. (2015). There were 106, 123, and 220 samples used in each of the three trials. The current study uses a sample of 313 farmers—all sampled from the five rice-growing regions in Mwea.

Thirdly, by using the most recent data, the research updates the Kuria et al. (2003) study. The Kuria et al. (2003) study might not be a genuine representation of the current state of affairs. Thus, the research fills the gap in the determinants of rice production and technical efficiency determinants by using the most current data. Additionally, Kuria et al. (2003) compared efficiencies of two farmer groups: one that planted rice once a year and the second group that grew rice twice per year.

Finally, in addition to examining farmers' efficiencies (technical efficiency) as other studies did, this study goes ahead to examine the determinants of these technical efficiencies and what affects rice production.

1.3 Research Questions

This research was designed to answer the following questions:

(i) What are the factors that affect rice production in Mwea Irrigation Scheme?

(ii) What is the level of technical efficiency of rice production in Mwea Irrigation Scheme?

(iii) What are the determinants of technical efficiency in rice production in Mwea Irrigation Scheme?

1.4 Research Objectives

The overall objective of this study was to assess rice technical efficiency in Kenya, with specific focus on Mwea Irrigation Scheme. The specific objectives of this study were to:

(i) Determine the factors that affect rice production in Mwea Irrigation Scheme.

(ii) Measure the technical efficiency level of rice production in Mwea Irrigation Scheme.

(iii) Establish the determinants of technical efficiency in rice production in Mwea Irrigation Scheme.

1.5 Significance of the Study

The findings of this research will contribute to the growing body of knowledge on rice farming in Kenya. Policymakers desirous of increasing rice output via the promotion of efficient and competitive agricultural practices will find this information crucial. It is thus expected that the implementation of the recommendations of the study based on the findings will help in boosting rice production to meet the high consumption demand. Government, development organizations, and farmers in the relevant field will all benefit from the study's findings on the nation's rice industry's production efficiency. It is also expected that other researchers will use this study's conclusions as a springboard for their own research that will confirm, extend, improve, or enrich the current body of knowledge.

1.6 Scope of the Study

The purpose of this study was to investigate the technical efficiency levels of rice farmers at Mwea irrigation scheme in Kirinyaga County. The study was carried out in the scheme due to its’ importance to the national rice production and the country’s food security. It is the largest irrigation project in Kenya and produces nearly 80% of the country's rice supply, as reported by the Ministry of Agriculture in 2008. According to data provided by the Republic of Kenya (2018), the scheme produced 73% of all the rice produced in Kenya in 2018.

1.7 Limitations of the Study

This research has some limitations. First, rice channels like marketing and consumer stages were not investigated. This does not mean they are less significant. Secondly, the findings of this research was derived from a small and representative sample of smallholder farmers in Kirinyaga county and may thus not be applicable to all smallholder farmers in other parts of the nation. Finally, it is unlikely that farmers keep accurate data on application of input levels. The research therefore depended on the responses provided by the participants in order to accomplish its goals.

1.8 Organization of the Study

This research is broken down into five chapters. In the first chapter, the subject is presented, the issue statement is outlined, and the goals that are to be addressed by the research highlighted. The review of both theoretical and empirical literature is covered in the second chapter, and the technique that will be used to meet the aims of the research is laid out in chapter three. The empirical analysis is presented in the fourth chapter, and the results and suggestions together with conclusions are discussed in the fifth chapter.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive overview of technical efficiency within the context of rice production. It follows a structured approach, starting with the foundational theories of measuring technical efficiency, which is critical for understanding the benchmarks and methods used to evaluate performance in agricultural production. Following this, the section delves into both the theoretical frameworks and empirical evidence that affect rice production and efficiency. This includes discussions on factors like input use, labor practices, technology adoption, environmental impacts, and policy frameworks, which can all influence the efficiency of rice production in various contexts.

The subsequent part of the section is dedicated to the specific measures of technical efficiency. Here, the focus would be on the metrics and models used to assess how effectively resources are being converted into rice yields. Commonly used measures might include data envelop analysis (DEA) and stochastic frontier analysis (SFA), among others. Finally, a summary of the literature review serves to recapitulate the key points, theories, methodologies, and findings discussed throughout the section. This synthesis aids in establishing a clear understanding of the current state of knowledge in the field, identifying gaps that might exist in the literature, and setting a foundation for future research or practical applications in improving technical efficiency in rice production.

2.2 Theoretical Literature Review

This research work reviewed theoretical literature on production theory and production function, frontier measures of efficiency theory, induced innovation in the theory of the firm, stochastic frontier analysis and Data Envelopment Analysis.

2.2.1 Production Theory and Production Function

One of the economic theories that examines the connection between the inputs for production and the final products and services is the production theory (Clayton, 2000). A mix of land, labor, capital, and entrepreneurship is needed to produce an economic good or service; some combinations are more technically efficient than others, and all combinations have an impact on production costs and output (Clayton, 2000).

The technical relationship between the transformation of inputs into outputs is described by a production function. An example of a general production function is as follows:

$$q = f(z) \tag{2.1}$$

Where q is the product to be produced (output) and z is the input used to produce the final product q. Within the function, every level of output q is determined by the level of input z that is being used.

The function described above however assumes that throughout the process of production, only one input is utilized to generate the output. This production method is only useful for agricultural products that can be produced with one input only.

Agricultural products produced using one input only are very few. Majority of agricultural produce make use of a variety of inputs. A production function with numerous inputs, of which one is held fixed at some constant level, may alternatively be written as follows;

$$q = f(z_{1,} \mid z_2 , z_3 , z_4 \, z_5 , z_6, z_7) \qquad (2.2)$$

Where:

q represents the total output or yield

z_1 is an input which is variable.

The inputs z_2 to z_7 are fixed

A variable input is described as one whose levels of use can be controlled while a fixed input refers to the input which for some reasons cannot be controlled. Categorization of variable inputs and fixed inputs can be confusing without time factors and hence time must be considered. From an economist point of view, time can be categorized as long run where all the inputs are regarded variable or very short run where all inputs are fixed. Other time categories are short run where only a few inputs are variable and then intermediate where most of the inputs can be termed variable. However, this argument becomes arbitrary since we cannot determine how long for example is short run. This leads to production economist arguing that before planting, all inputs are variable but when planting starts gradually inputs become fixed (Debertin, 2012).

Economic theory classifies production functions into four main categories. These are the linear model, the Cobb Douglas production function, the fixed proportions production function, and the constant elasticity of substitution (CES). Cobb Douglas production function is the most common of these. The theory is relevant in that the study adopts the production function (the production theory) in the theoretical framework, which forms the basis of this study.

The measurement of the technical efficiencies used in this study was based on the agricultural production theory where all farmer were assumed to have used their own resources to purchase farm inputs for rice production. The farmers production technology uses a vector of inputs as denoted here below:

X = $(x_1, x_2, x_3 \dots\ x_n) \in \Re^n_+$ (inputs are non negative) (2.3)

Similarly, the output is non negative and is defined similarly:

Y = $(y_1, y_2, y_3 \dots\ y_n) \in \Re^m_+$ (2.4)

The output is related to production using the formula: $Y = f(X)$

The production possibility set of every farmer is closed, non-empty and convex and is given as follows:

$PPS = \{(XY): X\ can\ produce\ Y\} \in \Re^{n+m}_+$ (2.5)

The Production Possibility Set can be displayed either as the required set of inputs or producible output set as below:

$$PPS(y) = \{X: (XY)\} \in PPS\} \quad (2.6)$$

$$PPS(x) = \{Y: (XY)\} \in PPS\} \quad (2.7)$$

The required set of inputs is the collection of all the vectors of inputs that yield at least as much as a given output vector. The output producible set is the collection of all the output vectors that can be produced from a given vector of input.

Since every farmer is assumed to be profit maximizing, he chooses input output choices in $(XY)\} \in PPS$. An analysis of the performance of each rice farmer therefore requires every farmer to combine the inputs in such a way that he is left with most output given the output set. This can be done by using input or output oriented measures. The input-oriented measures focus on the farmer using minimum inputs set to produce a given level of output. On the other hand, the output-oriented measures focus on maximizing the output from a given set of inputs.

Assuming a variable return to scale, we can present the production technology of a firm as follows:

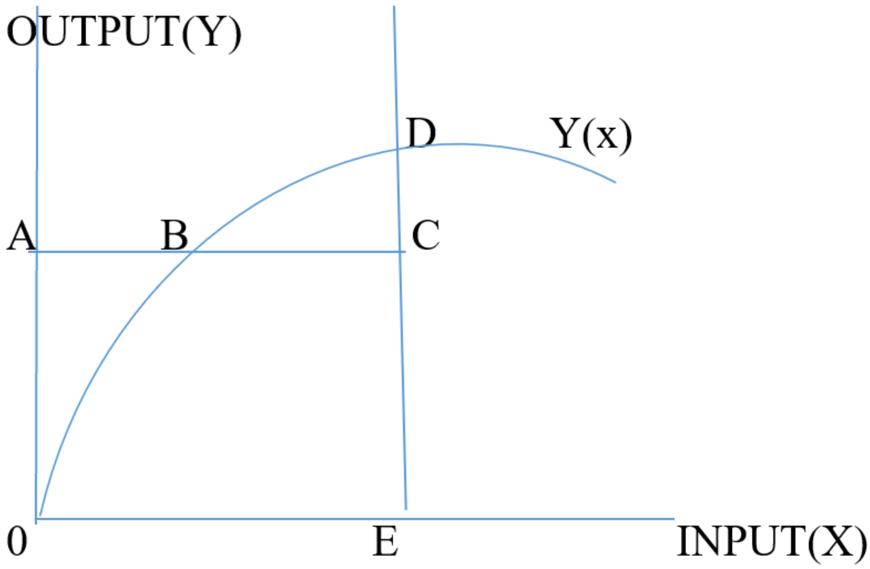


Figure 2.1: Input and output measures of technical efficiency

A farmer producing along the production function $Y(x)$ is said to be technically efficient. Points like C is inefficient since output can be increased by using same levels of inputs. The technical efficiency from an output orientation is given as EC/ED while the input orientation is given as AB/AC. The technical efficiency enables us to determine the quantity of inputs that can be shed off without affecting the output level, or increasing the level of output while using the same amount of inputs. A rice farmer is considered inefficient if the output he is producing can be produced using a fraction of the inputs he is using. The technical efficiency can be measured using Data Envelope Analysis (DEA) or the Stochastic Frontier Analysis (SFA). This study adopted the SFA approach.

2.2.2 Frontier Measures of Efficiency Theory

Farrell developed the theory of frontier measures of efficiency in 1957. In the course of developing this theory, he came up with three major components of efficiencies.

These are allocative efficiency, technical efficiency, and economic efficiency. All these three efficiencies can be derived from a production function. Technical efficiency, in the author's words, is a measure of how well or effectively, certain set of inputs can be used to produce a given output. A firm is said to be technically efficient when it is producing maximum possible output while using minimum inputs like capital, labour and technology.

Later, the frontier efficiency theory was extended to two new theories, namely the parametric and the non-parametric analysis. The most common parametric method is the stochastic frontier analysis developed by Aigner *et al*. (1977) and Meeusen and Van den Broeck (1977). It aimed at accounting for random errors that arise in measuring production efficiencies. On the other hand, the most popular non-parametric method is the data envelop analysis (DEA) postulated by Charnes, Cooper & Rhodes (1978). This approach does not impose any specific functional form on the data. Sections 2.2.3 and 2.2.4 dive into these functional forms in details.

Technical efficiency is measured as a ratio of total output produced from a set of inputs to the maximum potential output that can be produced from those inputs. A value close to one is preferred. Allocative efficiency on the other hand measures the farmers' capability of applying farm inputs in their best quantities with respect to their prices. It occurs at the output level where the prices of inputs equal their marginal cost. Finally, economic efficiency is a product of both the technical and allocative efficiencies defined above.

Majority of studies that look into the variations in farmers' technological efficiency applies a two-stage framework that was first applied by Coelli et al. (2005). The process starts by estimating the stochastic production function and projecting the degree of technological inefficiency in farming. In the second step, ordinary least-squares (OLS) regression is used to link the anticipated impacts of technical inefficiency to particular farmers' factors. However, OLS contradicts assumption of distributing identically the efficiency effects in the stochastic frontier function. Therefore, in order to estimate the technical efficiency estimates and get over the violation of the OLS, the maximum likelihood estimation is employed.

Ellis (1988) defined technical efficiency as the level to which a combination of inputs is used to produce maximum possible output. Therefore, for a farmer to be technically efficient, he must produce along the production frontier while a technically inefficient farmer will produce on the interior of the production frontier.

Apart from measures of technical efficiencies highlighted above, other alternative measures of efficiencies exist. For example, Lau and Yotopoulos (1971) utilized a profit function. However, it is crucial to note that profit function analysis assumes that all firms behave in accordance to some rules, including profit maximization, given the output prices, the variable inputs and quantities of production factors that are normally fixed. In the study, the profit function estimates that were obtained were statistically consistent. Using this methodology, the authors found that small firms attained higher levels of price efficiency and/or operated at higher levels of technical efficiency.

Kumbhakar and Lovell (2003), showed that measure of productive efficiency by the use of profit function failed to provide the arithmetical measure of efficiency. They all independently advocated for the use of stochastic frontier function to explains the occurrence of measurement error in the system of production and in the specification and measurement of the production function frontier. They noted that the error term was made up of two parts namely the error as a result of measurement also known as the statistical noise and the error that was beyond the control of the farmer. Frontier production functions have largely been applied in agricultural industries. Some studies apply Frontier production functions to find out the nexus between technical efficiency and the other social economic variables including farmer's education levels, age, availability of credit, farm size and access to agricultural extension services. Most of these studies conducting research on the variances in farmers technical efficiency normally apply a two-stage approach.

Various scholars have carried out empirical studies on different methods that have been used to estimate the technical efficiency and their determinants. Kuria *et.al* (2003) studied Mwea Irrigation Scheme in 2003 using two groups of rice producing farmers. In the former study, one group planted one crop in a year while the other second group planted two crops of rice in a year. The research utilised the stochastic frontier approach. The study established that farmers who grew a single crop per year had a higher level of technically efficiency than those who grew two crops in a year.

The results further showed that seeds, mechanized tractor, pesticides, irrigation water and chemical fertilizers were important in explaining rice production for one group. In the second group, the important variables were irrigation water, chemical fertilizers, irrigation water, land and pesticides. The coefficients of labour and animal draught power were not significant. The weakness of this study was small sample size bias and it could not be relied upon to give the overall picture of neither the factors of rice production nor the current measures of technical efficiency.

2.2.3 Stochastic Frontier Analysis

Developed by Aigner *et al*. (1977) and Meeusen and Van den Broeck (1977) the stochastic frontier analysis model has become the most popular measure of efficiency (Rahman, 2003; Coelli *et al*, 2005). The model specifies two terms namely: a random variable specified by ε_i and an error term specified by γ_i. The former error term ε_i captures the technical efficiency or the technical inefficiency of a certain firm and is strictly non – negative. It takes a value of one for a technically efficient firm and zero for a technically inefficient one (Koirala *et al.*, 2015). The latter error term γ_i on the other hand is identically and independently distributed and captures random output variation, for instance as a result of weather changes. The model is specified as:

$$Y_i = g(X_i, \theta)e^{\gamma_i.-\varepsilon_i} \quad (2.8)$$

Where,

Y_i is output,

X_i represents factor inputs,

$\theta's$ are the parameters which are to be estimated in the model and

ei denotes the exponent.

Assuming a production function that takes the form of Cobb Douglas and taking the natural log:

$$lnY_i = \theta lnX_i + \gamma_i - \varepsilon_i \quad (2.9)$$

$$\gamma_i \sim N(0, \sigma_\gamma^2) \quad (2.10)$$

This model can now be estimated using the maximum likelihood estimation. The variance of the overall error term, $\gamma_i - \varepsilon_i$, can be expressed as:

$$\sigma^2 = \sigma_\gamma^2 + \sigma_\varepsilon^2 \quad (2.11)$$

2.2.4 Data Envelopment Analysis

The Data Envelop analysis is a technique that use linear programming. It builds a non-parametric piecewise linear envelope to both inputs and outputs. The technique has been widely used in estimating the efficiencies of a firm, compared to similar firms but with the least input output ratios.

The output is rice production per acre while the inputs include seed, the quantity of fertilizer, working hours of machines and human, pesticides and herbicides among others. All inputs are measured in terms of how they are applied on the farm in per acre terms. We start by assuming that we have *K* number of farmers using *n* inputs to produce output *m* each. Let x_{jk} be the quantity of input used by each farmer and y_{ik} be the quantity of output produced by each farmer, and u_i and v_i are the respective input and the output weights. The two weights are strictly greater than or equal to zero. The overall technical efficiency (TE) will therefore be written as:

$$TE_K = \sum_{i=1}^{m} v_i\, y_{ik} / \sum_{j=1}^{n} u_i\, x_{jk} \quad (2.12)$$

The objective of the farmer is to maximize

$TE_K = \sum_{i=1}^{m} v_i\, y_{ik} / \sum_{j=1}^{n} u_i\, x_{jk} \leq 1$ (Technical efficiency cannot exceed one) (2.13)

The optimal weights are selected by specifying the following objective equation:

Min TE_K

s.t.

$$\sum_{i=1}^{m} v_i\, y_{ik} - y_{ik} + w \geq 0 \text{ and} \quad (2.14)$$

$$x_{jk} - \sum_{j=1}^{n} u_i\, x_{jk} \geq 0 \quad (2.15)$$

If w is equal to zero, the specification leads to technical efficiency. However, if it is a variable, it leads to pure technical efficiency.

2.3 Empirical Literature

This section reviewed empirical literature on factors that affect rice production. Rice being an agricultural product requires a combination of inputs which must be applied in the best way possible to realize high levels of output.

2.3.1 Factors that Affect Rice Production

Tiajani (2006) measured the technical efficiency of paddy rice in Nigeria, Osun State using SFA. The authors used a sample size of 50 farmers who were randomly selected in the state. The study further analysed the socioeconomic factors that determine its production. Explanatory variables used included farm size, labour, fertilizer, family size, farmer's age and experience, and off farm income, among others. The SFA technique was used to derive the TE and regression analysis was used to measure the determinants of rice production (the variables were linearized using logs). The variables were measured in their natural logarithms. The mean of technical efficiency was 86.6 and efficiency levels ranged from 29 to 98 per cent. Another key finding was that 75 per cent of the farmers were highly efficient (had a technical coefficient value of 90 per cent and above) while only seven per cent of them were least efficient, with a technical efficiency coefficient of between 30 and 40 per cent. The significant determinants of inefficiency were farm size, fertilizer, pesticides, presence of extension services, off farm income and cross product of labour and fertilizer. The limitation of the study was that it did not consider farm machines hours, which is quite instrumental in the production process. The research also did not state the sample size used in the analysis and how it was determined.

Mwatete *et al*. (2015), conducted a study in West Kano, Kenya using a sample of 123 rice farmers. The study compared farmers using Convectional farming methods with those using system of Rice Intensification and different socio – economic factors affecting rice production. The study found that use of SRI saved 64 per cent of the water and 90 per cent chemical less than conventional methods. The SRI farmers were eight per cent more efficient than the Conventional ones: their technical efficiencies were 83 and 75 per cent respectively. Results also showed that education, age, experience and the size of the household were the most important factors affecting rice technical efficiency. The study found out that 32 percent of farmers who used Conventional farming methods had technical efficiency of between 80 and 99 percent while 40 per cent had a technical efficiency ranging between 50 and 59 per cent, in each case. This implied that a large number of farmers were still technically inefficient.

Kea, Li and Pich (2016) analysed the level of technical efficiencies and the major determinants of rice output in Cambodia. The study applied panel data collected over a four-year period 2012 to 2015 across all the country's 25 provinces using a stochastic frontier analysis model (SFA). Rice output was found to vary depending on the number of agricultural machineries, capital invested, area harvested and amount of fertilizer applied. The mean rice efficiency was 78.4 per cent. The presence of agriculture supporting staff, techniques of production and irrigation were found to be key factors affecting rice production in Cambodia. The limitation of the study was that it covered only four years. A larger panel set would have been appropriate.

Chandio *et al.,* (2019) investigated the effect of agricultural credit and size of the farm on rice productivity technical efficiency in Sidh, Pakistan. The research utilised data for 180 rice farmers using data collected in Sidh province in 2016. The variables used in the study were land, seeds, fertilizer applied, loan, farmer's age, education levels, experience in rice growing, labour and loan availability. The study used the Stochastic frontier analysis model in estimating the technical efficiency while the Maximum Likelihood Estimation was used in analysing the effect of the variables on technical efficiency. The results revealed that the size of the farm, fertilizer use, access to agricultural credit and labour positively and significantly influenced the output of rice in Pakistan. Technical efficiency results showed that 97 per cent of the farmers were efficient. The limitation of the study was that it found negative and significant relationships between seed rate and labour on rice productivity contrary to the expectations of the present study.

Ali et.al (2022) examined the determinants of rice yields in Central Khyber Pakhtunkhwa in Pakistan. The study aimed at finding out the major determinants of rice production, and analysing how various inputs affect rice yields. A sample size of 275 farmers was used. The variables used included fertilizers, machine (tractor) hours, fertilizers, and labor hours. A Cobb-Douglas production function was specified and estimated using a regression. This was after carrying out diagnostic tests like normality, heteroscedasticity and multicollinearity. The study established a positive relationship between rice production (yield) and tractor hours, fertilizer and labor. However, the coefficient of chemicals was statistically insignificant. The main limitations of the study were that it was limited to one area (district) making generalizability of the results to the entire country difficult. The study also ignored many determinants of rice production, and failed to measure technical efficiency and its determinants.

Mulatu et.al. (2024) explored the determinants of rice production and market supply in Bench Sheko zone in Ethiopia. The study focussed on 119 households. Some of the variables of interest were gender, farm size, household size, extension services, inorganic fertilizers, farm income, level of education, and use of credit among others. A multiple linear regression was used to examine the determinants of rice production. The main determinants of rice production were found to be farm income, use of credit, household size and farm size. The study was limited by the use of small sample size (119) and similar to the previous study, did not consider rice technical efficiency.

2.3.2 Measure of Technical Efficiency

Udayanganie *et al*. (2006) undertook a study to determine the levels of technical efficiency of paddy rice output in three irrigation blocks of Sri Lanka for the cultivation season 2003/04. The study used a sample of 225 farmers and a stochastic frontier analysis to analyse their technical efficiency. The technical efficiency level of 0.37 was found which was quite low. In the study, the main determinants of technical efficiency among the farmers was the use of credit and the extension services. The study also found a negative relationship between rice production and pesticides. This indicates excessive use of pesticides. The study did not consider other types of inefficiencies apart from technical efficiency.

Kouser, Mushtaq and Abedullah (2007) measured the technical efficiency of rice production in Punjab, Pakistan and its determinants. The study used a sample size of 200 farmers for 2005 production season. The independent variables used in the Stochastic Frontier Analysis model study were the land area, ploughing hours, cost of fertilizer, seed dressing, location dummy, plant protection cost and planting. The coefficient of fertilizer was found to be negative and statistically significant, indicating inefficient mix of nutrients in the fertilizer or overuse. Farmer's age, literacy levels, size of the farm, plant to plant distance and tractor dummy were included in the inefficiency model.

All SFA coefficients except labour hours and plant protection cost were significant. The coefficient of technical efficiency, on average, was 91 per cent, implying limited opportunity for improving productivity through improved application of resources. Surprisingly, all the coefficients of the inefficiency model were significant. However, the study used only four variables in the inefficiency model, implying that the model could have suffered from omitted variables problem.

Kiatpathomchai (2008) analysed the technical, economic and allocative efficiencies of rice production and determinants of these efficiencies in southern Thailand using a sample of 247 farmers in the rice farming season 2010 and 2011. The study adopted the Two-stage data envelop analysis (DEA) methodology and Tobit regression analysis. The study revealed that only 17, 2 and 2 per cent of the farmers were on the frontiers of technical, economic and allocative efficiencies, respectively. In addition, the average efficiencies for the three measures were 14, 32 and 46 per cent respectively. Tobit regression results revealed that rice variety and soil type were the most significant determinants of the efficiencies.

Omondi and Shikuku (2013) analysed the technical efficiency of paddy rice farming in Ahero irrigation scheme in Kenya. The study used stratified and probability sampling where a sample of 220 respondents (rice farmers) were selected. Similar to the other studies, the study further examined the determinants of rice farming technical efficiency. The technical efficiency was calculated using SFA. The technical efficiency was found to be 82 per cent. The minimum technical efficiency was found to be 0.3 and the maximum was 0.95. Majority of the farmers (48.2 per cent) had technical coefficient in the range 0.8 to 0.9 while 0.5 per cent of the farmers had technical efficiency that ranged 0.2 and 0.3. The coefficients of labour and fertilizer were positive, while income, experience, gender and market distance were found to be the main determinants of technical efficiency.

Surprisingly, the coefficients of education and extension service were found to be insignificant. In addition, the study did not explain the methodology undertaken in addressing its second objective. Ndayitwayeko and Korir (2012) estimated rice production efficiency in Gihanga, Burundi using SFA. A sample of 125 rice farmers was used. The study further analysed the determinants of technical efficiency in the region. The variables used in the SFA model are labour, seed quality, fertilizer, pesticide, and irrigation water shortage dummy. The efficiency model considered the following variables: age of the farmer, farm size, extension services, farmer experience, the household head education and off farm income. Technical efficiency averaged 73 per cent. The coefficients of inorganic fertilizer and pesticide were positive and negative respectively. Other variables were insignificant. Experience was found to be positively related with technical efficiency, but a negative relationship was found with respect to age. The limitation of this study is that only two variables were found to be significant in each estimation technique. This makes the data used and the analysis questionable.

Watto and Mugera (2014) employed a data development analysis DEA to estimate rice technical and irrigation efficiency in 80 rice farmers in Punjujab provinces of Pakistan. The author identified three advantages, and hence justifications for using the DEA approach which assumes no functional form between the inputs and the output and no priori error distribution, allows handling of several inputs and outputs without leading to aggregation bias and is appropriate given a small sample size. 45 of the farmers used water from their wells while the rest were water buyers. The model adopted truncated regression to examine the determinants of technical efficiencies and the efficiencies associated with use of irrigation water (irrigation efficiency). The study found that technical efficiency was high for both water buyers and well owners. However, irrigation inefficiency was more evident with water buyers than well owners.

Prianthi *et al.*, (2015) estimated the technical efficiencies of rice farming in Indonesia's 15 provinces in 2008. The study further assessed the social economic factors that affect technical efficiency. The study used SFA model and inefficiency effect model to estimate the technical efficiency and the social economic factors in each province. Some of the input factors considered by the study are land area, fertilizer, seed, pesticide and labour. The coefficient of land area was significant in 11 out of 15 provinces, implying that land increase and farm production are positively correlated. However, the coefficient of land squared was negative in four of the provinces, implying diminishing returns for rice productivity. Another key finding was that pesticide use was insignificant in 10 provinces. The average technical efficiency levels were 77 per cent with 7 provinces having technical efficiency levels that were below 80 per cent, with the rest having technical efficiencies of above 80 per cent. The study, nevertheless, did not consider some important inputs in rice production, like herbicides and machines.

Lema, et.al. (2017) conducted a research of rice production in Fogera district, Ethiopia to determine the levels of technical efficiencies of farmers using a sample of 200 rice farmers in the 2015/16 production year. The research further sought to evaluate the socio-economic factors that affect the technical efficiency. In sample selection, a multi stage sampling was used in stage one to select the administrative units, and simple random sampling in the next two stages. The variables used in the stochastic production function frontier model were land, oxen, manure, size of the land, rice income and seed quality. Those included in the technical efficiency model were age, gender, extension services, training, experience, planning system, household size, education and agrochemicals. The study found that seed, labour, fertilizer land and oxen positively and significantly explain rice production. The coefficient for technical efficiency was found to be 77.2 per cent. 36 per cent of the farmers had their levels of technical efficiency ranging between 80 and 90 per cent while only one farmer had technical efficiency of between 20 and 30 per cent. Rice farming experience, education, agrochemicals, training on rice farming and use of extension services were significant while, the size of the household was not. The strength of this study is that it included many variables in both estimation of SFA and technical efficiency model.

Pedroso *et al.* (2018) estimated technical efficiency and inefficiency scores in Thun Bon River Basin in Central Thailand using SFA and a total of 113 rice growers. The study used data conducted in a survey of the growers in 2013. On average, the technical efficiency level was found to be 81 per cent. The coefficients of labour, capital and variable costs were found to be positive and statistically significant. The inefficiency model showed that the coefficients of land and pumping were negative and significant, while that of plots was positive and significant. The implication of this study is that increasing land size for production and increased pumping reduced inefficiency[2]. The drawbacks of this study were that it only considered three determinants of inefficiency, whereas there were many such factors to be considered.

Kumar (2022) measured the technical efficiency of rice farmers in Telangana, India. The study used a sample of 32 rice producing districts (decision making units). The variables used were fertilizers used, seeds planted, organic manure applied, rice produced and water supplied. The Data Envelope Analysis (DEA) was used to measure the technical efficiency, and the Malmquist Total Factor Productivity Index to measure productivity changes between 2019 and 2022. The average TE was found to be 0.86 ranging between 0.59 and 1. Malmquist indices revealed a technical efficiency change of 1.1 and technological change of 0.98. The main limitation of the study was ignoring the many other socio-economic factors that affect TE.

[2] Increased pumping reduces salinity, which increases efficiency.

Sinuraya et.a. (2024) examined the technical efficiency of rice productivity in Indonesia for the period 2018 to 2021 using provincial level data. The study aimed at measuring the TE of rice, and the roles played by agricultural machinery and fertilizers used in rice production in enhancing the TE. The variables used included rainfall, pest attacks, number of rice farmers in a household, fertilizers and machinery. The Cobb-Douglas Stochastic Production Frontier function was specified, and estimated using the stochastic frontier analysis and maximum likelihood methodology. The average rice technical efficiency was found to be 0.82. The variables which were found to affect the TE were fertilizers, dryers, milling units and small combine harvesters. The limitation of the study was the omitted variable bias (eg, farmer's education and market accessibility), reliance on secondary data which may have higher inaccuracies compared to primary data, and focussing on specific provinces only.

2.3.3 Determinants of Technical Efficiency

Tan *et al* (2010) investigated the determinants of rice technical efficiency in South East China, with special attention on land fragmentation. The study focused on 339 households who planted rice in 2490 plots. Among the surveyed households, 264, 206 and 261 planted early, one season and late rice respectively. Technical efficiency was found to range from 0.8 to 0.91. Land subdivision was found to be a major factor of both early and late rice growing seasons. The studies included several variables where age and education were measured in years, household size and number of plots as number, share of labor force members in household as a percentage and average distance from plots to homestead in minutes. Increase in the farmers plot size was found to increase efficiency while increase in distance between home and the farms reduced it. Other determinants of technical efficiency varied for each of the season.

The limitation of the study was that it used so many land interaction variables – 21 of them – of which only three were significant. This could have biased the results.

Khai and Yabe (2011) carried out research to determine the technical efficiency levels of rice farming and its determinants in Vietnam. The study used the Vietnam Household Living Standards Survey of 2005/06. A total of 4216 rice farmers were interviewed but only 3733 responses were considered as the rest of the surveys had missing data. The independent variables used in the research were costs of labour, machinery, pesticides and seed; and area of the land planted with rice and amount of family rice labourers. The amount of rice and fertilizer used were measured in Kgs, family labour in hours, land under rice in hectares and expenditures in thousand Vietnamese dollars (eg, pesticides costs, seed expenditures, machinery services, hired labour, small tools and machinery and other rice expenditures). The study used a stochastic frontier method and established that the mean technical efficiency was 81.6 per cent, while the minimum and maximum efficiency levels were 17 and 99 per cent respectively.

Using a Tobit model, the study found that education and intensive labour use were the key factors of technical efficiency. Nevertheless, agricultural policy was found to have negative and significant effect on the technical efficiency, contrary to expectations. Most government policies were geared towards improving rice farming which caused these results.

Galawat and Yabe (2012) investigated the efficiency and determinants of inefficiencies among rice farmers in Burnei, Tanzania. The study used data from interviewing 82 and 20 farmers from Brunei and Temburong, respectively. To measure the efficiency, the author collected data on fertilizer, pesticide, herbicide, labour and machinery. Yield was measured in tonnes per hectare, fertilizer in kgs per hectare, herbicide and pesticides in mililitres per hectare, machinery in Brunei dollars per hectare (B$/hectare), and labor as person per hectare. SFA was used to estimate the efficiencies while ordinary least squares (OLS) and maximum likelihood estimation (MLE) were used to investigate the determinants of inefficiencies. All the variables except pesticides had the expected positive signs. The study found the values of technical, allocative and economic efficiencies to be 76, 66 and 53 per cent respectively. Soil irrigation and irrigation improvements were found to increase rice productivity. Other key determinants of efficiency were found to be age, gender, cooperative/association membership, training and experience. The study, nevertheless, did not explain how it came up with the sample sizes in the two districts.

Ahmad and Sinhar (2017) explored the technical, allocative and economic efficiency of rice production in Bihar using DEA method. The study further analysed the determinants of efficiencies using the Tobit model. The study utilised data from the farm where 450 farmers from 45 administrative regions of Bihar were interviewed. The study used data from the cultivation seasons 2008/09 and 2010/11. Age was measured in years, education as categorical (primary, secondary and post-secondary), land size under rice in hectares, household occupation as a dummy (one for agriculture, 0 otherwise), seed type as a dummy (hybrid 1, non-hybrid 0) and irrigation machines as a dummy (have own irrigation machine 1, no irrigation machines 0). The three efficiencies were found to be 62, 62 and 38.8, respectively. Machinery, quality seeds and low training were found to be the major determinants of inefficiencies. The study, however, did not justify the use of DEA instead of SFA method, which has been widely used by many studies, unlike DEA.

Houngue and Nonvide (2020) conducted a study in Mono and Couffo in Benin to estimate and measure the determinants of TE in the country. A sample of 210 rice farmers was used. The variables of interest were rice production (output), herbicides, fertilizers, labor, education, credit access, gender, age and seeds. A one-step stochastic frontier analysis was used to estimate the TE. The one step simultaneous estimation method was used to derive the TE and measure its determinants. Further, a Chow Test was used to measure the differences in TE in the two regions (departments). The mean TE was found to be 0.78, with the key determinants being labor, seeds, education, credit, fertilizers and herbicides. The shortcomings of the study was failing to fully account for heterogeneity in the two regions analysed, limited generalizability and potential self-reported bias from the data.

Chandel et.al. (2022) examined the determinants of rice technical efficiency in Uttar Pradesh, India. The authors used a sample of 800 farmers. The variables used were labor, education, age, property ownership, irrigation practices and use of machinery (tractors). A stochastic frontier analysis was used to measure the TE and a regression analysis to find out the determinants. The mean TE was found to be 0.72 and the main determinants were labor, hybrid seeds, age, education (schooling) and property ownership. The coefficient of tractors was positive but insignificant. The main weaknesses was the limited scope: The region only focused only on Uttar Pradesh only, a region the authors asserted that it produced only 12% of India's rice. Thus, the recommendations could not generalize well to the entire country.

2.4 Overview of the Literature

Agricultural production has always lagged behind the ever-increasing demand for agricultural produce from the growing human population. However, irrigation production has always been viewed as a potential to overcome the challenge of increased population despite its high development costs. Several studies have discovered that a number of factors influence production of rice in various irrigation schemes. These include land under cultivation, availability of water, credit, labour, fertilizer used, farmers' literacy levels, the structures managing the irrigation schemes and the institutions themselves. For example, Udayanganie *et al*. (2006) found a positive relationship between credit services and productivity, Koirara et al (2016) found a similar relationship between land ownership, land area and the costs of fertilizer, irrigation, labour and fuel on rice productivity and Prianthi *et al.*, (2015) found diminishing effects of land size on rice productivity. Some studies like Udayanganie *et al*. (2006), found a negative relationship between use of pesticides and productivity (although it is not expected). Notably, most of the studies reviewed measured technical efficiency compared to other types of efficiencies (for example economic and environmental). The variables used in the current study as determinants of production were based on the literature reviewed in this section. Additionally, the production and the SFA framework used as theoretical basis for the current study was also sourced from this section (specifically the production theory and the frontier measures.

There are three different types of efficiency measures. These are allocative efficiency, technical efficiency, and economic efficiency. All the three efficiencies can be derived from a production function. Technical efficiency is a measure of how well or effectively, certain set of inputs can be used to produce a given output. A firm is said to be technically efficient when it is producing maximum possible output by utilising minimum inputs like capital, labour and technology.

Technical efficiency is measured as a ratio of output from a set of inputs to the maximum potential output that can be produced from given inputs. A value close to one is preferred. Allocative efficiency on the other hand measures the farmers' capability to apply farm inputs in their best quantities with respect to their prices. It occurs at the output level where the prices of inputs equal their marginal cost. Finally, economic efficiency is a product of both the technical and allocative efficiency

The Stochastic frontier analysis (SFA) is a parametric method of estimation while data envelop analysis (DEA) is a non-parametric approach (it is a programming method). Most of the studies reviewed such as (Udayanganie *et al*, 2006; Tiajani, 2006; Kouser, Mushtaq and Abedullah, 2007) used SFA to measure technical efficiency whereas only a few used the DEA approach, for example Kiatpathomchai (2008) and Watkins *et al* (2013). Based on the reviewed studies, the current study borrows the stochastic frontier analysis in its estimation of the technical efficiency.

The studies adopted Tobit regression to investigate the factors affecting efficiency (or inefficiency) of rice productivity (for example Kiatpathomchai, 2008 and Khai and Yabe, 2011, among others). With the exception of Kiatpathomchai (2008) and Udayanganie *et al*. (2006) who found very low levels of rice technical efficiency (14 and 37 per cent respectively), other studies found higher levels. For instance, Tiajani (2006) found an average of 86.6 per cent among rice farmers in Nigeria's Osun state, Kouser, Mushtaq and Abedullah (2007) found average efficiency levels of 91 per cent and Ndayitwayeko and Korir (2012) got 73 per cent. The current study borrowed Tobit model to measure the determinants of TE. Additionally, the variables used in the model were also adopted from these models.

Each of the study reviewed had its own limitations. For instance, Udayanganie *et al*. (2006) only considered technical efficiency; Kouser, Mushtaq and Abedullah (2007) only considered four determinants of technical efficiency while Tan *et al* (2010) used 21 interaction variables of which only three were significant.

Among the studies reviewed, only Kuria *et al.* (2003) and Omondi and Shikuku (2013) and Mwatete *et al*. (2015), have examined the technical efficiency of rice in Kenya. The latter two concentrated in Ahero and Kano Irrigation Schemes, while only the former studied Mwea Irrigation Schemes. In addition, although the government came up with the National Rice Development Strategy to boost rice production in the country in 2008, which was supposed to be implemented between 2008-2018, production has remained low and no study has investigated this in the post-NRDS implementation period. Further, the studies done in Kenya by Kuria et al. (2003), Omondi and Shikuku (2010), and Mwatete et al. (2015) suffered from small sample size bias. The sample sizes from the three studies were 106, 123, and 220, respectively. Additionally, the study is undertaken in the largest rice irrigation scheme in Kenya. The current study uses a sample of 313 farmers—all sampled from the five rice-growing regions in Mwea. This study, therefore, sought to measure the technical efficiencies of rice farmers in Mwea irrigation scheme and determine the factors affecting its production efficiency.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter presents the research design of the study, theoretical framework and the econometric model adopted in the study. Moreover, the study also outlines the data sources of the study together with the techniques used in the data analysis to achieve the objectives.

3.2 Research Design

This study utilised cross sectional survey research design. This design was chosen since time series data on rice production by farmers, and the associated variables that affect production and technical efficiency were not available. Moreover, use of the cross-sectional survey research design enabled the use of most recent field data. In this research design, data is collected among a sample in one point of time-in this case October 2019. A total of 313 farmers were sampled from five regions of Mwea Irrigation Scheme. The type of current research is explanatory as it seeks to explain the causal determinants of rice production and technical efficiency. Structured questionnaires were prepared and administered to rice farmers. The data collected was across various categories that allowed for the analysis of the technical efficiency. These categories are general information of the farmer, financial information, production characteristics, extension and training services, selling characteristics and marketing of rice.

3.3 Theoretical Framework

(a) Theoretical Framework for rice production

The Cobb Douglas production function was used to analyse the factors that affect rice production in Mwea Irrigation Scheme. This theory was adopted from the theoretical literature reviewed in Chapter two. It was deemed the best, given the nature of the study's inputs and output. The theory was used by several authors, for example Tijani (2006) , Lema, et.al. (2017) and Pedroso *et al.*, (2018). Inputs are required in the process of production to produce a given level of output. In case of rice farming, the inputs include labour, machinery, fertilizer, herbicides, land, chemicals and seeds.

The production function (Cobb Douglas) can be presented as follows:

$$Y_i = g(X_i, \theta)e^{\mu_i} \tag{3.1}$$

Where,

Y_i is output,

X_i represents factor inputs,

θ are the parameters for estimation,

e is the exponential and

μ_i is the overall error term.

Taking the natural log of equation (3.1):

$$lnY_i = \theta lnX_i + \mu_i \tag{3.2}$$

Equation (3.2) can be re-written as:

$$lnY_i = \theta_0 + \theta_1 lnX_{11} + \theta_2 lnX_{12} + \theta_k lnX_{13} + \cdots + \theta_n lnX_{1n} + \mu_i \qquad (3.3)$$

Where,

$X_i's$ represent the inputs used by farmer i and

Y_i represents the rice output by farmer i

There are two major methods that have been cited in literature for measuring technical efficiency: stochastic frontier analysis (SFA) and the data envelop analysis (DEA). The SFA is stochastic and parametric while the data envelop analysis is non-parametric and non-stochastic. SFA separates noise from inefficiency effects and generates good results when multiple inputs are used to generate single output. However, the DEA cannot separate noise from inefficiency but works best when comparing multiple inputs and multiple outputs (Khai and Yabe, 2011). Since rice is a single output produced using multiple inputs, this study used SFA to measure rice production technical efficiency. The SFA was based on the production frontier model.

According to Ogada et.al. (2014), production efficiency is made up of two components namely technical and allocative efficiency. Allocative efficiency occurs when the farmer is able to produce maximum output from a given set of inputs (or, put in another way, when a farmer is able to utilise the least number of inputs to produce maximum output). Allocative efficiency is the use of a mix of farm inputs to maximize a farmers revenue given the input prices. Due to the distortion of farms input prices through subsidies and legislations, allocative efficiency is thus not suitable to measure prices. Ogada et.al. (2014), thus advocates for the use of technical efficiency to measure the levels of efficiency.

Estimations techniques are generally categorized into two: stochastic and deterministic approaches. Parametric methods impose a functional form on the production function considering the assumptions of the error term distribution. In addition, these methods split the error term into two components namely the random and farm-specific inefficiency components. On the other hand, non-parametric methods do not impose any functional restriction on the production function and they do not specify the distribution of the error term.

Examples of the parametric methods are the Cobb–Douglas, constant elasticity of substitution (CES) and translog production functions. DEA is the most popular of the non-parametric methods and it uses linear programming to calculate the efficiency. Coelli, Rahman and Thirtle (2002), and Jacobs, Smith and Street (2006) have demonstrated that there is no systematic difference in the results of the two approaches, unless there is a mis-specification of the functional form of the production function. The authors further argue that the data envelop analysis performs better than the stochastic frontier analysis when functional form of the production function is known. The opposite is also true. Based on the existing literature on production functions, this study used the SFA approaches instead of DEA.

(b) Theoretical framework for measuring technical efficiency

3.3.1 Empirical Model/ Model specification

3.3.1.1 Factors affecting rice production

To analyse the factors affecting rice output in Mwea Irrigation Scheme, this study utilized the Cobb Douglas production function. Agricultural inputs are required to produce a given level of output. In the case of rice farming, the inputs include labour, machinery, fertilizer, herbicides, land, chemicals and seeds.

The Cobb Douglas production function can be presented as follows:

$$Y_i = g(X_i, \theta)e^{\mu_i} \qquad (3.4)$$

Where,

Y_i is output,

X_i represents factor inputs,

θ are parameters for estimation,

e is the exponent and

μ_i is the overall error term.

Assuming equation 3.4 takes a multiplicative Cobb Douglas production function, we can linearize as follows

Taking the natural log of equation (3.4):

$$lnY_i = \theta lnX_i + \mu_i \quad (3.5)$$

Equation (3.5) can be re-written as:

$$lnY_{ij} = \theta_0 + \theta_1 lnX_{11} + \theta_2 lnX_{12} + \theta_k lnX_{13} + \cdots + \theta_n lnX_{1n} + \mu_i \quad (3.6)$$

Where,

$X_{ij}'s$ is a vector of inputs

Y_{ij} represents the rice output by farmer i

Equation (3.6) can be explicitly displayed as follows:

$$lny_{ij}=\delta_0 + \delta_1 lnLab + \delta_2 lnChem + \delta_3 lnSds + \delta_4 lnFert + \delta_5 lnMach + \delta_6 FarmingCourse + \delta_7 AdvVisit + \delta_8 Water + \delta_9 Credit + \epsilon \quad (3.7)$$

Where:

y_i is rice production by farmer i per acre per season,

Lab is amount of labor per acre per season,

$Chem$ is amount of chemicals used to produce rice per acre per season.

Sds is quantity of seeds planted in kilograms per acre per season,

$Fert$ is the amount of fertilizer used per season per acre per season,

$Mach$ is the cost of machine used per acre per season,

Farming Course is whether a farmer has gone to a farming course, *AdvVisit* is the advisory visits,

Water is an indicator of adequate water supply and

Credit shows whether the farmer had accessed credit

3.3.1.2 Measuring the Technical Efficiency Level of Rice Production

Technical efficiency is measured as a ratio of actual output from a given set of inputs to maximum possible output from a given set of inputs. Stochastic frontier analysis (SFA) specifies two terms: a random variable specified by ε_i and an error term specified by γ_i. (The derivation of the model is given in this section, for example see equation 3.10)

Stochastic Frontier Analysis is used because, unlike the Data Envelop Analysis (DEA), it takes into account both the measurement error and other noise out of the farmers control (Coelli, *et al* 2005; Salau *et al*., 2012; Addai and Victor, 2014; Lema, et.al. (2017). Two popular SFA approaches that were adopted for calculating Technical Efficiency are similar to those used by Balttese and Coeli (1987) and Jundrow *et.al*. (1982). The two methods give very close estimates of TE, with the difference being that the former calculates TE using the expression E[exp(-u)|e], while the latter uses exp[-E(u|e)]. This study was based on the stochastic frontier model which measures how a given set of inputs is used in producing a given amount of output. A general production function is re-specified as follows:

$$Y_i = f(X, \delta) + \mu_i \tag{3.8}$$

Equation (3.8) can also be written as:

$$Y_i = f(X_i, \theta)e^{\mu_i} \tag{3.9}$$

Y_i is rice output by the $i'th$ farmer,

Where: $f(X, \delta)$ is Cobb Douglas functional form,

μ_i is the error term and has two components, that is $\mu_i = \gamma_i - \varepsilon_i$ (3.10)

and

X, δ are the factor inputs

ε_i captures the technical efficiency/inefficiency of each farmer and

γ_i is identically and independently distributed error that captures random output variation.

The variance of ϵ_i is given by $\sigma^2_{\varepsilon_i} + \sigma^2_{\gamma_i}$

The Cobb Douglas functional form is preferred when a linear relationship is assumed between inputs and is widely used in many production and efficiency measurement studies, including the reviewed ones. It is also suitable for smaller datasets, compared with the translog model. Another advantage of this model is that most TE estimation techniques like DEA and SFA are well modelled with Cobb Douglas compared with translog model. The main limitations of this model are its linearity and constant returns to scale assumption. On the other hand, translog production function is used in complex situations where relationship between inputs and outputs is assumed to be non-linear. It's computationally demanding and may lead to an over-fitted model. Moreover, it requires larger dataset as many parameters are to be estimated – and most of these parameters are hard to interpret. Finally, it has also been found that the differences in the TE obtained using the two methods are trivial (mild and negligible) (Pechrová and Ondrej, 2020). For this reason, the study adopted the Cobb Douglas production function.

The technical efficiency of every farmer is calculated as the ratio of observed output to the maximum output possible (SFA output):

$$TE = \frac{Y_i}{Y_i^*} \tag{3.11}$$

$$TE = \frac{y_i}{\exp(X_i'\delta + v_i)} = \frac{\exp(X_i'\delta + \gamma_i - \varepsilon_i)}{\exp(X_i'\delta + \gamma_i)} = \exp(-\varepsilon_i), \quad \varepsilon_i \sim iid(0, \sigma_\varepsilon^2) \tag{3.12}$$

Assumption that ε_i is normally distributed leads to biased estimates of δ (Pedroso *et al.*, 2018)

Heteroscedasticity is dealt with by parameterizing ε_{it} as:

$$\sigma_\varepsilon^2 = \exp(z_{\varepsilon,i}' w_\varepsilon) \tag{3.13}$$

Where:

w_ε is a vector of parameters to be estimated and

$z_{\varepsilon,i}'$ is a vector of variables

The model estimates are estimated by maximizing the log likelihood equation (L). The likelihood equation is given by:

$$lnL = \sum_{i=1}^{N} \left\{ \frac{1}{2} ln\left(\frac{2}{\pi}\right) - ln\sigma - ln\Phi\left(\frac{-\epsilon_{i\vartheta}}{\sigma}\right) - \frac{\epsilon_i^2}{\sigma^2} \right\} \tag{3.14}$$

Where:

$\sigma = \sqrt{\sigma_\gamma^2 + \sigma_\varepsilon^2}$,

$\vartheta = \frac{\sigma_\varepsilon}{\sigma_\gamma}$ and

$\epsilon_i = y_i - x_i'\delta$

The technical inefficiency is estimated as the conditional distribution of $f(\varepsilon/\epsilon_i)$

$$E(\varepsilon/\epsilon_i) = \varepsilon_{*i} + \sigma_* \left\{\frac{\phi\left(-\frac{\varepsilon_{*i}}{\sigma_*}\right)}{\Phi\left(-\frac{\varepsilon_{*i}}{\sigma_*}\right)}\right\} \qquad (3.15)$$

Where:

$\varepsilon_{*i} = -\frac{\epsilon_i \sigma_\varepsilon}{\sigma^2}$ and

$\sigma_* = \frac{\sigma_\varepsilon \sigma_\gamma}{\sigma}$

Finally, the technical efficiency is given as:

$$TE = E\{\varepsilon/\epsilon_i\} = \left\{\frac{1-\Phi\left(\sigma_* - \frac{\varepsilon_{*i}}{\sigma_*}\right)}{1-\Phi\left(-\frac{\varepsilon_{*i}}{\sigma_*}\right)}\right\} exp\left(-\varepsilon_{*i} + \frac{1}{2}\sigma_*\right) \qquad (3.16)$$

Equation (3.18) was used to measure technical efficiency and was estimated using a maximum likelihood method. Three different error distribution can be specified: half normal, truncated normal and exponential. Different assumptions regarding the distribution of the error terms lead to different technical efficiency measures. However, the difference is minimal and when the efficiencies are ranked, the rankings are robust to distributional choice. The principle of parsimony favors the half normal and the exponential models (Coeli *et.al*, 2005). The exponential error term is used when the error terms are believed to be positive and follow a declining exponential trend, when the error terms are independent of rice TE and when the error terms decline as TE increases. On the other hand, half normal error terms assume that most of the errors are positive, and there are some skewness of the error terms (TE) towards zero. Half normal error term was assumed and used (Pedroso *et al.*, 2018).

The half normal error term can be specified as follows:

$$u_i \sim iidN^+(0, \sigma_u^2) \tag{3.17}$$

This means that the probability density function of each error term is a truncated version of a normal random variable with a mean of zero and a variance σ_u^2. The authors' parameterize the log likelihood for the half normal model in terms as:

$$\sigma^2 = \sigma_u^2 + \sigma_\varepsilon^2 \tag{3.18}$$

and $\gamma^2 = \frac{\sigma_\varepsilon^2}{\sigma_u^2}$. (3.19)

Technical inefficiency is zero when gamma (γ) is zero. The log likelihood is given as:

$$lnL(y|\beta, \sigma, \gamma) = -\frac{1}{2} ln\left(\frac{\pi\sigma^2}{2}\right) + \sum_{i=1}^{L} ln\phi\left(\frac{-\varepsilon_i\gamma}{\sigma}\right) - \frac{1}{2\sigma^2}\sum_{i=1}^{L} \epsilon_i^2) \tag{3.20}$$

Where y is a vector of output,

$\varepsilon_i = v_i - u_i = lnq_i - x_i{}'\beta$ is a composite error term,

ϕ is the cumulative error term (CDF) evaluated at x

After calculating the technical efficiency, its descriptive statistics and the distribution across the sample by deciles were computed. Furthermore, a comparison of the less and highly efficient farmers was conducted using the median TE as the threshold value, for both the continuous and the categorical predictors.

3.3.1.3 Factors Affecting Rice Production Technical Efficiency

Factors that determine the technical efficiency of a farmer can be grouped into institutional, characteristics of the farmer and that of the farm (Ogada *et. al.,* 2014; Ateka *et.al*, 2018). These are institutional characteristics like access of credit, market extension and marketing channel, farmer characteristics like education of the farmer, age, gender and labour, and farm characteristics like the rice seeds variety, farm size, and location of the farm and presence of irrigation machines.

Using the efficiency scores obtained from objective two, the determinants of the technical efficiency were then modelled using the Tobit model. Tobit model is used when the dependent variable is constrained in a given interval. In this case, technical efficiency varied from zero to one. The Tobit model is defined as:

$$Y = \{ 0 \leq y^* \leq 1\} \tag{3.21}$$

Where:

$$y^* = \theta x_i + \varepsilon_i \tag{3.22}$$

Where:

Y is the technical efficiency score,

y^* is a latent variable (efficiency),

θ is a vector of parameters and

x_i is a vector of explanatory variables.

A firm is considered efficient when it is producing a maximum possible output given minimum quantities of inputs like labour, technology and capital. Therefore, to establish the determinants of technical efficiency of rice production in Mwea irrigation scheme, a Tobit model was used (Maddala, 1999; Fethi*et al.*, 2000, Hwang and Oh, 2008; Greene, 2012; Ahmad and Sing, 2017) among others.

The explicit Tobit model to be used in this study, therefore, is expressed as follows:

$$TE = \theta_0 + \theta_1 Educ + \theta_2 Lsize + \theta_3 St + \theta_4 Exper + \theta_5 Ext + \theta_6 Gender + \theta_7 Water + \theta_8 Credit + \varepsilon \tag{3.23}$$

Where:

TE is technical efficiency,

$Educ$ is education,

$Lsize$ is size of the land in acres,

St is seed type,

$Exper$ is experience,

Ext is availability of extension services,

Gender is gender of the farmer,

Water is adequate irrigation water supply and,

Credit is whether the farmer had used loans (credit).

Since the results of the Tobit model are not directly interpretable as probabilities, the marginal effects of the Tobit model were calculated, after estimating the equation.

Note: There is limited literature on the role of the interaction of variables on technical efficiency, and thus the effect of interaction variables was not included, e.g., gender*education or gender*seed Type.

3.4 Study Area

The study was conducted in the Mwea Irrigation Scheme, situated in Kirinyaga County, approximately 100 kilometres northeast of Nairobi. This region is recognized as a vital agricultural hub, primarily focused on rice production, and has been developed extensively since its establishment in 1954. The scheme is composed of 7022 farmers, who grow rice in 26,000 acres out of 30,350 acres of the gazetted area. 22,000 acres are situated within the main scheme while the remaining 4,000 acres are in the out growers. The main rice variety grown is Basmatti 370. The main types of irrigation are application, conveyance and distribution (National Irrigation Board, 2018). The scheme is segmented into five areas: Karaba, Wamumu, Thiba, Tebere and Mwea. The area is further divided into 8, 7, 12, 19 and 18 subsections, respectively. These schemes have varying numbers of farmers, with Mwea and Tebere having the largest number of farmers.

3.5 Sampling Technique

There are different techniques that are used in calculating the sample size. This study adopted the approach by Lema, et.al. (2017). The sample size can be calculated as shown below:

$$n = \frac{z^2 pq}{e^2} \tag{3.24}$$

Where:

n is the size of the sample,

z is the level of confidence,

p and q are proportions of attributes that are present in the population and

e is the desired precision level.

A sample size of 298 was determined, which was rounded up to 300, with a provision for 30 non-responses, bringing the total target to 330 respondents. The aim was to obtain 300 valid responses. This sample size was calculated assuming a 95 percent confidence level, a proportion of 50 percent, and a precision level of 2.75 percent. Based on this data and the desired sample size, the allotment of the sample in each region was done as shown in Table 3.1.

Table 3.1: Targeted sample and the actual sample

Region	**Acreage**	**Targeted sample**	**Actual sample**	**Deficit / surplus**
Tebere	3252.26	63	68	6
Mwea	2957.5	57	63	6
Wamumu	3593.45	69	62	-7
Karaba	2936.73	57	60	3
Thiba	2806.75	54	60	6
Total	15, 546.75	300	313	13

Source: Author's calculation (2019)

Note: The allotment was done based on acreage because the data on the number of all rice farmers in Mwea Tebere (the sampling frame) was not available at the board's offices. However, the total acreage in the irrigation scheme was available, and it was evident that there was high correlation between acreage and the number of farmers, that is, the distribution of rice area in each of the five regions – the larger the area, the higher the number of farmers. The total acreage and the distribution were thus used as the sampling frame. For example, the total Tebere rice area is 3252.26, and the total acreage in Mwea Irrigation Scheme is 15,546.75. Thus, the total sample was calculated as 3252.26/15546.75*300 = 63.

The results presented in Table 3.1 reveal that the sample size was well achieved, with the exception of Wamumu where a deficit of seven farmers was recorded. Thiba, Mwea and Tebere had the highest oversampling of six farmers. Before the actual survey was carried out, a pre-test using 60 respondents within the sample was carried out to familiarize with the area, gauge possible responses, evaluate the interviewers and identify areas of improvement before the actual survey. The interviewers were trained before the actual data collection. The interviewees were selected at random using systematic sampling, where every 5th household farmer was sampled.

3.6 Definition and Measurement of Variables

The variables used and their respective definition and measurement are as shown on Table 3.2.

Table 3.2: Definition and Measurement of Variables

Variable	Description	Measurement Variable
Output	Amount of rice produced by the farmer.	Measured in kilograms per season per acre.
Labour	Number of rice workers employed.	Number of rice workers per acre per season.
Land size	Land acreage under rice production.	Size of the land under rice production in acres.
Chemicals	Substance used to control harmful weeds.	Amount of pesticide and herbicides in litres applied per season per acre.
Machinery	Machinery hired to work on the rice farms.	Cost of using machine/machinery in rice per season per acre. Measured in Kenyan shillings.
Seeds	Total amount of seeds planted.	Measured in kilograms planted per season per acre.
Fertilizer	Amount of inorganic fertilizer applied.	Measured in kilograms applied per season per acre. Since the farmers use various fertilizers, the means (averages) of the amount used was calculated and used in the analysis.
Technical efficiency	Measure of how well the farmers utilize inputs to produce a given output.	Was measured as a percentage. It ranges from 0 to 1.
Education	The topmost level of farmers' education.	0 if none, 1 if primary, 2 if secondary and 3 if tertiary.
Gender	Sex of the farmer	1 if male and 0 if female.
Age	How old a farmer is.	Measured in years.
Occupation of the farmer	Major profession of the farmer.	1 if the main occupation of the farmer is farming, 0 if otherwise.
Seed type	A measure of the quality of the rice seeds planted.	1 if hybrid seeds used and 0 if otherwise
Irrigation machines	Various irrigation machines used by the farmer.	A dummy variable, taking the value of 1 if the farmer has their own irrigation machines and 0 if otherwise.
Experience	A measure of how long a farmer has been growing rice.	The number of years that the farmer has cultivated rice.
Extension services	Education on farming methods to farmers meant to improve productivity.	A dummy variable. 1 if the farmer has attended and 0 if otherwise.
Water shortages	An indication of water rationing in the scheme.	A dummy variable. 1 if a farmer has no water shortages and 0 if otherwise.
Credit availability	A measure of whether the farmer has access to credit	A dummy variable. 1 if a farmer had used credit and 0 if otherwise.
Advisory visits	A measure of whether the farmer has received advisory visits from the agricultural officers	A dummy variable. 1 if a farmer had received advisory visit, and 0 if otherwise.

Source: Author's illustration (2019)

Note: Inorganic fertilizers were considered because farmers exclusively rely on inorganic fertilizers for production and not organic ones. Surprisingly, no farmer indicated that they used organic fertilizers only.

3.7 Data Type and Source

Primary data was collected from 313 farmers in Mwea Tebere Irrigation Scheme. Farmers were identified using disproportional sampling method. Disproportional Sampling method divides the population into subgroups or strata. It employs a sampling fraction that is not similar to the strata as some of the strata are oversampled as relative to others. A questionnaire (well structured) was developed and used as the main tool of data collection. Data was coded and cleaned appropriately before the estimations were done.

3.8 Validity of Research Instruments

According to Kothari (2008), validity of research instruments measures how accurate the research findings resonate with the actual situation/phenomenon. A research instrument is valid if it gives sound results. To ensure that the results are valid, the questionnaire was discussed with a sample of the rice farmers, refined and corrected before the actual survey.

3.9 Reliability of the Research Instruments

Reliability measures consistency and stability of research instruments. Data collection assistants were identified and trained on data collection to ensure consistent results. In addition, a pretest study was done on 60 farmers and the consistency observed.

3.10 Ethical Consideration

This study observed all the ethical consideration. These included: observing the privacy of the farmers and holding it in great confidence for purpose of the research only, obtaining a research permission letter from National Commission for Science, Technology and Innovation (NACOSTI) and Kenyatta University (KU). A copy of the findings is to be given to the NIB Mwea offices so that they can use the policy suggestions to improve rice farming among rice farmers in Mwea Irrigation Scheme.

3.11 Data Cleaning and Analysis

Before delving into the descriptive statistics of the study, data was cleaned and prepared accordingly. This ensured harmonization in the data. New variables like the average amount of fertilizer that a farmer uses was derived at by averaging the different amounts of fertilizer that the farmer used. The variable average machine cost was entered as the average cost of machine hire per acre. To get the cost of machine hire per season per acre, the average cost of machine was multiplied by the number of times that the farmer used it per season. Similarly, to enable comparison, all the other variables that required comparison were converted to per acre per season terms. They include pesticides, herbicides, fertilizer, harvest (output), seeds and labor.

Having thoroughly prepared the data, it was then coded and analysed. Descriptive analysis was done first. Afterwards, the objectives of the study were addressed. This study had three objectives. The first objective focused on identifying the determinants of rice production in Mwea irrigation scheme, was answered using a multiple regression analysis. Technical efficiency in Mwea irrigation scheme was measured using a stochastic frontier analysis. To further explore the determinants of technical efficiency, a Tobit model was employed, utilizing the maximum likelihood method for analysis.

CHAPTER FOUR

EMPIRICAL FINDINGS

4.1 Introduction

The response rate, the descriptive analysis, the empirical findings and the diagnostic tests are discussed in this chapter. The results are ordered in respect to the specific objective as discussed above.

4.1.1 Response rate

As described in Chapter three, the study targeted 300 respondents from five different rice growing regions of Mwea namely: Mwea, Tebere, Thiba, Wamumu and Karaba. The field work was carried out between 11.09.2019 and 16.09.2019. To cater for non-response, the study targeted a total of 330 respondents so as to achieve the required target of 300. Of these, four respondents refused to answer. This left 326 observations. Among these, only 12 questionnaires were invalid. One of the farmers in Tebere had just started farming rice and had not harvested. He was also excluded from the study. Therefore, a total of 313 observations were used. Thus, the actual response rate was 94.84 per cent. This is the sample that was used in the study.

4.2 Descriptive Statistics

4.2.1 Summary Statistics

Before the estimations were done, summary statistics of the variables that affect rice production in Mwea Irrigation were computed. The descriptive statistics were categorized into two: the continuous variables and the categorical variables. The descriptive statistics for the continuous variables are presented in Table 4.1, while the ones for the categorical variables are presented in Table 4.2.

Table 4.1: Descriptive Statistics of the Variables that Affect Rice Production (continuous variables)

	Measurement unit	mean	std	min	median	max
Period growing rice	**Years**	20.7	16.51	0.75	15	61
Total land size under rice	**Acres**	2.05	1.51	0.125	1.5	6
Seed	**Kgs**	21.11	5.98	5	20	36
Amount harvested	**Kgs**	2,344.08	516.39	400	2,500	4,000
Labor days	**Number of days**	16.51	16.88	0	10	132
Labor hired	**Number of people**	4.16	3.45	0	3	20
Total labor hired	**Number of people hired*days hired**	72.97	66.39	0	51	480
Total machine cost	**Ksh**	12,839.7	7,205.91	0	11,332	48,000
Herbicide	**Litres**	0.98	0.71	0	1	8
Pesticide	**Litres**	1.25	11.29	0	0.5	20
Fertilizer	**Kgs**	68.66	28.98	8.33	66.67	200

Note: The seeds planted, harvest, labor hired, total labor, total machine cost, pesticides, herbicides and fertilizer are in per acre per season terms.
Source: Author’s illustration (2019)

The results presented in Table 4.1 show the mean amount of rice harvested was 2,344.08 kgs per acre per season. This implies an average of 2.344 tonnes per acre per season. This is far below the Sub-Saharan Africa (SSA) average of between 3.4 to 5.4 tons per acre between 2008 and 2012 (Global Yield Cap Atlas, 2020). This implies that rice productivity is low in Mwea compared to Sub Saharan Africa. The median harvest was 2.5 tonnes per season per acre. The minimum amount of rice harvested was 400 kgs per season per acre. Similarly, the largest amount of rice harvested was 4 tonnes per season per acre.

Hired labour in the rice farms per season per acre averaged 16.51 days and a standard deviation of 16.88 days. The minimum was zero, which implies that farmers with very small lands (mostly less than one acre) used unpaid family labour. The median number of days that the workers were hired was 10 days. A mean larger than the median implies that there were few large farmers who hire labourers for many days and many farmers who hire labourers for fewer days. The mean number of people hired per season per acre averaged 4.16 people with a median of 3 people and a standard deviation of 3.45 people. The maximum is 20 workers. As in the previous case, the minimum labourers hired were zero since some small firms did not hire any work.

The mean and median amount of pesticides applied per season per acre was 1.25 and 0.5 litres, respectively, with a standard deviation of 11.29 litres and a minimum of zero. A higher standard deviation than the mean implies that there were large variabilities in the data, meaning that some farmers applied a lot of pesticides in their rice farm. The mean volume of herbicides used per season per acre was 0.98 litres with a standard deviation of 0.71 litres, a minimum of zero and a maximum of 8 litres.

The mean amount of the fertilizer used per season per acre was 68.66 kilograms with a standard deviation of 28.98 kilograms, a minimum of 8.33 kilograms, a median of 66.67 kilograms and a maximum of 200 kilograms. This implies that the amount of fertilizer used was important in explaining the yield the farmer got.

The mean cost of rice farming machines in per acre per season was Ksh 12,839.68 with a standard deviation of Ksh. 7,205.91, a minimum of zero, a median of Ksh 11,332 and a maximum of Ksh. 48,000. The majority of the machines used were rotavators for breaking, churning and aerating the soil before planting, levelling machines for breaking soil particles and smoothening land, tractors for land cultivation and harvesters for harvesting rice. Finally, the mean quantity of seeds planted per season per acre was 21.11 kilograms with a standard deviation of 5.98 kilograms, a minimum of 5 kilograms, a median of 20 kilograms and maximum of 36 kilograms.

Descriptive statistics for categorical variables are as presented in Table 4.2.

Table 4.2: Descriptive Statistics of the Categorical Variables

Sex	**Count**	**Percentage**
Male	196	63
Female	117	37
Total	**313**	**100**
Education level	**Count**	**Percentage**
None	37	12
Primary	155	50
Secondary	100	32
Tertiary	21	7
Total	**313**	**100**
Training	**Count**	**Percentage**
Yes	196	63
No	117	37
Total	**313**	**100**
Main Occupation	**Count**	**Percentage**
Farmer	298	95
Others	15	5
Total	**313**	**100**
Irrigation machines?	**Count**	**Percentage**
Yes	53	17
No	260	83
Total	**313**	**100**
Accessed credit	**Count**	**Percentage**
Yes	129	41
No	183	58
Missing	1	0
Total	**313**	**100**
Adequate water supply	**Count**	**Percentage**
Yes	33	11
No	280	89
Total	**313**	**100**
Seeds variety	**Count**	**Percentage**
Hybrid	263	84
Non Hybrid	50	16
Total	**313**	**100**
Extension services	**Count**	**Percentage**
Yes	184	59
No	129	41
Total	**313**	**100**

Note: The variables are sorted by frequency.

Source: Author's illustration (2019)

Table 4.2 shows that there were more male farmers (63 per cent) than females (37 per cent) in Mwea Irrigation Scheme. This could be explained by the fact that a greater proportion of males owns land as compared to the females. Half of the farmers at Mwea had primary level of education. This high value could be as a result of fewer economic alternatives for the less educated. Moreover, farming could be less attractive for the highly educated individuals. They were followed closely by secondary school certificate holders who were approximately 32 per cent. Only 12 per cent of the farmers had no education at all while 7 per cent had tertiary education. Over 90 per cent of the farmers (95 per cent) had their main occupation as farming. This is not a surprise as farming is the major economic activity in rural areas. The other 5 per cent comprised of business people, health officers and other smaller categories. The proportion of farmers who use hybrid seeds was 84 per cent. This is due to high production capacity of the hybrid variety compared to the non-hybrid one. Farmers use the hybrid seeds in order to maximise output from their farming activities.

The table reveals that close to 83 per cent of the rice growers do not have irrigation machines to use on their farms. It can also be observed that a small proportion of farmers (17%) can afford machines for irrigation. This figure does not compare favourably to the 89 per cent of the farmers who do not have adequate irrigation water supply. Only 63 per cent of the farmers had an opportunity to attend at least one rice farming training course. Extension services from agricultural field officers are key in rice growing but only 59 per cent of the rice growers had accessed these vital services. Only 41 per cent of the farmers had used credit facilities in the course of rice growing. Having examined the descriptive statistics, the study proceeded to answer the objectives.

4.3 Factors Affecting Rice Production in Mwea Irrigation Scheme

The first objective of the research was to determine the factors that affect rice ouput in Mwea Irrigation Scheme. To achieve this objective, equation (3.6) which links both the agricultural inputs applied to produce a given level of output was estimated using the production function model specified in equation (3.7). Before the results were presented and the findings discussed, several diagnostic tests were conducted to ensure sound results. These included multicollinearity, heteroscedasticity, normality and link test. Section 4.3.1 discusses these results.

4.3.1 Diagnostic Tests

(a) Multicollinearity test

When two independent variables are closely related to each other (highly correlated), they give rise to cases of multicollinearity. If estimation is done in the presence of this problem, the results are not reliable since the estimates will be inaccurate. The standard errors are inflated leading to insignificance of the coefficients, and the tests of hypothesis and predictions are wrong (Gujarati, 2022). Values above 0.8 indicate serious multicollinearity problems and in such cases, several actions should be taken to address the problem. These include feature selection, collection of more data, ridge regression and data transformation (for example logging and differencing) among others. Table 4.3 shows the statistics of multicollinearity.

Table 4.3: Correlation analysis for the categorical variables

	Log of total labor hired	Log of average fertilizer	Log of pesticides	Log of herbicides	Log of total machine cost	Log of total seeds planted	Total land size under rice	Period growing rice
Log of total labor hired	1							
Log of average fertilizer	0.48	1.00						
Log of pesticides	0.35	0.42	1.00					
Log of herbicides	0.42	0.61	0.62	1.00				
Log of total machine cost	0.28	0.37	0.04	0.34	1.00			
Log of total seeds planted	0.53	0.80	0.42	0.67	0.41	1.00		
Total land size under rice	0.49	0.78	0.46	0.65	0.30	0.87	1.00	
Period growing rice	0.23	0.38	0.18	0.27	0.15	0.37	0.42	1

Source: Author's calculations (2019)

Table 4.3 shows that the only correlation that exceeds 0.8 is between total land size under rice and log of total seeds planted. The value was 0.87. However, this was not a problem, because the two variables were not used in the same regression. The log of total seeds planted was used in objective one, while the total land size under rice was used in objective three.

(b) Other diagnostic tests

The other diagnostic tests are presented in Table 4.4.

Table 4.4: Additional Diagnostic Tests

R-squared: 0.8531		
Adjusted R-squared: 0.8478		
Prob >F: 0.00		
Root MSE: 0.3180		
Diagnostics		
Heteroscedasticity	Statistic	
chi2(1)	27.29	
Prob > chi2	0	
Normality test	Statistic	
Chi(2)	2.64	
Prob > Chi(2)	0.27	
Link test		
Dependent variable: log of total harvest	Coef (se)	
Hat	1.62***	
	-0.4	
Hat squared	-0.04	
	-0.02	

Source: Author's calculations (2019)

It was observed that heteroscedasticity was mainly a cross-section problem. It occurs when the errors have non-constant variances. This study utilized the Breush Pagan/ Cook Weisberg test for heteroscedasticity. The null hypothesis was that the model's residuals were homoscedastic. The results are displayed in Table 4.4. The results show that the model had heteroscedasticity, since the p value was equal to zero. Heteroscedasticity persisted in the data even after transforming the data (through logging). Robust standard errors were used to overcome the problem of heteroskedasticity. The F test tests whether the coefficients in the model satisfies a given constraint. In this case, the coefficients were tested against the hypothesis that they were equal to zero. The null hypothesis was rejected since the probability was zero.

To ascertain that the model was properly specified, a link test was carried out which produced positive results. The null hypothesis was that the model was well specified. The results presented in Table 4.4 shows that the model had well specified variables since the coefficient of hat squared was not statistically significant. Finally, the results also show absence of non-normality as the value of the probability exceeded 0.05.

Having ascertained the appropriateness of the diagnostic tests, the Table 4.5 displays the results as follows:

Table 4.5: Factors affecting Rice Production in Mwea Irrigation Scheme

Dependent variable: **Log of total harvest**	Coef.(se)	t	P>t
Log of total labor	0.02** (0.01)	1.96	0.05
Log of fertilizer	0.27*** (0.05)	4.97	0.00
Log of pesticides	0.02 (0.03)	0.64	0.53
Log of herbicides	0.05 (0.04)	1.27	0.21
Log of total machine cost	0.09** (0.04)	2.55	0.01
Gone for a farming course	0.06 (0.04)	1.42	0.16
Advisory visit	0.02 (0.04)	0.57	0.57
Adequate irrigation water supply	0.04* (0.02)	1.68	0.08
Used loans (credit)	0.02 (0.04)	0.45	0.65
Log of total seeds planted	0.60*** (0.06)	9.82	0.00
Constant	3.88 (0.39)	9.88	0.00

Source: Author's calculations (2019)
Note: The values in parenthesis are standard errors. The asterisks denote significance (*** 1%, ** =5% and * =10% significance level)

The values of total harvest, total labour cost, fertilizer, pesticides, herbicides, seeds planted and total machine are in per season per acre terms. Gone for a farming course, advisory visits, adequate water supply and used credit are dummy variables, with one representing the presence of the indicator.

Having carried out all checks to ascertain the correctness of the model, the next step was to interpret the results. It was important to first of all ensure the signs of the coefficients were in tandem with the theoretical expectations, save for the insignificance of a few of them. Since the continuous variables are in logs, the coefficients can be interpreted in two ways. One of the ways to explain the coefficients is by use of elasticities which measures the responsiveness on one economic variable as a result of a change in the other variable or alternatively, by use of percentage change on a variable against the other.

From Table 4.5, coefficient of the quantity of seeds planted is 0.6 which is statistically significant at one per cent level. Given a double log model, other things being equal, a one per cent change in the total amount of seeds planted increases rice output per season per acre by 0.6 per cent. The coefficient of the amount of fertilizer applied was 0.27 and was statistically significant at one per cent level of significance. Labour and machine cost were both statistically significant at five percent level of significance with a coefficient of 0.02 and 0.09 respectively while coefficient of adequate irrigation water had a coefficient of 0.04 and was statistically significant at ten per cent.

An increase in the amount of fertilizer used by one percent increases the amount of rice harvested by 0.27 per cent per season per acre. Albeit small magnitude, these results are similar to those of Kuria *et.al* (2003) and Ndayitwayeko and Korir (2012).

Specifically, Ndayitwayeko and Korir (2012) found out that increasing amount of fertilizer use by one per cent increases output by 20 per cent in Gihanga, Burundi.

Lema, et.al. (2017) found that an increase in the amount of fertilizer use increases rice production by 0.10 per cent in Fogera District in Ethiopia. Tijani (2006) found that an increase in the amount of fertilizer by one per cent led to 0.64 per cent increase in rice production in Nigeria. Galawat and Yabe (2012) also found a positive and statistically significant coefficient of fertilizer, with an increase in fertilizer usage by one percent leading to an increase in the amount of rice harvested by 0.02 per cent.

A one percent increase in the quantity of seeds planted increases the amount of rice harvested per season per acre by 0.60 per cent. Lema, et.al. (2017) got corresponding outcome in Fogera in Ethiopia. They got a value of 0.173 indicating that, increasing the quantity of seeds planted by one percent increases the amount of rice harvested by 0.17 per cent. However, Ndayitwayeko and Korir (2012) found a positive but insignificant coefficient of seeds.

The coefficient of total cost of machine was 0.09. This meant that an increase in total machine cost by one percent increases the rice output per season per acre by 0.09 per cent. Galawat and Yabe (2012) found a positive relationship between machine cost (machine use) and the amount of rice harvested in Brunei in Tanzania. The coefficient of the machinery was 0.26. This meant that increasing machine use by one percent increased the amount of rice output by 0.26 per cent. The results are also consistent with Kea, Li and Pich (2016) who found that a one per cent increase in agriculture machinery used in rice production increased output by 1.86 per cent in Cambodia.

The coefficient of labour was found to be 0.02. Increasing total labour by one per cent has a corresponding increase in total rice output per season per acre by 0.02 per cent. This is in line with Galawat and Yabe (2012) who found a coefficient of 0.02 which was statistically significant in Brunei, Tanzania.

However, Tijani (2006) found the coefficient of labour to be negative and statistically significant in Nigeria. The authors found a value of 0.17, which implies that an increase in labourers by one percent decreased rice production by 0.17 per cent. The author attributed this to use of excessive labour in the farms.

Adequacy of irrigation water was also found to be a statistically significant determinant of rice output in Mwea Irrigation scheme with a coefficient of 0.04. Those with adequate irrigation water were found to be 0.04 per cent higher than those with no adequate irrigation water. However, Ahmad and Sinhar (2017) found the coefficient of adequate water (as proxied by rice irrigation machines) to be positive and insignificant in Bihar in Eastern India. Galawat and Yabe also found a similar relationship in Tanzania.

The coefficients of pesticides, herbicides, farming course, advisory visits and credit accessibility were not useful in explaining rice yields. However, the five variables have the expected positive coefficients. Ndayitwayeko and Korir (2012) found a negative and statistically significant relationship between the quantity of pesticides and the amount of rice harvested (the coefficient was negative 0.23). The authors attributed the negative coefficient to overutilization of pesticides. Galawat and Yabe (2012) found a positive but insignificant coefficient of pesticide (the value of the coefficient was 0.042). Udayanganie (2006) found that an increase in the cost of pesticides by one per cent decreased rice output by 0.1 per cent. Hussain (2012) found a positive but insignificant coefficient of credit, just as in line with the current study. The author attributed this unexpected finding to ineffectiveness and inefficiencies in the disbursement of credit, which could also be the case in the present study.

4.4 Measuring Rice Technical Efficiency Among Farmers at Mwea Irrigation Scheme

Having examined the factors that affect rice production in Kenya, the next objective was to measure the levels of technical efficiency of rice farmers at Mwea Irrigation scheme. The technical efficiencies were computed using the Balttese and Coeli (1987) methodology discussed in chapter three.

To calculate the (predicted) technical efficiency of rice of each rice farmers in Mwea Irrigation Scheme Balttese and Coeli (1987) methodology was applied, (the alternative is to use the Jundrow et.al. (1982) method, the two methods give almost the same predictions). Table 4.6 below shows the descriptive statistics and distribution of technical efficiency across the different deciles.

Table 4.6: Technical Efficiency levels of farmers at Mwea Irrigation Scheme.

<table>
<tr><th colspan="2">Efficiency score range</th><th>N</th><th colspan="2">Percentage</th><th colspan="2">Cumulative Percentage</th></tr>
<tr><td colspan="2">0.1 ≤TE<0.2</td><td>0</td><td colspan="2">0.00</td><td colspan="2">0.00</td></tr>
<tr><td colspan="2">0.2 ≤TE<0.3</td><td>1</td><td colspan="2">0.35</td><td colspan="2">0.35</td></tr>
<tr><td colspan="2">0.3 ≤TE<0.4</td><td>0</td><td colspan="2">0.00</td><td colspan="2">0.35</td></tr>
<tr><td colspan="2">0.4 ≤TE<0.5</td><td>2</td><td colspan="2">0.70</td><td colspan="2">1.05</td></tr>
<tr><td colspan="2">0.5 ≤TE<0.6</td><td>1</td><td colspan="2">0.35</td><td colspan="2">1.40</td></tr>
<tr><td colspan="2">0.6 ≤TE<0.7</td><td>24</td><td colspan="2">8.39</td><td colspan="2">1.79</td></tr>
<tr><td colspan="2">0.7 ≤TE<0.8</td><td>93</td><td colspan="2">32.52</td><td colspan="2">42.31</td></tr>
<tr><td colspan="2">0.8≤TE<0.9</td><td>154</td><td colspan="2">53.85</td><td colspan="2">96.15</td></tr>
<tr><td colspan="2">Above 0.9</td><td>11</td><td colspan="2">3.85</td><td colspan="2">100</td></tr>
<tr><td colspan="2">Total</td><td>286</td><td colspan="2">100</td><td colspan="2">100</td></tr>
<tr><td></td><td>Count</td><td>Mean</td><td>Std</td><td>Min</td><td>Median</td><td>Max</td></tr>
<tr><td></td><td>286</td><td>0.80</td><td>0.08</td><td>0.29</td><td>0.81</td><td>0.95</td></tr>
</table>

Source: Author's calculation (2019)

Note:

(a) 27 observations were missing from the final calculations as they had either missing value of the independent variable, or they had a value of one in either of the variables under analysis (the log of one is zero), and columns with one or zero as the observations are excluded from the efficiency estimates.

(b) The sample size for the efficiency scores is 286. This is because the computations of the technical efficiency scores, either using Jundrow et.al. (1982) or the Battese and Coeli methods (1988) ignores any row with missing value.

The results are presented in a histogram as shown in the Figure 4.1

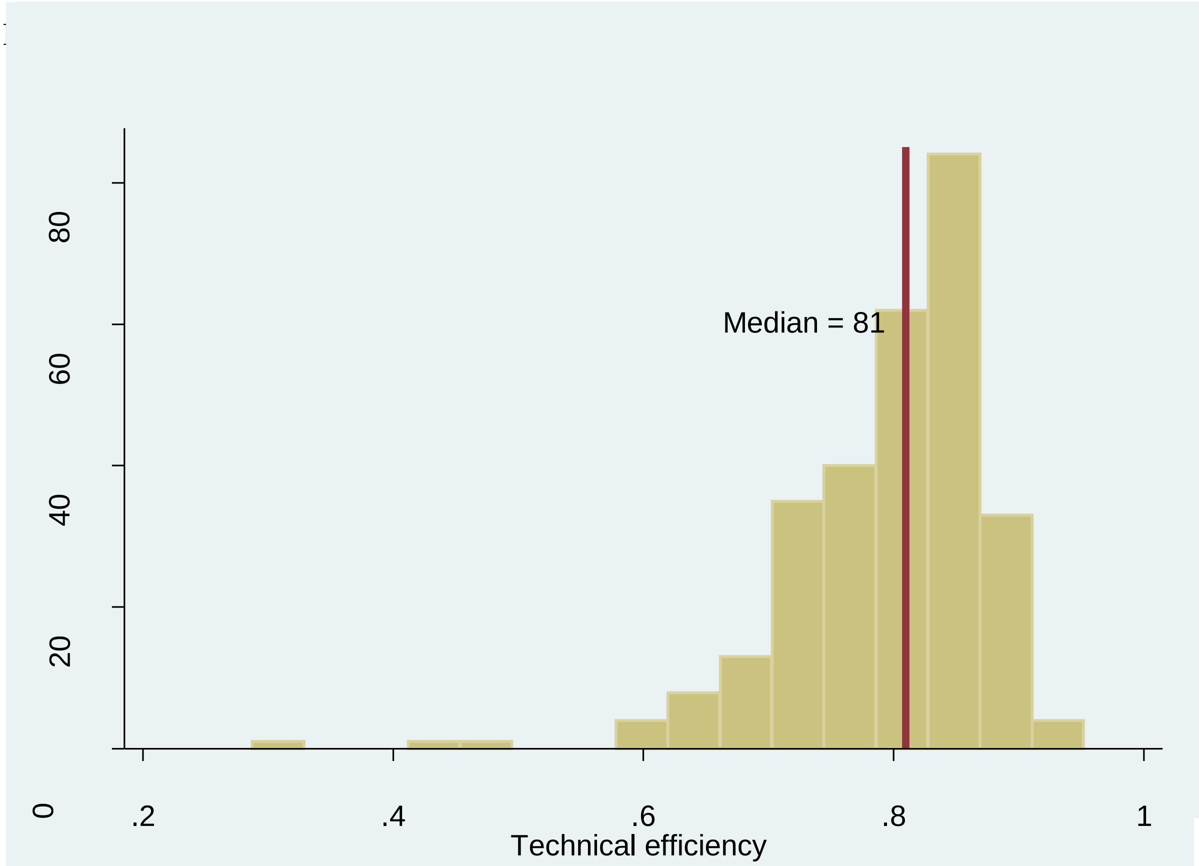


Figure 4.1 Technical Efficiency

4.5. Determinants of Technical Efficiency in Rice Production in Mwea Irrigation Scheme

The third objective of the study was to find out the factors affecting rice technical efficiency among farmers at Mwea Irrigation Scheme. As explained in Chapter three, the objective was achieved using a Tobit model. As in the first objective, the diagnostic results were conducted and discussed before the results were interpreted. These include the link test, normality, Wald and the likelihood ratio test. The diagnostic results are presented in Table 4.7.

Table 4.7: Diagnostic results for the TE model

Diagnostic tests	
Link test	
Efficiency scores	**Coef (se)**
Hat	26.20
	(20.32)
Hat squared	-15.73***
	(10.98)
Constant	-10.09***
	(4.61)
Likelihood ratio test	
Log-likelihood	**value**
LR chi2(9)	22.45
Prob > chi2	0.01
F test	
Test	**Statistic**
F (6, 275)	250.17
Prob > F	0.01

Source: Author's calculation (2019)

Link test was carried out to ascertain that the model was well specified. The diagnostic results presented in Table 4.7 shows that the model was well specified since the coefficients of hat was not statistically significant. An F test was carried out to check whether the coefficients were all equal to zero. The null hypothesis was that the coefficients were jointly equal to zero. Since the probability of the F test was 0.01, the null hypothesis was rejected. Thus, the study concludes that the coefficients were not equal to zero.

The likelihood ratio test was carried out to check whether the model with the intercept only or the one with the independent variables included was better. The null hypothesis was that the model with intercept only was better. The results displayed in Table 4.7 show that the model with the independent variables included was better than the one with intercept only, since the probability value is 0.01.

The Tobit results are as shown Table 4.8 while the Tobit marginal effects at mean results are displayed in Table 4.9.

Table 4.8: Determinants of Rice Technical Efficiency in Mwea Irrigation Scheme

Dependent variable: Efficiency scores	**Coef (se)**
Education level	
Primary	0.04** (0.02)
Secondary	0.03* (0.02)
Tertiary	0.05* (0.03)
Female	-0.02** (0.01)
Total land size under rice	0.01** (0.00)
Seeds variety	0.02
Adequate irrigation water supply	0.01* (0.00)
Experience of the farmer	0.00 (0.00)
Used loans (credit)	-0.01 (0.01)
Extension services	0.06* (0.03)
Constant	0.74

Source: Author's calculation (2019)

Notes: The standard errors are robust standard errors. The base category for the education level is those with no education. The base category for gender is male.

Under the Tobit Model, the coefficients cannot be interpreted directly and thus their marginal effects are as shown below.

Table 4.9: Tobit Model Marginal Effects

Dependent variable: Efficiency scores	Coef.
Education level	
Primary	0.04**
	(0.02)
Secondary	0.03*
	(0.02)
Tertiary	0.05*
	(0.03)
Female	-0.03**
	(0.01)
Total land size under rice	0.01**
	(0.01)
Seeds variety	0.02
	(0.01)
Adequate irrigation water supply	0.01*
	(0.00)
Period growing rice	0.00
	(0.00)
Used loans (credit)	-0.01
	(0.01)
Extension services	0.06*
	(0.03)

Source: Author's calculation (2019)

Notes: The standard errors are robust standard errors; The base category for the education level is those with no education

Having carried out and ensuring the model passed and addressed all the diagnostics, the interpretations of the model presented in Table 4.9 were done. The coefficient of education was found to be positive and significant across all the education levels (primary, secondary and tertiary). As would be expected, the coefficient was largest for the tertiary education level. Those with primary education were found to have a value of 0.04 higher compared with those with no education. The respective values for those with secondary and tertiary education were 0.03 and 0.05, respectively.

These results suggest that the level of education is an important matter that explains efficiency. The results are similar to those of Abedullah *et al.* (2007), Ojo (2012), Maganga (2012) and Lema, et.al. (2017) who found the coefficient of education to be positive and statistically significant. However, Omondi and Shikuku (2013) and Mwatete *et al*. (2015) found the coefficient of education to be positive but insignificant in Ahero and West Kano in Kenya, respectively. Similarly, Mochebelele and Winter-Nelson (2000) and Ogada *et.al.* (2014) failed to find any significant relationship between education and technical efficiency.

The coefficient of gender was negative though statistically significant. Females were found to have an efficiency of 0.03 lower than males. This suggests that males are more productive than females. This corresponds to the findings of Omondi and Shikuku (2013) who established that males had a technical efficiency of 0.05 higher than females. Kibaara (2005) also found a positive and statistically significant coefficient of gender in Kenya. Lema, et.al. (2017) found the coefficient of gender to be positive but insignificant. Mochebelele and Winter-Nelson (2000) and Ogada et.al. (2014) also failed to find any significant relationship between gender and technical efficiency.

The coefficient of adequate irrigation water was small but positive and statistically significant. Those with adequate irrigation water supply were found to have a technical efficiency of 0.01 higher than those without. Galawat and Yabe also found a similar relationship in Tanzania. The authors found a coefficient of 0.12, implying that those with adequate water irrigation supply had a technical efficiency of 0.12 higher than those who did not. However, Kea, Li and Pich (2016) found the coefficient to be negative and statistically significant in Cambodia. The authors attributed this to poor irrigation water management. Watto and Mugera (2014) found the coefficient of adequate water to be negative but statistically significant.

The coefficient of total land size was positive, very small but positive and statistically significant. An increase in total land size by one per cent was found to increase technical efficiency by 0.01 per cent. This is consistent with Ogada *et.al* (2014) who found the coefficient to be positive and statistically significant. The authors found the coefficient to be 1.7, implying that an increase in the size of the land by one percent increases technical efficiency by 1.7 percent. However, these findings contrast those of Mochebelele and Winter-Nelson (2000) who failed to find any association between the two variables in Lesotho. Townsend *et al*. (1998) argues that the effect of the size of the land on technical efficiency is not constant but varies from study to study. For example, Igliori (2005) and Thirtle and Holding (2003) found large scale farmers to be more efficient than in Brazil and UK, respectively. Authors like O'Neill, Leavy and Mathews (2001) and Herdt and Mandac, 1981) found small lands to be more efficient.

The coefficient of extension services was positive and statistically significant. Those with extension services were found to have a technical efficiency of 0.06 higher than those who did not. Galawat and Yabe found a positive and statistically significant relationship between the extension services and allocative efficiency but a statistically insignificant relationship between the variable and economic efficiency and technical efficiency. Watto and Mugera (2014) found the coefficient of extension services to be

0.034 which was statistically significant in Pakistan. This implied that the farmers utilizing the services were 0.034 more technically efficient than those who did not. Similarly, Tijani (2006) found the coefficient of 0.80 which was statistically significant at five per cent. Abele, Lema and Tesema found the coefficient to be 0.092 which was statistically significant at one per cent significant level. However, Omondi and Shikuku (2013) found the coefficient of extension services to be negative but statistically insignificant.

The coefficients of seed variety, period growing rice and access to credit were found to be insignificant determinants of technical efficiency. The coefficient of seeds variety was correctly signed but statistically insignificant. Galawat and Yabe found the coefficient to be positive but weakly significant (the coefficient was 0.13 and significant at ten per cent level). The coefficient of the period growing rice was positive, very small and statistically insignificant. However, Narala and Zala (2010), and Maganga (2012) and Omondi and Shikuku (2013) found the coefficient to be positive and statistically significant. Mwatete et al. (2015) found a negative and insignificant coefficient of experience of the farmer in West Kano Irrigation Scheme in Kenya. Ogada *et.al* (2020) found the coefficient to be negative and statistically significant. Specifically, an increase in experience of the farmer by one year reduced technical efficiency by 0.1 per cent. The author attributed this to the resistance of the old farmers to change their old farming methods. Udayanganie *et al*. (2006) found the coefficient of credit to be positive and statistically significant, contrary to the findings of the current study. In the present case, these unexpected results can be attributed to the initial finding that most farmers (about 50 per cent) have primary school education. Thus, it is most likely that they are using outdated or old technologies in rice farming. Moreover, they may be reluctant to learn new farming skills. Thus, the older the farmer gets, the less efficient they may become. This indicates a need to upgrade their farming skills and close knowledge gaps, as discussed in details in the policy implications.

CHAPTER FIVE

SUMMARY, CONCLUSION AND POLICY IMPLICATION

5.1 Introduction

This chapter summarizes the study, gives the conclusions, suggests policy recommendations and highlights the areas of further study.

5.2 Summary

This research was motivated by the problem the Country has been experiencing where demand of rice has been outstripping supply by far. For instance, between 1990 and 2020, the annual consumption and production of rice averaged 19.8 and 6.5 per cent, respectively. The huge differences have been attributed to minimal increase in land under rice farming, rain dependent rice farming techniques, high demand from the growing population, urbanization, rise in consumption of rice-based value-added products and higher incomes.

As the country grappled with the problem of decreased rice production, the Ministry of Agriculture, instituted the National Rice Development Strategy (NRDS) in 2008. Its goal was to increase this important food crop to meet the consumption demand, and thus make the country rice sufficient. The strategy also sought to close the rice production gap by 2030, by increasing the production annually by 9.3 per cent. However, despite these efforts, the gap between production and consumption has been rising, with consumption outstripping production by far. For example, instead of the targeted deficit of 175 thousand metric tons by 2020, the actual deficit was 650 thousand tons. This is despite the government taking concerted efforts to close the gap, including increasing the irrigable land, building infrastructure and improving production technology.

This was the basis under which this research was carried out to understand the productivity and technical efficiency of rice production in Kenya, with an aim of increasing rice production in the country. To do this, the study targeted Mwea Tebere Irrigation Scheme which is leading in rice growing. The study sampled 313 respondents from five sub-regions of the Scheme: Karaba, Wamumu, Thiba, Tebere and Mwea.

The study deviated from the previous ones in four main aspects. First, no other study had been carried out in the post National Rice Development Strategy (2008) to evaluate its performance. Second, the previous studies conducted in the country used a small sample size: the three studies conducted in Kenya previously by Kuria et.al (2003), Omondi and Shikuku (2013) and Mwatete et al (2015) used sample sizes of 106, 123 and 220, respectively. This research applied a sample size of 313.

Third, the other similar study that was undertaken in Mwea Irrigation Scheme was last conducted in 2003 by Kuria and others. The value addition of the paper is that it uses updated data to measure the determinants and the TE in the post NRDS period. The older studies did not reflect this. Finally, unlike the previous studies which focused on measuring technical efficiency only, this paper explored the determinants of technical efficiency, and the factors that affect the amount of rice produced.

The study had three specific objectives: To determine the factors that affect rice production in Mwea Irrigation Scheme, to measure the technical efficiency level of rice production in Mwea Irrigation Scheme and to establish the determinants of technical efficiency in rice production in Mwea Irrigation Scheme. The first objective was answered using ordinary least squares method. All the inputs and outputs were converted to per season per acre terms before the estimation was carried out. Diagnostic tests were then conducted prior to the interpretation of the model. The model was found to be heteroscedastic, and the robust standard errors were used to solve this problem. The F-test showed that all the coefficients of the model were not jointly equal to zero.

The link test also showed that the model was well specified. The study established that the main determinants of rice production were total labor, fertilizer, machine cost, water and the amount of seeds planted. All the coefficients of these variables were positive. The coefficients of fertilizer and seeds planted were statistically significant at one per cent; that of machine cost and labor at five per cent and that of adequate irrigation water supply at ten per cent.

The second objective was to measure the technical efficiency of rice at Mwea Irrigation scheme. The two methods used to measure TE were the Jundrow et.al. (1982) and the Balttese and Coeli (1987) methods. It was found that the mean TE using the two methods were 0.8 and 0.81, respectively. The median values were both 0.81. Although these values seemed high, they were lower than those of the comparable countries, which exceeded 0.85.

The study in addition sought to establish the character traits of the highly efficient farmers, with respect to both the continuous and the categorical variables. Farmers were deemed less technical efficient if their TE score was less than the median. The coefficients of the continuous variables that were found to be statistically significant are larger land sizes, higher fertilizer use and more farming experience. Considering the categorical variables, vast differences were found to exist within TE by gender. The other differences were not large enough.

Having measured the technical efficiency, the third objective explored the factors affecting the technical efficiency. A Tobit model was used for the estimation, and the marginal effects were calculated. The diagnostic tests were first conducted before the results were interpreted. The link test showed that the model was well specified, the F-test revealed that the models' coefficients were not jointly equal to zero, and the likelihood ratio test indicated that the fitted model was far better than the one fitted with intercept only.

The results indicated that education, gender, land size, adequate irrigation water and extension services were the main determinants of TE. With the exception of gender, all the other coefficients were positive. None of the coefficients of these variables was statistically significant at one per cent. The coefficient of primary education, gender and land size were statistically significant at five per cent; the rest were statistically significant at 10 per cent.

5.3 Conclusion

Based on the findings, three key points can be derived. First, rice production per season per acre in Mwea Tebere is lower than in other schemes in similar countries. The amount of rice harvested by farmers depends majorly on labor used, fertilizer used, machines costs, availability of adequate irrigation water and the quantity of seeds planted. Of these, the variables with the strongest effects were fertilizer and total seeds planted. The coefficient of chemicals (herbicides and pesticides), whether gone for a farming course, advisory visit and loans were not statistically significant.

Second, the technical efficiency in Kenya was found to average 0.8. with a median of 0.81. This value is lower than values in other similar countries, which was above 0.85. It can therefore be concluded that Kenya's TE is below the comparable countries and there exists a room for its improvement. Increase in farmers TE is therefore expected to increase rice production in Kenya, reduce rice imports and ensure food sufficiency.

Third, the main determinants of rice TE in Kenya are education, gender, total land size under rice, adequacy of irrigation water and use of extension services. Therefore, to increase the TE, the main variables to be targeted are education, gender, land size, adequate water supply and extension services. Notably, the adequacy of irrigation water was found to determine both production and technical efficiency positively. The quantity of seeds planted was found to positively influence output, but not technical efficiency. Loans were not an important variable in determining both output and technical efficiency.

5.4 Policy Implications

Based on the research findings, this study recommends several policies, which are geared towards improving the productivity of rice in the scheme, and improving the technical efficiency of farmers in the country. The recommendations will improve rice production not only in Mwea Tebere Irrigation scheme, but in other rice growing schemes in Kenya.

Labour was found to positively affect output. The more the labour employed, the higher was the output. Since more labour is costly, encouraging farmers to use more labour on their farms may not work out. Thus, they should be encouraged to invest in and adopt more efficient and labour cost saving technologies such as use of equipment and machines. This will help to lower labour costs and increase rice productivity. In addition, more training opportunities need to be availed to farmers on modern rice farming methods. This will help to increase their productivity and efficiency while reducing the labour costs.

Higher application of fertilizer was found to affect production positively. Specifically, a one per cent increase in fertilizer usage was found to lead to an increase in rice production by 0.27 per cent. This means the farmers were applying less fertiliser than required. One possible reason for lower application was the cost associated with acquisition of this important farm input. The management of the Mwea Irrigation Board should ensure that farmers have access to fertilizers at affordable prices. The board can liaise with the government to subsidize the fertiliser costs to enable farmer acquire them conveniently. The government can also explore ways of producing fertilisers locally and thus bring the cost down since much of the fertiliser used in the country is imported and very expensive. Furthermore, the farmers should be educated on optimal use of fertilizers on their farms.

The use of farming machines contributed significantly to the farm yields. Farmers with high rice production were also found to be using machines. This implies the need for use of more machines in rice farming. Use of machines increases efficiency. However, since the more the machine use the higher the cost, the issue can be handled in different ways. The board and the government can come up with subsidy programs to reduce the acquisition costs of the machines, the government can reduce or zero-rate the import taxes for rice farming machines thus making it easier to acquire them, the government can offer low interest loans to farmers with bigger grace periods to enable them buy the farming machines, the board could also buy the machines and lease them to the farmers at lower prices and finally the board and the government can provide funds through the research and development department in research institutions to manufacture low cost rice farming machines in the country. This can lead to both cost reduction and increase in rice productivity.

The presence of adequate irrigation water was found to positively affect production (and technical efficiency also). The board and the government need to invest in better water management infrastructure to ensure that every farmer has access to adequate irrigation water. The government has previously failed to consider this angle due to budget constraints and missed (and competing) priorities. A possible solution is to have public private partnerships (PPPs) in water management systems. Moreover, research can be conducted to develop newer technologies that enable a more efficient use of water (for example, more efficient irrigation methods).

Finally, on the production side, considering a fixed land size (as the analysis was conducted in per season per acre terms) the more hybrid seeds that the farmers planted, the higher was the harvest. This means there was a sub optimal application of seeds on the farms.

The implication is that farmers need to be educated on the need to plant hybrid seeds at optimal levels in order to realize higher harvests. There is also need for increased collaboration among the farmers to learn from one another (say via more exposures to exhibitions and shows). For example, it could be the case that farmers who plant more seeds per acre, also use other techniques to ensure higher production such as higher rate of fertiliser application. They should also be given subsidies to meet the high cost of additional seeds. It could also be imperative to research on newer high-quality varieties that produce more per acre.

The finding that technical efficiency in Mwea Tebere irrigation scheme is lower compared to other rice producing countries calls for measures to increase it. Some of the areas that should be targeted to raise it based on the study are education, land size, adequate water and extension services.

Based on the finding that education and technical efficiency are positively related means that the farmers should be encouraged to pursue more education as it positively affects their technical efficiency. Educated farmers are likely to adopt better farming techniques. Moreover, there is need to offer further training through seminars, shows, exhibitions and other outlets. This should mostly target the farmers who are less efficient, and who were found to be primary school graduates. The highly efficient farmers can use this platform to share their experience with the low efficient ones. In the same vein, more extension officers should be employed by the board, and the frequency of their visit to the farmers increased, especially to the less efficient farmers. This is in line with the finding that farmers who use extension services had higher technical efficiency.

Finally, it was found that technical efficiency increases with land size. This can be attributed to the fact that farmers with larger land sizes have access to better farming technologies. The larger land sizes could imply more usage of modern machine and equipment in large farms, compared to small land sizes that are more labour intensive. The board and the government should put measures and policies in place to ensure that small scale farmers have access to modern technologies and farming resources, such as inputs. Land redistribution and consolidation could also allow access of larger lands by small scale farmers and should therefore be encouraged. It is further is expected to reduce time used to get to the farms, and improve resource management. In addition, consolidated farms are expected to have easier access to markets, credit and extension services. Nevertheless, there is likely to be resistance from landowners who are used to their small landholdings and administrative complexities. These should be addressed as well when consolidation is being considered.

5.5 Suggestions for Further Research.

This study explored the determinants of rice production in Mwea Tebere Irrigation Scheme, measured the technical efficiency and examined its determinants. For an exhaustive study in this area, future researches may study the following areas:

(i) Focus on more irrigation schemes and not just Mwea Tebere Irrigation Scheme, and explore how the determinants of production, the technical efficiency and its determinants vary across the schemes.

(ii) Conduct several cross-section studies over time (longitudinal or panel, say over intervals of three years) in Mwea Tebere to examine how and whether TE and production and their determinants are changing over time.

(iii) Conduct a study to measure technical efficiency by gender. This will help policy makers to understand whether TE and its determinants vary significantly by gender, and if so, what interventions can be done to close this gap.

REFERENCES

Aigner, D., Lovell, C. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of econometrics,6*(1),21-37.

Ali, S., Ahmad, W., Israr, M., Khan, A., & Shah, S. A. (2022). Determinants of Rice Yield in Central Khyber Pakhtunkhwa, Pakistan. Sarhad Journal of Agriculture, 38(1).

Abedullah, S.K & Mushtaq, K. (2007). Analysis of Technical Efficiency of Rice Production in Punjab (Pakistan); Implications for Future Investment Strategies. *Pakistan Economic and Social Review, 45*(2): 231-244.

Addai, K. N., & Owusu, V. (2014). Technical efficiency of maize farmers across various agro ecological zones of Ghana. *Journal of Agriculture and Environmental Sciences*, 3(1), 149-172.

Africa Rice Centre. (2009). African Rice Centre annual report 2008. Responding to the rice crisis, *Cotonou, Benin.*

Ahmad, N., Sinha, D., & Singh, K. (2017). Estimating production efficiency in rice cultivation of Bihar: an economic approach. *Economic Affairs, 62 (3*), 353-360

Ali, M. & Chaudhury, A. (1990), Inter-regional farm efficiency in Pakistan's Punjab: A Frontier production function study. *Journal of Agricultural Economics*, *41* (3), 62-74.

Atera, E. A., Onyancha, F. N. & Majiwa, E. B. (2018). Production and marketing of rice in Kenya: Challenges and opportunities. *Journal of Development and Agricultural Economics, 10*(3), 64-70.

Ateka, J. M., Onono, P. A., & Etyang, M. (2018). Technical efficiency and its determinants in smallholder tea production: evidence from Nyamira and Bomet counties in Kenya. *Global Journal of Science Frontier Research: Agriculture and Veterinary*, *18,* 43-54.

Bardhan, P. (2000). Irrigation and cooperation: An empirical analysis of 48 irrigation communities in South India. *Economic Development and cultural change,* 48(4), 847-865.

Bravo-Ureta, B. E., & Pinheiro, A. E. (1997). Technical, economic, and allocative efficiency in peasant farming: evidence from the Dominican Republic. *The developing economies,* 35(1), 48-67.

Capalbo, S. M., & Antle, J. M. (Eds.). (2015). *Agricultural productivity: measurement and explanation.* Routledge.

Chandio, A. A., Jiang, Y., Gessesse, A. T., & Dunya, R. (2019). The nexus of agricultural credit, farm size and technical efficiency in Sindh, Pakistan: A stochastic production frontier approach. *Journal of the Saudi Society of Agricultural Sciences*, 18(3), 348-354.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research*, *2*(6), 429-444.

Clayton, G. E. (2000). *Economics principles and practices.* McGraw: Glencoe.

Chandel, R. B. S., Khan, A., Li, X., & Xia, X. (2022). Farm-level technical efficiency and its determinants of rice production in indo-gangetic plains: A stochastic frontier model approach. *Sustainability, 14*(4), 2267.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis*. Springer Science & Business Media.

Coelli, T., Rahman, S., & Thirtle, C. (2002). Technical, allocative, cost and scale efficiencies in Bangladesh rice cultivation: a non‐parametric approach. *Journal of agricultural economics*, 53(3), 607-626.

De Laulanié, H. (2011). Intensive rice farming in Madagascar. *Tropicultura*, 29(3), 183-187..

Debertin, D. L. (2012). *Agricultural production economics.* Pearson Education: Upper Saddle River, N.J.

Erhie, E., Iwelumo, M., Agbeyi, E., Oladipo, O., Oyaniran, T., Akinbiyi, A., & Adegunle, E. (2018). Boosting rice production through increased mechanisation. *Pricewaterhouse Coopers, Nigeria. Legos: PwC.* Available at: https://www.pwc.com/ng/en/assets/pdf/boosting-rice-production.pdf Accessed 23rd Feb 2021.

FAO (1981). Food and Agriculture Organization of the United Nations: Agriculture towards 2000. Rome.

FAO (2020). Rice Production in the Asia-Pacific Region: Issues and Perspectives - M.K. Papademetriou. Available at: https://www.fao.org/3/x6905e/x6905e04.htm Accessed 25th March 2021.

FAO (2021). Crops and livestock products. Available at: http://www.fao.org/faostat/en/#data/QC. Accessed 23rd Feb 2021.

Farrell, M.J. (1957). "The measurement of productive efficiency". *Journal of the Royal Statistical Society*, Series A. 120, 253–81

Fethi, D., Jackson, M. & Weyaman-Jones, G. (2000). Measuring the efficiency of European airlines: An application of DEA and Tobit analysis. Available at: *h*ttps://pdfs.semanticscholar.org/c9b1/204a75a9fabb86898b60498d94fe32f5fba5.*pdf* Accessed 23rd May 2021.

Galawat, F., & Yabe, M. (2012). Evaluation of technical, allocative, and economic efficiency in Rice Production; A Case Study on Rice Farmers in Brunei Darussalam. *J. Fac. Agr., Kyushu Univ*, 57(1), 317-325.

Global Yield Cap Atlas (2020). Rice production in nine Sub-Saharan African countries. Available at: https://www.yieldgap.org/ssa-rice Accessed 2nd July 2021.

Greene, W. (2012). *Econometric analysis*. New Jersey: Pearson Education Publishers.

Gujarati, D. N. (2022). *Basic econometrics*. Prentice Hall.

Herdt, R. W., & Mandac, A. M. (1981). Modern technology and economic efficiency of Philippine rice farmers. Economic Development and Cultural Change, 29(2), 375-399.

Houngue, V., & Nonvide, G. M. A. (2020). Estimation and determinants of efficiency among rice farmers in Benin. Cogent Food & Agriculture, 6(1), 1819004.

Hussain, A. H. (2012). Impact of credit disbursement, area under cultivation, fertilizer consumption and water availability on rice production in Pakistan (1988-2010). *Sarhad J. Agric.* 28(1), 94 - 101.

Hwang, D. S. & Oh, D. (2008). Do software intellectual property rights affect the performance of firms? Case study of South Korea. *The Third International Conference on Software Engineering Advances*, *2*(12), 307 – 312.

Igliori, D. C. (2005). Determinants of technical efficiency in agriculture and cattle ranching: A spatial analysis for the Brazilian Amazon. *University of Cambridge Land Economy Working Paper*, (09.2005).

Jacobs, R., Smith, P. C., & Street, A. (2006). *Measuring efficiency in health care: analytic techniques and health policy.* Cambridge University Press.

Jondrow, J., Lovell, C. K., Materov, I. S., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of econometrics*, *19*(2-3), 233-238.

Kalirajan, K. P., & Shand, R. T. (1985). Types of education and agricultural productivity: a quantitative analysis of Tamil Nadu rice farming. *The Journal of Development Studies*, 21(2), 232-243.

Kea, S., Li, H., & Pich, L. (2016). Technical efficiency and its determinants of rice production in Cambodia. *Economies, 4*(4), 22.

Khai, V. & Yabe, M. (2011). Technical efficiency Analysis of Rice Farming in Vietnam. *J. ISSAAS 17*(1), 135 – 146.

Kiatpathomchai, S. (2008). *Assessing economic and environmental efficiency of rice production systems in Southern Thailand: An application of data envelopment analysis* (Unpublished Doctoral dissertation, University of Justus-Liebig Giessen.).

Koirala, K. H., Mishra, A., & Mohanty, S. (2016). Impact of land ownership on productivity and efficiency of rice farmers: The case of the Philippines. *Land use policy*, 50, 371-378.

Kuria, J.N., H. Ommeh, L., Kabuage, S. Mbogo and C. Mutero (2003). 'Technical efficiency in rice producers in Mwea Irrigation Scheme'. In *Africa Crop Science Conference Proceedings*, *6*, 668-673.

Kumar, K. (2022). Technical efficiency of rice farmers in Telangana, India: data envelopment analysis (DEA). *Research on World Agricultural Economy*, *3*(3), 1-12.

Kumbhakar, S. C., & Lovell, C. K. (2003). *Stochastic frontier analysis*. Cambridge university press.

Lema, T. Z., Tessema, S. A., & Abebe, F. A. (2017). Analysis of the technical efficiency of rice production in Fogera district of Ethiopia: a stochastic frontier approach. *Ethiopian Journal of Economics*, 26(2), 88-108.

Liu, Y., & Shumway, C. R. (2007). *Demand and supply of induced innovation: An Application to US Agriculture* (No. 381-2016-22326).

Maganga, A.M. (2012). Technical efficiency and its determinants in Irish potato production: Evidence from Dedza District, Central Malawi. *African Journal of Agricultural Research*, 7(12): 1794-1799

Maddala, G. (1999) *Limited Dependent and Qualitative Variables in Econometrics.* Cambridge University Press, New York.

Mochebelele, M. T., & Winter-Nelson, A. (2000). Migrant labor and farm technical efficiency in Lesotho. *World development*, *28*(1), 143-153.

Ministry of Agriculture. (2008). National Rice Development Strategy (2008 –2018). Nairobi: Ministry of Agriculture.

Mwatete, G. K. K., Kipkoech, A. K., Kipkorir, E. C., & Sumukwo, J. (2015). Technical efficiency differentials between rice production methods: the case of Conventional and System of Rice Intensification in West Kano Irrigation Scheme, Kenya. Journal of Agricultural and Crop Research, 3(8), 130-140.

Muthayya, S., Sugimoto, J. D., Montgomery, S., & Maberly, G. F. (2014). An overview of global rice production, supply, trade, and consumption. *Annals of the new york Academy of Sciences*, *1324*(1), 7-14.

Mulatu, E. (2024). Determinants of rice production and market supply: A study of Bench Sheko zone in Ethiopia. *PloS one*, *19*(9), e0302115.

National Irrigation Board. (2018). Mwea Irrigation Scheme. Available at: https://nib.or.ke/schemes/mwea-irrigation-scheme Accessed 2nd June 2021.

Ndayitwayeko, W., & Korir, M. (2012). Determinants of technical efficiency in rice production in Gihanga (Burundi) Irrigation Scheme: A stochastic production frontier approach. *Egerton Journal of Science & Technology*, *12*(3), 1 – 12.

Ngigi S. (2002). Review of Irrigation development in Kenya. In Sally H, Abernethy CL (eds). Proceedings of private irrigation in sub Saharan Africa. IWMI, FAO, ACP-EU.

Noij, F. & Niemeijer, R. (1988). Resident tenants at the Ahero Irrigation Scheme, Household economics and nutrition, Ministry of Planning and National Development Report No. 29/1988. Available at: https://www.kalro.org/kainet/node/262881 Accessed 2nd July, 2021.

Narala, A., & Zala, Y. C. (2010). Technical Efficiency of Rice Farms under Irrigated Conditions in Central Gujarat. *Agricultural economics research review*, 23(2), 375-381.

Onyango, A. O. (2014). Exploring options for improving rice production to reduce hunger and poverty in Kenya. *World environment*, 4(4), 172-179.

Office of the Official Publication for the European Communities. (2013). *Agriculture in the European Union: Statistical and economic information*. Madrid: Office of the Official Publication for the European Communities.

Ogada, M. J., Muchai, D., Mwabu, G., & Mathenge, M. (2014). Technical efficiency of Kenya's smallholder food crop farmers: do environmental factors matter? *Environment, development and sustainability*, 16(5), 1065-1076.

Omondi, O., Shikuku, M. (2013). An analysis of technical efficiency of rice farmers in Ahero Irrigation Scheme, Kenya. *Journal of Economics and Sustainable Development*, *4*(10), 9 – 16.

Ojo, C. O. (2012). Technical efficiency of rural women farmers in Borno State, Nigeria. *Developing Country Studies*, 2(7), 61-66.

O'Neill, S., Leavy, A., & Matthews, A. (2001). *Measuring productivity change and Efficiency On irish farms*. Teagasc.

Pandey, S., & Pal, S. (2007). Are less-favored environments over-invested? The case of rice research in India. *Food policy*, 32(5-6), 606-623.

Pedroso, R., Tran, H., Viet, Q., Le. V., Dang, T., & Le, P. (2018). Technical efficiency of rice Production in the delta of the Vu Gia Thu Bon river basin, Central Vietnam. *World Development Perspectives 9*(4), 18–26.

Pechrová , M., & Ondrej, S. (2020). *Cobb-Douglas or Translog production function in efficiency analysis?*Available at: https://www.researchgate.net/publication/349109705_Cobb-Douglas_or_Translog_Production_Function_in_Efficiency_Analysis Accessed 2nd January, 2021.

Pudasaini, S.P (1983), The effects of education in agriculture: Evidence from Nepal. *American Journal of Agricultural Economics*, 65(3): 509-515.

Rahman, S. (2003). Profit efficiency among Bangladeshi rice farmers. *Food policy*, 28(5-6), 487-503.

Republic of Kenya. (2002). *Economic Survey*. Nairobi: Government Printer.

Republic of Kenya. (2018). *Economic Survey*. Nairobi: Government Printer.

Saito, K., Senthilkumar, K., Dossou-Yovo, E. R., Ali, I., Johnson, J. M., Mujawamariya, G., & Rodenburg, J. (2023). Status quo and challenges of rice production in sub-Saharan Africa. *Plant Production Science*, *26*(3), 320-333.

Sinuraya, J. F., Ulpah, A., Setiyanto, A., Astari, A. F., & Dabukke, F. B. (2024). Technical efficiency of rice productivity in Indonesia. In *BIO Web of Conferences* (Vol. 119, p. 01010). EDP Sciences.

Salau, S., Adewumi, M., & Omotesho, O. A. (2012). Technical efficiency and its determinants at different levels of intensification among maize-based farming households in Southern Guinea Savanna of Nigeria. *Ethiopian Journal of Environmental Studies and Management*, *5*(2), 195-206.

Tan, S., Heerink, N., Kuyvenhoven, A., & Qu, F. (2010). Impact of land fragmentation on rice producers' technical efficiency in South-East China. *NJAS-Wageningen Journal of Life Sciences*, 57(2), 117-123.

Tijani, A. (2006). Analysis of the technical efficiency of rice farms in Ijesha Land of Osun State, Nigeria. *Agrekon*, *45*(2), 126-135.

Todaro, P., Michael, S.& Smith, C. (2008). Economic development in the third world countries. Singapore: Longman Publishers.

Thirtle, C., & Holding, J. (2003). Productivity of UK agriculture: causes and constraints. *Report to Department for Environment, Food and Rural Affairs. Wye, Kent: Imperial College*.

Udayanganie, A., Prasada, D., Kodithuwakku, K., Weerahewa, J. & Little, D. (2006). Efficiency of the agrochemical input usage in the paddy farming systems in the dry zone of Sri Lanka. Available at: http://ageconsearch.umn.edu/record/34181 Accessed 2nd January, 2022.

United States Department of Agriculture. (2020). Kenya Milled Rice Production by Year. Available at: https://usdasearch.usda.gov/search?utf8=%E2%9C%93&affiliate=usda&query=kenya+rice & commit=Search. Accessed 2nd May, 2021.

Uphoff, N., Meizen-Dick, R., & Julien, N. (1985). Getting the process right: Farmer organization and participation in irrigation water management. *A State-of-the-Art prepared at Cornell University for the Water Management Synthesis II, Project, Consortiun for International Development, Cornell University.*

Varian, H. R. (2014). Intermediate Microeconomics: A modern approach: Ninth International Student Edition. WW Norton & Company.

Villano, A. R. (2005), Technical efficiency of rain fed rice farms in the Philippines: A stochastic frontier production function approach (School of Economics, University of New England, *Working Paper* no. 2351).

Watto, M. A., & Mugera, A. W. (2014). Measuring Production and Irrigation Efficiencies of Rice Farms: Evidence from the P unjab P rovince, P akistan. *Asian Economic Journal*, 28(3), 301-322.

Watkins, K. B., Hristovska, T., Mazzanti, R., Wilson Jr, C. E., & Watkins, B. (2013, February). Measuring technical, allocative, and economic efficiency of rice production in Arkansas using data envelopment analysis. In *Annual Meeting, February, 3*(7), 2-5.

APPENDICES

Appendix A: Table A1: Rice technical efficiency scores for rice farmers at Mwea Irrigation Scheme.

Farmer No	Efficiency score	Farmer No	Efficiency score
1	0.90	27	0.84
2	0.86	28	0.90
3	0.85	29	0.87
4	0.79	30	
5	0.78	31	0.94
6	0.86	32	
7		33	0.85
8	0.86	34	0.82
9	0.84	35	0.72
10	0.83	36	0.84
11	0.78	37	0.83
12	0.77	38	0.77
13	0.86	39	0.86
14	0.82	40	0.80
15	0.73	41	0.89
16	0.82	42	0.83
17		43	0.78
18		44	0.84
19	0.72	45	0.84
20		46	
21	0.84	47	0.78
22	0.70	48	0.80
23	0.78	49	0.82
24	0.83	50	
25		51	0.77
26	0.89	52	0.76

Farmer No	Efficiency score	Farmer No	Efficiency score
53	0.89	79	0.86
54	0.86	80	0.83
55	0.75	81	0.90
56	0.80	82	0.87
57	0.90	83	0.80
58	0.76	84	0.80

59		85	0.91
60		86	
61		87	0.73
62		88	0.77
63	0.75	89	0.89
64		90	0.44
65		91	0.89
66	0.87	92	0.83
67	0.73	93	0.58
68	0.73	94	0.46
69	0.75	95	0.70
70	0.87	96	0.87
71	0.85	97	0.74
72	0.75	98	0.74
73	0.82	99	0.73
74	0.91	100	0.66
75		101	0.80
76	0.65	102	0.82
77	0.85	103	0.84
78	0.85	104	0.68

Farmer No	**Efficiency score**	**Farmer No**	**Efficiency score**
105	0.70	131	0.84
106	0.29	132	0.72
107	0.80	133	
108		134	0.71
109		135	0.82
110	0.66	136	0.90
111	0.87	137	0.85
112	0.69	138	0.77
113	0.83	139	0.79
114	0.76	140	0.74
115	0.83	141	0.75
116	0.88	142	0.61
117	0.85	143	0.81
118	0.81	144	0.65
119	0.88	145	0.84
120	0.77	146	0.74
121	0.78	147	0.78
122	0.83	148	0.73
123	0.80	149	0.79
124	0.80	150	0.81

125	0.89	151	0.81
126	0.75	152	0.79
127	0.78	153	0.80
128	0.84	154	0.80
129	0.84	155	0.83
130	0.81	156	0.85

Farmer No	Efficiency score	Farmer No	Efficiency score
157	0.71	183	0.85
158	0.86	184	0.78
159	0.79	185	0.90
160	0.81	186	0.73
161	0.86	187	0.90
162	0.78	188	0.86
163	0.92	189	0.88
164	0.85	190	0.84
165	0.85	191	0.87
166	0.80	192	0.71
167	0.86	193	0.86
168	0.85	194	0.69
169	0.83	195	0.84
170	0.83	196	0.71
171	0.80	197	0.74
172	0.88	198	0.95
173	0.85	199	0.83
174	0.87	200	0.86
175		201	0.86
176		202	0.83
177	0.90	203	0.79
178	0.81	204	0.80
179	0.85	205	0.62
180	0.83	206	
181	0.74	207	0.82
182	0.83	208	0.82

Farmer No	Efficiency score	Farmer No	Efficiency score
209	0.71	235	0.86
210	0.66	236	0.83
211		237	0.73
212	0.85	238	
213	0.89	239	0.78

214	0.72	240	0.78
215	0.85	241	0.84
216		242	0.91
217		243	0.83
218	0.87	244	0.87
219	0.78	245	0.68
220	0.83	246	0.68
221	0.88	247	0.86
222	0.85	248	0.84
223	0.78	249	0.91
224	0.82	250	0.89
225	0.70	251	0.65
226	0.73	252	0.68
227	0.87	253	0.83
228	0.77	254	0.78
229	0.87	255	0.72
230	0.80	256	0.84
231	0.78	257	0.71
232	0.71	258	0.84
233	0.80	259	0.74
234	0.85	260	0.80

Farmer No	**Efficiency score**	**Farmer No**	**Efficiency score**
261	0.76	288	0.85
262	0.79	289	0.78
263	0.76	290	0.81
264	0.90	291	0.74
265	0.69	292	0.66
266	0.80	293	0.81
267	0.65	294	0.82
268	0.87	295	0.62
269	0.83	296	0.68
270	0.82	297	0.73
271	0.85	298	0.73
272	0.90	299	0.70
273	0.87	300	0.85
274	0.81	301	0.82
275	0.80	302	0.68
276	0.71	303	0.78
277	0.84	304	0.85
278	0.77	305	0.81
279	0.72	306	0.84

280	0.81	307	0.78
281	0.90	308	0.79
282	0.64	309	0.81
283	0.81	310	0.76
284	0.80	311	0.83
285	0.82	312	0.86
286	0.80	313	0.84
287	0.82		

Appendix B: Table A2: Descriptive statistics of the TE obtained using the Jondrow (1982) method

Method	Count	Mean	Std	Min	25th Percentile	50th Percentile	75th Percentile	Max
Value	286	0.79	0.08	0.28	0.75	0.81	0.85	0.95

Appendix C: Questionnaire

SURVEY QUESTIONNAIRE TO ASSESS THE RICE PRODUCTION EFFICIENCY IN MWEA IRRIGATION SCHEME

My name is Mr. Muigai Wainaina. I am currently a PhD student at Kenyatta University in the School of Economics. My supervisors are Prof. Martin Etyang and Dr. Diana Muchai. I am conducting a study on the technical efficiency of rice production in Kenya and factors determining its production. The survey will further measure the technical efficiency of rice. I have selected Mwea Tebere irrigation scheme as my study area. The study findings will present alternative policy in promoting rice production efficiency in the region and in Kenya as a whole. Your responses to the following questions will be very helpful. All the information obtained will be treated confidentially and the responses will be analyzed and reported collectively. The information provided will strictly be used for the purposes of this study only. Kindly, accord the research teams with the necessary support and provide them with the relevant information and data that may be required. For each answer choice question, you should place a mark in the brackets where you feel your opinion is best represented. For the open-ended questions, please give up to five responses. Where the answer has an option ‘others, please specify’ please indicate the other answers as you may find relevant.

Should you have any questions regarding the research, please feel free to contact my research team members, my senior field researcher Mr. James or me, Mr. Wainaina.

Start-time: -----------------   Completion-time: ---------------------- (please adopt the 12-hour clock)

Interviewer’s Name: -------------------------------------- Date of interview {-------/-------/2019}

Region: -------------------------------------- Sub region: ----------------------------------

Sign (interviewer)………………………………………………………………………………

Sign (respondent)………………………………………………………………………………

A. GENERAL INFORMATION

(i) Name: ………………………………………………………………………………

(ii) Please indicate your gender (Do not ask this question. Observe and tick appropriately)

Male [ ]

Female [ ]

(iii) Contact (email/phone---OPTIONAL): …………………………………………

(iv) Main occupation of the farmer: ………………………………………………

(v) Indicate your age

18-25 [ ]

26-35 [ ]

36-45 [ ]

46-55 [ ]

56-65 [ ]

66 and above [ ]

(vi) Please indicate your highest education level.

None [ ]

Primary [ ]

Secondary [ ]

Post-Secondary [ ]

(vii) Region in which you grow rice

karaba [ ]

wamumu [ ]

Thiba [ ]

Terebe [ ]

Mwea [ ]

B. FINANCIAL INFORMATION

1) How do you finance your rice production?

i) Sacco [ ]

ii) Relatives/friends/neighbours [ ]

iii) Organized lending groups [ ]

iv) Commercial bank [ ]

v) Others (specify below)

……………………………………………………………………………………………

……………………………………………………………………………………………

……………………………………………………………………………………………

……………………………………………………………………………………………

………………………………

2a) Have you ever used loans (credit) in rice production?

i) Yes [ ]

ii) No [ ]

b) If yes, please indicate how many times

i) One time [ ]

ii) Two times [ ]

iii) Three times [ ]

iv) Four times [ ]

v) Five times [ ]

vi) more than five times [ ]

c) What was the source of your credit?

i) Sacco [ ]

ii) Relatives/friends/neighbours [ ]

iii) Organized lending groups [ ]

iv) Commercial banks [ ]

v)Others(specify)

…………………………………………………………………………………………

…………………………………………………………………………………………

…………………………………………………………………………………………

………………………

d) If no in 2a, please indicate the reasons (at most five reasons)

…………………………………………………………………………………………

…………………………………………………………………………………………

…………………………………………………………………………………………

…………………………………………………………………………………………

………………………………..

3) What can be done to improve access to loans/credit (at most five reasons)?

…………………………………………………………………………………………

…………………………………………………………………………………………

…………………………………………………………………………………………

…………………………………………………………………………………………

…………………………………………………………………………………………

………………………………………..

C. PRODUCTION CHARACTERISTICS

1a) How long have you been growing rice (years, if months, please indicate month/year, for example 3 months as 3/12)?

…………………………………………………………………………………………

b) How many seasons do you plant rice per year?

…………………………………………………………………………………………

c) If land is available, are you willing to increase your acreage under rice

i) Yes [ ]

ii) No [ ]

2a) What is the total size of your land (in acres)?

………………………………………………………………………………………………

b) What is the size of your land under rice? (In acres. If less than acre, give the fraction, for example, ½ an acre).

………………………………………………………………………………………………

c) Is the rice farm in use rented?

Yes [ ]

No [ ]

d) On average, how much do you harvest? (In tons or kilograms. Please specify the measurement unit. Alternatively, state the number of bags and the weigh per bag, for example, 20 90kg bags)

………………………………………………………………………………………………

………………………………………………………………………………………………

………………………………………………………………………………………………

………………………

e) How much labour do you hire per day?

…………………………………………………………………………………………

…………………………………………………………………………………………

………………

f) How many days on average do you hire labourers in a season?

…………………………………………………………………………………………

…………………………………………………………………………………………

……………….

g) What is the average cost per person per day?

…………………………………………………………………………………………

…………………………………………………………………………………………

…………………………………………………………………………………………

……………………..

h) Do you use rice farming machines in your rice production?

i) Yes [ ]

ii) No [ ]

3a) Do you own the machine?

i) Yes [ ]

ii) No [ ]

b) If yes in 7a), what rice farming machines do you use?

…………………………………………………………………………………………

…………………………………………………………………………………………

…………………………………………………………………………………………

……………………………………………………………………………………………

………………………………………………

c) On average, how many times do you use/hire rice farming machines in a season?

…………………………………………………………………………………………

…………………………………………………………………………………………

…………………………………………………………………………………………

………………………

d) What is the average cost of machine hire/service per service rendered?

…………………………………………………………………………………………

…………………………………………………………………………………………

…………………………………………………………………………………………

……………………

e) Do you have rice irrigation machines?

i) Yes [ ]

ii) No [ ]

4) Why do you insist on rice growing?

a) Requirement by cooperative society [ ]

b) Rice is more profitable [ ]

c) Only crop which performs well in this area [ ]

d) Lack of labour to work on other enterprises [ ]

e) Other (specify)

…………………………………………………………………………………………

…………………………………………………………………………………………

5 a) Do you use fertilizer in your farming?

i) Yes [ ]

ii) No [ ]

b) If yes, do you use organic, inorganic or both?

i) Organic [ ]

ii) Inorganic [ ]

iii) Both [ ]

c) If yes in 10a), how much in a season (in Kgs and cost per kg)?

Brand	**Amount used in Kgs**	**Cost per kg**	Total
CAN			
DAP			
NPK			
Others (specify) (i)			
(ii)			
(iii)			

d) If you use inorganic fertilizer, explain what drives you to use inorganic fertilizers?

…………………………………………………………………………………………

…………………………………………………………………………………………

…………………………………………………………………………………………

………………………..

6a) Are you aware of the optimal levels of farm inputs such as fertilizer, herbicides, seeds etc?

i) Yes [ ]

ii) No [ ]

b) Do you undertake soil testing for plants suitability?

i) Yes [ ]

ii) No [ ]

7a) How many litres of pesticides and herbicides do you use per season?

i)Pesticides:

……………………………………………………………………………………

ii)Herbicides:

……………………………………………………………………………………

b) What is the cost of pesticides and herbicides per litre?

i) Pesticides: ……………………………………………………………………………

ii) Herbicides:……………………………………………………………………………

8 a) Do you have adequate supply of irrigation water?

i)Yes [ ]

ii) No [ ]

b). If no, does it affect your rice production?

i) Yes [ ]

ii)No [ ]

9a) What variety of seeds do you use?

i) Hybrid [ ]

ii) Non hybrid [ ]

b) If you use non-hybrid seeds, explain why.

…………………………………………………………………………………………
…………………………………………………………………………………………
…………………………………………………………………………………………
…………………………………………………………………………………………
………………………………..

10. How much seeds do you plant?

…………………………………………………………………………………………
…………………………………………………………………………………………
…………………………………………………………………………………………
…………………………………………………………………………………………
………………………………

11. What problems do you face in rice production?

…………………………………………………………………………………………
…………………………………………………………………………………………
…………………………………………………………………………………………
………………………

12. Suggest remedies for these challenges

…………………………………………………………………………………………
…………………………………………………………………………………………
…………………………………………………………………………………………
………………………

13. Can you suggest institution and legal framework gaps realized in production of rice?

…………………………………………………………………………………………
…………………………………………………………………………………………
…………………………………………………………………………………………
………………………

14. How has rice impacted the economy of the region?

…………………………………………………………………………………………
…………………………………………………………………………………………

D. MARKETING OF RICE

1a) Are you satisfied with the present marketing facilities for rice available to you?

i) Yes [ ]

ii) No [ ]

b) If no, why not?

i) Society exploitative [ ]

ii) Transport expensive [ ]

iii) No suitable storage [ ]

iv) Unavailability of transport [ ]

v) Others (specify)……………………………………………………………………

c) Where do you sell your rice?

i) Cooperative society [ ]

ii) NIB [ ]

iii) Local middlemen [ ]

iv) Local wholesalers [ ]

v) Local retailers [ ]

vi) Others (specify)

…………………………………………………………………………………………

d) After how long were you paid for rice delivered to your agent last year?

......................................Months.

e) Has delayed payment for rice made you reduce your rice production?

i) Yes [ ]

ii) No [ ]

f) Do you experience price fluctuations from season to season?

i) Yes [ ]

ii) No [ ]

g) If yes above, do you store your produce awaiting price improvements?

i) Yes [ ]

ii) No [ ]

2) What are the main challenges you face during marketing?

…………………………………………………………………………………………

…………………………………………………………………………………………

…………………………………………………………………………………………

………………………

3) Suggest remedy measures for these challenges

…………………………………………………………………………………………

…………………………………………………………………………………………

…………………………………………………………………………………………

…………………

E. EXTENSION AND TRAINING SERVICES

a) Do you get any advisory visits from extension agents?

i)Yes [ ]

ii) No [ ]

b) If yes, how frequent are their visits per season?

…………………………………………………………………………………………

…………………………………………………………………………………………

…………………………………………………………………………………………

………………………

c) How do you rate the advice given?

i) Excellent [ ]

ii) Good [ ]

iii) Fair [ ]

iv) Not useful [ ]

d) Have you ever gone for a course about farming?

i) Yes [ ]

ii) No [ ]

iii) If yes, how many times per year

……………………………………………………………………………………………
…

iv) If no, please give the reasons

……………………………………………………………………………………………

F. SELLING CHARACTERISTICS

1) On average, how much rice do you sell in a season? (Specify whether kgs, tons, or bags and their respective measure)

……………………………………………………………………………………………
……………………………………………………………………………………………
……………………………………………………………………………………………
………………………

2) How do you attract more buyers?

i) Advertising [ ]

ii) Discounting [ ]

iii) Repackaging [ ]

iv) Fair treatment [ ]

v) other (please specify below)

………………………………………………………………………………………

………………………………………………………………………………………

……………….

3) Which value addition activities do you engage in?

i) None [ ]

ii) Sorting [ ]

iii) Cleaning [ ]

iv) Packaging [ ]

v) Grading [ ]

vi) Other (please specify below)

………………………………………………………………………………………

………………………………………………………………………………………

………………………………………………………………………………………

………………………

4) Please indicate constraints that you encounter in marketing and selling of rice. ………………………………………………………………………………………………

………………………………………………………………………………………………

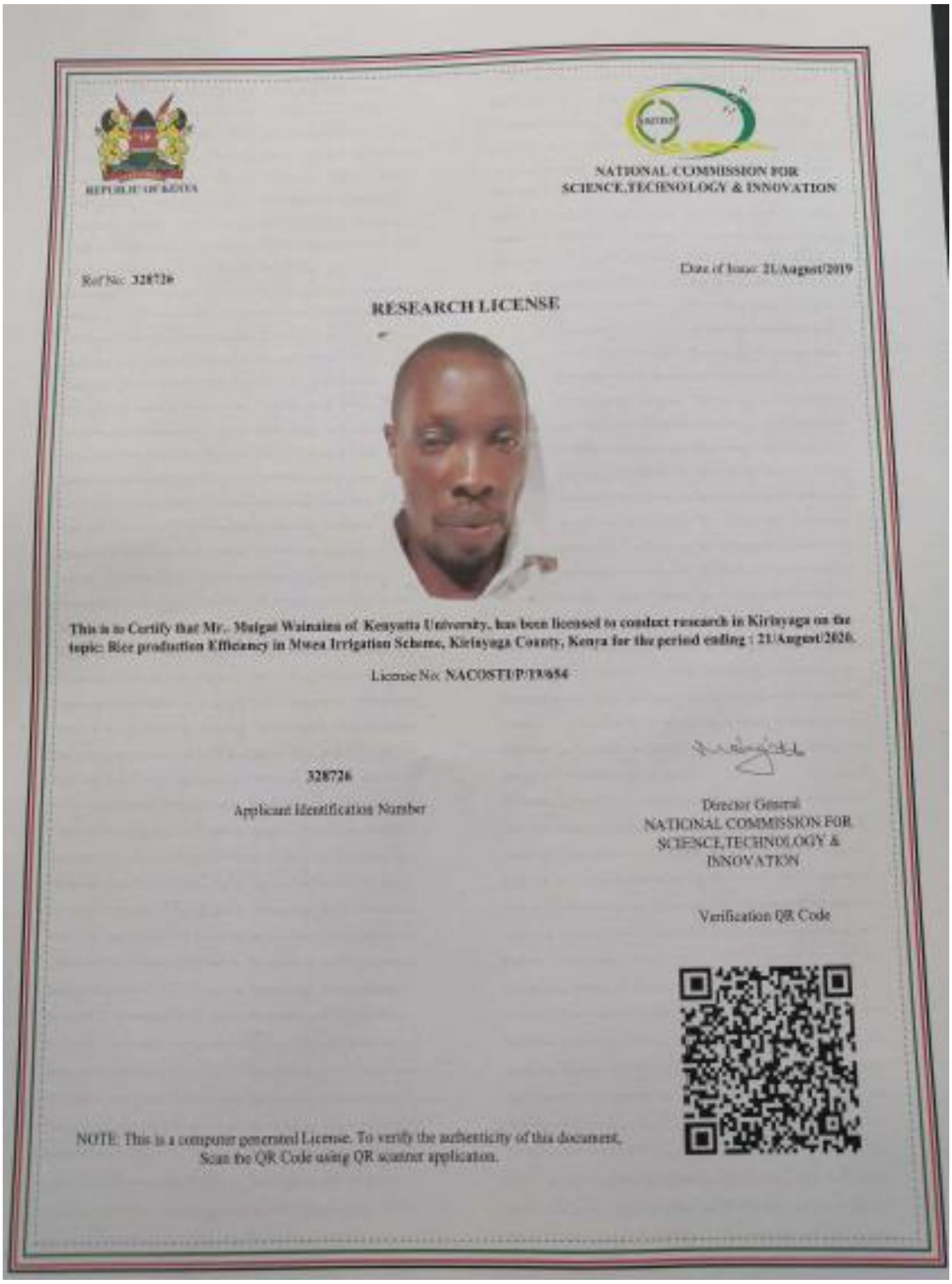
………………………………………………………………………………………………

………………………

---END---

Thank you very much for your time and response.

Appendix D: Research Permit



REPUBLIC OF KENYA

NATIONAL COMMISSION FOR
SCIENCE,TECHNOLOGY & INNOVATION

Ref No: 328726

Date of Issue: 21/August/2019

RESEARCH LICENSE

This is to Certify that Mr.. Muigai Wainaina of Kenyatta University, has been licensed to conduct research in Kirinyaga on the topic: Rice production Efficiency in Mwea Irrigation Scheme, Kirinyaga County, Kenya for the period ending : 21/August/2020.

License No: NACOSTI/P/19/654

328726

Applicant Identification Number

Director General
NATIONAL COMMISSION FOR
SCIENCE,TECHNOLOGY &
INNOVATION

Verification QR Code

NOTE: This is a computer generated License. To verify the authenticity of this document,
Scan the QR Code using QR scanner application.