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SUSTAINABLE AGRICULTURAL PRODUCTION IN AFRICA: THE ROLES OF FINANCE AND INVESTMENTS

BY

MICHAEL LAWER TETTEH

(ID. NO. 10358755)

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DECLARATION

I declare that the thesis is my own work produced from research under supervision, and it has not been presented anywhere else for the award of a degree.

Name of Candidate	Signature	Date
Michael Lawer Tetteh	………………….	04/09/2025

Names of Supervisors	Signature	Date
Prof. Charles Andoh	………………….	05.09.2025
Prof. Anthony Q. Q. Aboagye		Sept 4, 2025
Prof. Godfred Amewu	………………….	09/09/2025

ABSTRACT

Agriculture, a vital contributor to the socio-economic well-being of African nations, is facing increasing environmental uncertainty. Therefore, substantial financing and investments are required to adapt to current conditions and mitigate future risks. This thesis explores the potential of various financing and investments to foster environmentally sustainable and resilient agricultural production in Africa. It consists of four empirical chapters that offer crucial insights to inform policy and practice in the field.

The first empirical chapter examined the green efficiency of agricultural production using the slacks-based measure data envelopment analysis with the undesirable outputs approach. Our findings reveal that Africa's agricultural sector exhibits an estimated average green efficiency score of 66%. Unsustainable input intensification involving arable land, fertiliser, irrigation water, and pesticides were identified as the primary source of the inefficiency. Our study shows the exact optimal levels of input usage and emission reductions required to address the identified inefficiencies.

The second empirical chapter examined the impact of financial investments and agri-environmental fiscal policies (fiscal policies that promote environmental sustainability in agricultural production) on African climate-smart agriculture in a two-stage approach. The first stage relied on the slacks-based measure data envelopment analysis with the undesirable outputs approach. At the second stage, we applied the fractional heteroscedasticity probit model to estimate the influencing factors of agricultural green efficiency (optimising agricultural output without harming the environment). Our findings show that investments in agricultural technology and prudent capital expenditure can enhance green efficiency. Financial aid to agriculture is a crucial driver of green productivity, and climate financing can be adequate when implemented through agri-environmental fiscal policies. Carbon-related

fiscal policies were found to have a positive impact on green productivity, while methane-related policies yielded mixed results. Interestingly, urbanisation threatens green efficiency, while environmental management and eco-vitality promote sustainable productivity.

In the third empirical chapter of the thesis, we studied the dynamic interconnections between agriculture output value, domestic credit, foreign direct investment in agriculture, food price variation, and sustainable agriculture practices using the panel vector autoregression methodology. The empirical results demonstrate statistically significant interdependence among all the variables, with a one-way transmission effect of agriculture output value to domestic credit, FDI, and sustainable farming practices. Additionally, bi-directional causality is established between food price anomalies and output value, FDI and domestic credit, and FDI and sustainable farming practices.

The final empirical chapter analysed the influence of research and development (R&D) expenditure and globalisation on agriculture value-added in Africa. The chapter applied the dynamic common-corrected effects mean group and local projection estimators as estimation techniques. The empirical evidence shows that R&D investments positively influence agriculture value-added in the medium to long term. However, globalisation has yet to significantly impact agriculture value-added in Africa except through financial development synergies requiring a continued and consistent R&D investment and a definite globalisation strategy.

Keywords and phrases: *Agriculture, Green Efficiency, Agricultural Finance, Sustainable Agricultural Finance, Sustainable Fiscal Policies, Globalisation, R&D Investments.*

JEL classification: D25, O3, Q1, Q14, Q16, Q28, Q56

DEDICATION

To my wife, Kate and daughters, Michelle and Caitlyn.

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CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Agricultural production in Africa represents a multifaceted and dynamic sector that is pivotal in the continent's socio-economic landscape. Africa's agriculture is characterised by its diversity, with a wide range of agroecological zones, crops, and farming systems. This overview provides a comprehensive perspective on critical aspects of agricultural production in Africa.

Africa boasts diverse agroecological zones, including arid and semi-arid regions, tropical rainforests, savannahs, and highland areas. This diversity has led to various agricultural practices and crop choices tailored to local conditions. Subsistence farming predominates in many regions, where smallholder farmers grow crops primarily for household consumption. However, there is also a growing trend towards commercial agriculture (Clay & Zimmerer, 2020; Paparrizos et al., 2023) in rural and peri-urban areas, producing various outputs for local and export markets. Notwithstanding, much of the agricultural produce in Africa is by smallholder farmers. Local and international development partners, including the Food and Agriculture Organisation (FAO), International Finance Corporation (IFC), International Fund for Agricultural Development (IFAD), and World Bank, among other local, continental, and international agencies, continue to offer financial support. Multilateral and bilateral donors working through their international development agencies, like the German Agency for International Cooperation (GIZ), Stichting Nederlandse Vrijwilligers (SNV), and the United States Agency for International Development (USAID), are augmenting national plans in their respective functional African jurisdictions to shape Africa's agriculture for a better future. Non-governmental organisations such as the Alliance for a Green Revolution in Africa (AGRA) and the African Development Bank (AfDB) have also played crucial financial and technical roles in agricultural development in Africa. The African Union (AU) also provides financial and technical support to the sector through member states.

The continent is home to a wide array of crop and animal products. The crops consist of both staple and cash crops. Staple crops such as maize, rice, cassava, millet, and sorghum are widely produced and form the basis of diets in many African countries. The widely produced cereals are maize, rice and wheat. Cash crops such as cocoa, coffee, cotton, tea, rubber, oil palm, and tobacco are produced mainly for the export market in their raw states with minimal value addition, coupled with an underdeveloped value chain enablers. Fruits and vegetables also contribute largely to production value and export revenue. The livestock and fisheries sectors have also contributed significantly to the agricultural output value on the continent. Notwithstanding, the continent's share of global agricultural production remains below all other continents except Oceania (FAOSTAT, 2023b). Among these products, African countries rely on a few of them as major export income-generating sources with their associated volatilities and risks.

Another cause for concern is the low share of production volumes and value in the primary staples with implications for food sufficiency and security. For example, we observe that, of the world's top ten most produced cereals (maize, rice, wheat), Africa produces only 7.3% of the share of maize, 3.7% share of rice, and 3.4% share of wheat (FAOSTAT, 2023b). The crop varieties of production that the continent has significant proportions in are millet (47.5% share), sorghum (39.4% share) and cassava (57% share) (FAOSTAT, 2023b). The extremely low shares of contribution to maize, rice, and wheat production expose the continent to massive external shocks to the global food systems, just as was witnessed during the COVID-19 pandemic.

Despite the production potential, Africa's agriculture faces several constraints. These include low financing and investment, unavailability and/or expensive quality agricultural inputs such as improved seeds, fertilisers, modern and efficient farming equipment, as well as high exposure to environmental shocks. Poor infrastructure, including roads and storage facilities, has also been a setback to the timely and cost-efficient movement of agricultural produce to markets. These negatively impact the livelihoods of farmers in Africa, many of whom are smallholders. While the bottlenecks associated with inputs and distribution (value-chain processes) could be resolved in the short term, provided financing and logistics are available, immediate investments and financing are required to safeguard agricultural production against the disruptive potential of climate change. Africa is particularly vulnerable to climate change and variability, which result in erratic rainfall patterns, prolonged droughts, and increased temperatures (Ortiz-Bobea et al., 2021). These climatic shifts disrupt farming cycles, leading to crop failures, food scarcity, and financial losses for farmers. Nonetheless, climate adaptation strategies or climate-resilient practices exist to secure consistent food production amid environmental uncertainties. But climate adaptation is expensive for the predominantly low-income farmers in Africa, and adaptation finance has been a significant challenge for African governments and developing countries.

Essentially, the fiscal policy environment is Africa's most significant influencer of agricultural production because the sector is predominantly government funded. Despite the importance of the agricultural sector to African economies, current policies and initiatives, such as input subsidy programmes and market reforms, have yet to deliver food security, rural development, and agricultural transformation. One of the unifying commitments and measurable road map to sustainable agriculture production in Africa is the 2015 Malabo Declaration. The declaration aims to secure food, end hunger, and transform agriculture sustainably. Nonetheless, with the target year (2025) fast approaching, only one African country (Rwanda) is on track to meeting the target according to the third biennial report on the progress of the declaration (African Union, 2022), and the continent still grapples with extreme hunger, starvation, food security, low climate adaptation rates and high vulnerability.

In this thesis, the scope of sustainable agriculture is grounded in the principles established by the Food and Agriculture Organisation of the United Nations. This indicates that "*to be sustainable, agriculture must meet the needs of present and future generations, while ensuring profitability, environmental health, and social and economic equity*" (FAO, 2025). This contributes to all four pillars of food security: availability, access, utilisation, and stability, as well as the dimensions of conservation, which centre on environmental, social, and economic aspects (FAO, 2025). One of the key foundations of sustainable agriculture is climate-smart agriculture, which aims to increase agricultural productivity while using fewer inputs, build climate resilience, and reduce greenhouse gas emissions from agricultural activities.

Aside from the public and private expenditure needed to fund sustainable agriculture, investments in research and development have become critical in the current internal and external circumstances to propel the development of drought-resistant crop varieties, sustainable farming practices, and improved post-harvest management techniques, thereby curbing vulnerabilities. The commitment of the public sector, the participation of the private sector, and collaboration on technical and financial matters are essential to revitalise Africa's agriculture sector, which is vital for both microeconomic and macroeconomic growth. Additionally, Africa's position and reputation in the global market will influence the extent of economic benefits gained from these efforts. Therefore, it is essential to comprehend the various sources of financing and investment in Africa's agriculture and their impact on its productive and sustainable development.

1.2 Justification of the Study

Africa is uniquely positioned with different ecological zones that are ideal for producing a diverse range of agricultural goods, yet it is highly vulnerable to the impacts of climate change. Understanding how these distinct ecosystems can be harnessed efficiently is essential for developing tailored strategies that promote sustainability. Additionally, Africa faces significant climate variability, characterised by frequent droughts and floods that impact agricultural productivity (FAO, 2021). Studying green efficiency in this context can help develop resilient and specific agricultural benchmarks and practices that improve productivity while causing minimal or no environmental harm. Furthermore, Africa's rich biodiversity presents opportunities for sustainable farming practices that harness traditional knowledge to enhance green efficiency, as outlined in the concept of agroecology.

The study of green efficiency in Africa is crucial for economic development and food security. Agriculture is a significant economic driver and source of livelihood in Africa. Improving green efficiency in agriculture can have a profound impact on economic development and food security. Enhancing green efficiency can significantly boost agricultural productivity, contributing to economic growth and poverty reduction. Efficient and sustainable farming practices are crucial for improving food production, which in turn helps alleviate food insecurity and malnutrition in many African countries. Green efficiency enhances productivity in agriculture by primarily optimising resources, promoting sustainability, and improving yields (Beckman et al., 2024).

Africa's progress towards achieving the UN SDGs is closely linked to its agricultural sector. Efficient green agriculture can contribute to achieving SDG 2, Zero Hunger, and SDG 13, Climate Action. Focusing on Africa in green efficiency research can provide valuable insights and contribute to sustainable agricultural practices that are crucial for the continent's future. Nevertheless, addressing climate change requires significant funding, but it is often inadequate to tackle the challenges in Africa's agricultural sector. The challenges require effective adaptation and mitigation strategies, which are equally expensive to deploy and require constant capital.

The current financial landscape is further complicated by a significant decline in government funding, low private sector engagement, and limited utilisation of alternative financing mechanisms such as foreign direct investment (FDI), coupled with the growing gap between promised and actual donor disbursements. As such, there is a need to explore innovative and sector-specific financing solutions to better fund the sector. This must also be done using novel and robust econometric methods to obtain accurate and consistent results that inform policy interventions necessary to build resilience and achieve sustainable agricultural development in Africa.

This thesis is also justified by the critical need to enhance agricultural value addition in Africa, which holds the potential to improve the economic well-being of smallholder farmers. Despite its importance, progress has been slow due to limited investment in research and development, as well as a scarcity of comprehensive empirical studies. Additionally, globalisation has expanded market opportunities for African agriculture, but increased competition underscores the necessity for a deeper understanding of its impacts. By adopting a robust methodological approach that addresses cross-sectional heterogeneity and common misspecifications, this research aims to provide valuable insights into how financial development can facilitate agricultural transformation in Africa, ultimately contributing to sustainable economic growth.

Ultimately, this thesis contributes to the broader goal of promoting sustainable agricultural development and resilience in Africa amidst increasing climate risks, informing more effective policy design and resource allocation.

1.3 Problem Statement

Agriculture is the backbone of many African economies, providing employment opportunities and a lifeline to many individuals and households. It contributed 14.7% to the overall GDP in 2022 (FAOSTAT, 2023a) and accounted for 51.57% of the total employment across the continent, with a gross output value of US$288.38 billion in 2021 (FAOSTAT, 2023a).

Despite these substantial socio-economic contributions, Africa continues to struggle with food insecurity, importing about $43 billion worth of food annually. At the same time, a significant part of its population faces extreme poverty and hunger (World Bank, 2022). These challenges directly hinder the achievement of the United Nations' Sustainable Development Goals 1 (No Poverty) and 2 (Zero Hunger). One major obstacle to addressing these issues has been the low and ineffective allocation of resources to the sector (see Agricultural Orientation Index of FAOSTAT, 2023a). The limited financial commitment to the sector has significantly undermined its resilience to climate change, primarily due to inadequate adaptation.

The unfavourable climatic conditions have resulted in pest attacks, prolonged droughts, erratic rainfall patterns, extreme heat, and declining soil fertility, which have worsened the plight of farmers in Africa, who are mostly smallholders (Musango & Peter, 2007; Ortiz-Bobea et al., 2021). In particular, a swarm of desert locusts in the Horn of Africa (Kenya, Somalia, Ethiopia, Djibouti, and Eritrea) caused the locust crisis between 2020 and 2021, which was exacerbated by a prolonged drought in the same region in 2020 (FAO, 2021).

These climate-induced catastrophes destroyed the crops and pastureland of pastoral households (FAO, 2021) with severe socio-economic implications. Substantial financial interventions by the FAO and its funding partners enabled the control of further spread and brought relief to farmers through input distributions. Exceptional droughts in the Horn of Africa and, more recently, Southern Africa between 2023 and 2024, caused by El Niño, a climatic condition with the potential of causing dramatic, harsh weather conditions, led 27 million people in the Horn of Africa to become food insecure, with impacts spreading into 2025 (WFP, 2024). The worst-affected countries include Lesotho, Malawi, Namibia, Zambia, and Zimbabwe. Mozambique and Angola.

North Africa experienced the most significant warming due to extreme temperature rises, which led to wildfires in Algeria and Tunisia in 2022 (UN Ghana, 2023). Nigeria, Niger, Chad, and the southern half of Sudan, however, faced significant losses due to heavy monsoon rains that resulted in flooding (UN Ghana, 2023). Land degradation, including soil erosion, desertification, nutrient imbalances, acidity, salinisation, deforestation, and soil compaction, has also significantly contributed to the decline in agricultural productivity across Africa (Mesele, 2025). A World Bank report states that over 80% of Africa's agricultural land is degraded, with profound implications for agricultural output and food security, resulting in an increased reliance on food imports (Koh et al., 2025). While major cash crops such as cocoa have been impacted by climate change in West Africa (Wessel, 2015), their cultivation has also been linked to deforestation (Sassen et al., 2022).

To address the vulnerabilities of climate change, climate-smart agriculture (CSA) has emerged as a viable approach to improving agricultural productivity while conserving the environment (Princess et al., 2022; Weniga et al., 2020). CSA emphasises the importance of achieving optimal and climate-resilient agricultural production at minimal environmental costs, referred to as agricultural green productivity (Clay & Zimmerer, 2020; Liu et al., 2022; Shen et al., 2022).

Although substantial contributions have been made in other contexts, primarily in Asia (e.g., He et al., 2021; Liu et al., 2022; Shen et al., 2022; Xu et al., 2022), the African perspective remains largely unknown. It is vital to know the African perspective for several reasons: first, unique environmental conditions. Africa's diverse environmental conditions, ranging from arid deserts to tropical rainforests, present unique challenges and opportunities for green agriculture.

Though some contributions have been made by Clay and Zimmerer (2020), Jayne et al. (2019), Koch et al. (2019), and Heidenreich et al. (2022) in the efficiency literature, the studies did not estimate the agricultural green efficiency levels or the required input-output targets for reaching green-efficient agricultural productivity in Africa. Also, the approaches adopted in the specific African contexts did not adopt robust green efficient methods compared to the Tone (2003) Slacks-Based Measure (SBM) Data Envelopment Analysis (DEA) with undesirable outputs. In addition, previous studies did not include a comprehensive set of negative agricultural externalities in their estimates of agricultural green efficiency, thereby providing a deeper and more realistic measure of environmental efficiency in agricultural production.

Despite the existing contributions to the green efficiency literature, none have addressed the African agricultural case. Meanwhile, Africa urgently needs to boost green agricultural productivity to reduce resource wastage, which has financial implications, while also ensuring food security. Essentially, Africa lacks an empirical benchmark to guide efficient and environmentally sustainable agricultural productivity. In this light, the thesis aims to determine the green efficiency of African agricultural production, identify the causes of inefficiencies, and propose a benchmark to optimise production sustainably.

The World Bank indicates an increasing climate risk to the socio-economic well-being and physical infrastructure of the most vulnerable countries. The impacts of climate change are more severe in Africa and other developing regions. According to Kray et al. (2022), Africa alone may suffer an estimated annual loss and damage worth around US$201 if no action is taken. The World Bank (2022) estimates that at least US$80 billion is required annually to deal with environmentally related production challenges. However, inadequate preparedness and the adoption of ineffective strategies contribute to these challenges (Martey et al., 2020). Climate adaptation and mitigation have been proposed to manage the current challenges and prepare for the vulnerabilities while protecting the environment (FAO, 2013). However, climate adaptation and mitigation require significant financial commitments and investments. Nonetheless, they are under-investigated in distinct ways.

Budget constraints have been a primary challenge to Africa's climate resilience efforts, particularly in the agricultural sector. Although Africa receives significant funding support from various sources for climate-smart agriculture purposes, the effectiveness and efficiency of these initiatives on productivity have been mixed, unsatisfactory, or questioned (Savvidou et al., 2021), with a growing gap between promised and actual disbursed funding (FAOSTAT, 2023a). The growing financing disparity necessitates an urgent and innovative approach to financing sustainable agriculture, as further borrowing could exacerbate the already high debt burdens of African countries (Savvidou et al., 2021). As a contribution, we explored data on rarely used agri-environmental fiscal policies to provide deeper understanding of public sector intervention using an equally unexplored second-stage econometric approach (fractional regression) in the agriculture finance literature. The departure of our second-stage regression approach to existing literature is founded on the theoretical basis and nature of DEA scores. As such, failure by earlier studies to account for the boundary nature of DEA scores (see He et al., 2021, for instance) is likely to result in misleading outcomes (Amore & Murtinu, 2021; Banker & Natarajan, 2008; Villadsen & Wulff, 2021).

Agriculture in Africa is predominantly government funded (Binswanger et al., 2000). This has witnessed a significant decline to 2.27% (on average) as of 2021 (FAOSTAT, 2023a), far below the 10% lower-bound investment threshold set by African countries to enable them to meet the Malabo 2015 targets by 2025. Private capital, however, remains a viable alternative or supplement. Although the empirical literature has explored this avenue, it has primarily focused on access (e.g., Assouto & Houngbeme, 2023; Diamoutene & Jatoe, 2021). Also, the use of aggregated private sector credit data has widely been the norm in the literature as a proxy for credit to the sector (see Ngong & Fonchamnyo, 2022). Meanwhile, data aggregation can lead to the loss of valuable and specific insights peculiar to agriculture and misleading results.

Foreign direct investment (FDI) in agriculture has been another financing avenue. Various studies (see Edeh & Ugwuanyi, 2020; Kubik, 2023; Nyiwul & Koirala, 2022; Ali et al., 2023; Udemba, 2020) have explored the potential and relevance of FDI to agriculture from different angles, perspectives, and contexts. In Some cases, aggregated FDI data has been applied for agriculture-specific studies (see Ali et al., 2023) with associated consequences. Our sustainability stance in this thesis also allowed us to evaluate the pollution halo hypothesis from a novel data stance and a rigorous methodological approach. High vulnerability to market dynamics is one key underlying challenge of Africa's agriculture output. In this thesis, we take a unique approach to showcasing the market vulnerabilities through food price anomalies, a measure of food price variations and an indicator of SDG target 2.c.1 of the United Nations to measure the agriculture output exposure of the continent to external shocks arising from environmental and or geopolitical sources.

Agricultural value addition has been identified as one of the ways to improve the value of agriculture outputs and, consequently, the economic well-being of the predominantly small-holder farmers in Africa. Nevertheless, it has remained an illusion saddled with slow growth and very low investments, particularly in research and development (R&D), necessary to drive the required transformation. Meanwhile, the empirical literature on this remains scanty. Globalisation has equally opened the agriculture market to a broader consumer base. Coupled with this, though, is competition. While empirical literature exists, it takes a narrow stance on globalisation (see Alagidede et al., 2020; Ibrahim & Vo, 2020). The thesis also provides significant avenues through which financial development can play a significant role in agricultural transformation in Africa, using a robust methodological approach that efficiently and consistently models cross-sectional heterogeneity and other misspecifications common in the literature for cross-country studies.

Indeed, several critical challenges face African agriculture. Key issues include inadequate financial and resource allocation to the sector, which weakens its resilience to climate change, as well as a limited understanding of the specific benchmarks needed to optimise productivity while conserving the ecosystem. The effectiveness of public sector agricultural financing is uncertain, while private sector financing options remain limited, and the study of fiscal policies supporting sustainable agricultural productivity is notably absent. The effects of these factors and other market-driven elements on agricultural productivity are also not thoroughly assessed. Furthermore, socio-economic factors influencing agricultural resilience have not been sufficiently studied. Additionally, there is a disconnect between investments in agricultural innovation and value addition, as well as their complex roles in the global competitive market. Addressing these gaps is essential for designing effective interventions to enhance agricultural productivity and resilience across Africa.

Therefore, our study provides significant insights into the existing literature by estimating Africa's green agricultural efficiency level robustly and holistically. The study also estimated the optimal levels of input efficiency (targets) in Africa and identified the causes of inefficiencies, along with their respective empirical excesses thereby establishing a benchmark for sustainable agricultural production in Africa. Empirical factors influencing agricultural green efficiency were also examined using a robust approach that was contrary to what pertains in the field. Fresh empirical evidence from novel data sets sheds unique light on the interconnections between food price variations, private capital, and sustainable agriculture practices. Finally, the study offers a deeper and broader understanding of the roles of agriculture R&D and globalisation and their interdependencies with financial development to influence agriculture value addition in Africa.

1.4 Research Objectives

In view of the above, the main objectives of the study are as follows:

1. To assess Africa's agricultural green efficiency, identify inefficiencies, and propose benchmarks.
2. To determine the roles of financial investments and environmental fiscal policies in enhancing agricultural green productivity in Africa.
3. To understand the dynamics of agricultural output, private capital, food price variations and sustainable agriculture practices in Africa.
4. To examine the impacts of agriculture R&D investments and globalisation on the value added in African agriculture.

1.5 Research Questions

1. Is agricultural production in Africa green efficient? What are the causes?
2. What are the contributions of financial investments and agri-environmental fiscal policies in enhancing climate-smart agricultural productivity in Africa?
3. What are the dynamics in agricultural output, private capital, food price variations and sustainable agriculture practices in Africa?
4. How have agricultural R&D investments and globalisation affected the value added in agriculture in Africa?

1.6 Significance of the Study

The thesis offers numerous insights into sustainable agricultural production in Africa from empirical, contextual, methodological, and managerial perspectives.

The empirical significance of our research on agricultural green efficiency in Africa is immense. It is essential for enhancing productivity, informing policy, supporting economic development, building climate resilience, ensuring food security, managing natural resources, fostering social benefits, and promoting technological advancements. Our empirical estimates of agricultural efficiency levels, shortfalls, and targets to achieve green efficiency are unique in the agricultural green efficiency literature due to their broad adoption of undesirable outputs in the estimation process. These provide crucial and hitherto nonexistent benchmarks to guide sustainable agriculture production in Africa, paving the way for effective and efficient resource allocation in light of the challenging financial times facing African states and, more importantly, the appropriate policy formulation and implementation required to drive the needed transformation in the agriculture sector in Africa.

The significance of this thesis is also entrenched in the methodological rigour of the estimation approaches, the exposition of underexplored financial and environmentally sustainable agriculture production data, and environmental-related fiscal policy data that drive agriculture production in Africa. Our comprehensive analysis of the research problem provides a deeper understanding of the issues at hand and their broader implications for agriculture financing, instilling confidence in the robustness of our findings and their rich contribution to the literature.

Globalisation is upon the continent, and integration has become inevitable in a fast-changing global village. However, the benefits are available only to the nations that position themselves to receive them and set out to provide what the world needs. In this thesis, we provide resounding evidence supporting the benefits of Africa's participation in the global market through agriculture, as well as the essential need for consistent investments in research and development. The outcome will go a long way in shaping Africa's disposition in the ever-evolving global market.

By addressing these key areas, our empirical research provides valuable insights and solutions that are crucial for the sustainable development of Africa's agricultural sector. As the continent faces growing challenges related to population growth, climate change, and resource depletion and a new path towards harnessing the substantial benefits inherent in agriculture, the thesis offers a practical pathway to a more sustainable and resilient agricultural future.

1.7 Organisation of the Study

The thesis is organised into seven chapters. The first chapter covered the introduction to the thesis. Chapter two provides a general overview of African agriculture, presenting several stylised facts. The first empirical chapter (chapter three) presents agricultural green efficiency.

It was followed by chapter four, which examined the financial and agri-environmental fiscal factors affecting African climate-smart agriculture. The fifth chapter studied the dynamics of agricultural output and its interdependencies on private capital, food price variations and sustainable agricultural practices in Africa. Chapter six contains the fourth empirical chapter of the thesis, which explores the relationships between agricultural innovation, global economic integration, and agricultural value added in Africa. The seventh chapter summarised and concluded the thesis. Policy recommendations of the thesis were also provided in chapter seven.

1.8 Contributions to the Body of Knowledge

The thesis makes a compelling and multifaceted contribution to the literature on agricultural sustainability, climate resilience, and development finance in Africa. It bridges critical gaps in empirical analysis, methodological rigour, and policy relevance, offering a robust framework for understanding and improving agricultural green efficiency across the continent.

1.8.1 Benchmarking of Agricultural Green Efficiency

Despite agriculture's central role in African economies, previous research has lacked a continent-wide empirical benchmark for green agricultural productivity. This study addresses that gap by employing the Slacks-Based Measure (SBM) Data Envelopment Analysis (DEA) with undesirable outputs, an advanced technique rarely utilised in African contexts. This methodological innovation allows for a more precise assessment of environmental efficiency, considering negative externalities such as pollution and land degradation. The development of input-output targets and the identification of inefficiency drivers offer a foundational empirical benchmark for sustainable agricultural productivity, which has been notably absent in prior African studies. As a result, this thesis establishes a crucial benchmark for sustainable agricultural production in Africa. Additionally, it contributes to the theoretical advancement of sustainable production efficiency models, aligning with emerging paradigms in ecological economics and green growth theory.

1.8.2 Contextualising Climate-Smart Agriculture (CSA)

While CSA has been extensively studied in Asia, its application in Africa remains underexplored. This thesis advances the literature by tailoring CSA to Africa's diverse agro-ecological zones, climate variability, and socio-economic conditions. It emphasises agroecology and traditional knowledge systems, aligning CSA with the continent's biodiversity and cultural practices. This contextualisation is crucial for designing locally relevant and resilient agricultural strategies. The thesis therefore contributes to the theoretical literature on adaptive development and resilience theory, emphasising context-specific pathways to sustainability.

1.8.3 Innovative Use of Fiscal Policy Data and Econometric Techniques

The study introduces fractional regression in the second stage of DEA analysis, addressing a methodological oversight in prior research regarding the boundary nature of DEA scores. This methodological innovation contributes to the theoretical literature on fiscal policy evaluation, particularly in the context of environmental public goods. It introduces a novel econometric approach to modelling bounded dependent variables in environmental efficiency analysis. By leveraging rarely used environmental fiscal policy data, the thesis deepens our understanding of public sector interventions and their impact on green efficiency. This approach enhances the precision of policy evaluation and contributes to the growing literature on environmental fiscal policy.

1.8.4 Critical Evaluation of Agricultural Financing Mechanisms

The thesis offers a nuanced critique of agricultural financing in Africa. It highlights the inefficiencies of public sector funding, the limitations of aggregated private credit data, and

FDI flows, proposing a disaggregated, sector-specific approach to financial modelling. We introduced in this thesis, how financial flows interact with environmental and market uncertainties associated with geopolitical risks or events. This contributes to the literature on financial development and price risk theory, particularly in fragile and climate-sensitive economies. By examining the pollution halo hypothesis through rigorous methods, this study contributes to debates on sustainability finance. It also calls for disaggregated and sector-specific financial data to improve policy targeting and investment effectiveness.

1.8.5 Market Vulnerability and Food Price Anomalies

Introducing food price anomalies as a proxy for market vulnerability and Sustainable Development Goals (SDGs) target 2.c.1, the thesis provides a novel indicator for assessing agricultural exposure to external shocks. This contribution is particularly relevant in the context of climate change and geopolitical instability, offering policymakers a tool to monitor and mitigate food insecurity.

1.8.6 Exploration of Understudied Drivers of Agricultural Transformation

The thesis expands the literature by investigating the roles of agricultural research and development (R&D), globalisation, and financial development in value addition. It critiques the narrow scope of existing studies and employs robust cross-country modelling to account for heterogeneity and misspecification. This comprehensive approach reveals the complex interdependencies between innovation, market access, and financial systems in driving agricultural transformation.

By synthesising environmental, financial, and socio-economic dimensions, the thesis proposes a holistic framework for agricultural resilience. It aligns its findings with the UN SDGs, particularly SDG 2 (Zero Hunger) and SDG 13 (Climate Action), reinforcing the global relevance of its contributions.

CHAPTER TWO

STYLISED FACTS OF THE AGRICULTURAL INDUSTRY IN AFRICA

2.1 Introduction

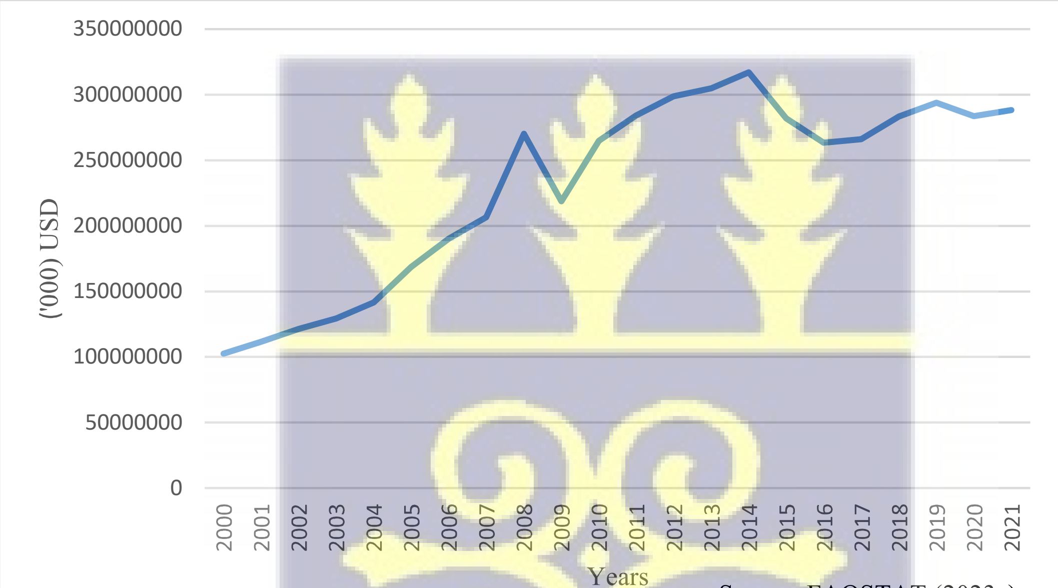
In this chapter, we present an overview of the agriculture industry in Africa from economic, financial and environmental perspectives.

2.2 Economic Contribution of Agriculture in Africa

The economic impact of agriculture in Africa is profound, underscored by its substantial output value, a significant share of value added to GDP, and its pivotal role in employment generation. Agriculture is a cornerstone of the continent's economy, yielding a substantial output value that underpins various sectors and livelihoods. Figure 2.1 indicates an overall upward trend of output value from the year 2000 up to 2021. The 2021 value, however, shows a decline from the highest recorded value of $317.19 billion in 2014 to the 2021 total output value of $288.38 billion, all in current terms. Low financial commitments to the sector (private and public), an upsurge in adverse environmental conditions, and/or low adoption of advanced production techniques could have accounted for the drop in the overall output value from 2009.

Moreover, the sector's contribution to the overall GDP is substantial, reflecting its integral role in the broader economic landscape. As can be observed from Figure 2.2, the value addition of the sector alone recorded the highest average of 16.4% to the GDP of African countries in 2002 but has since witnessed a decline to 14.7% as of 2022. Notwithstanding, the sector is one of Africa's single most significant contributors to GDP. Substantial in the economic significance is its robustness over time as the single largest source of employment, providing livelihoods for a significant proportion of the population, particularly in rural areas where alternative opportunities are mostly limited. The data again show (see Figure 2.3) that although the proportion of total employment is dwindling, it currently provides 51.57% of the total employment in Africa. This contribution underscores agriculture's role in poverty reduction and inclusive development and its potential to enhance socio-economic resilience. The downward trend of the ratio may be attributed to more workers (especially the youthful population) opting for alternative livelihoods or potentially due to mechanisation and technological advances in agricultural production. These factors firmly establish agriculture as a crucial driver of economic growth and social and economic stability across the African continent.

Figure 2.1: Gross Agriculture Output Value (Current)



Source: FAOSTAT (2023a)

Figure 2.2: Agriculture Share of GDP

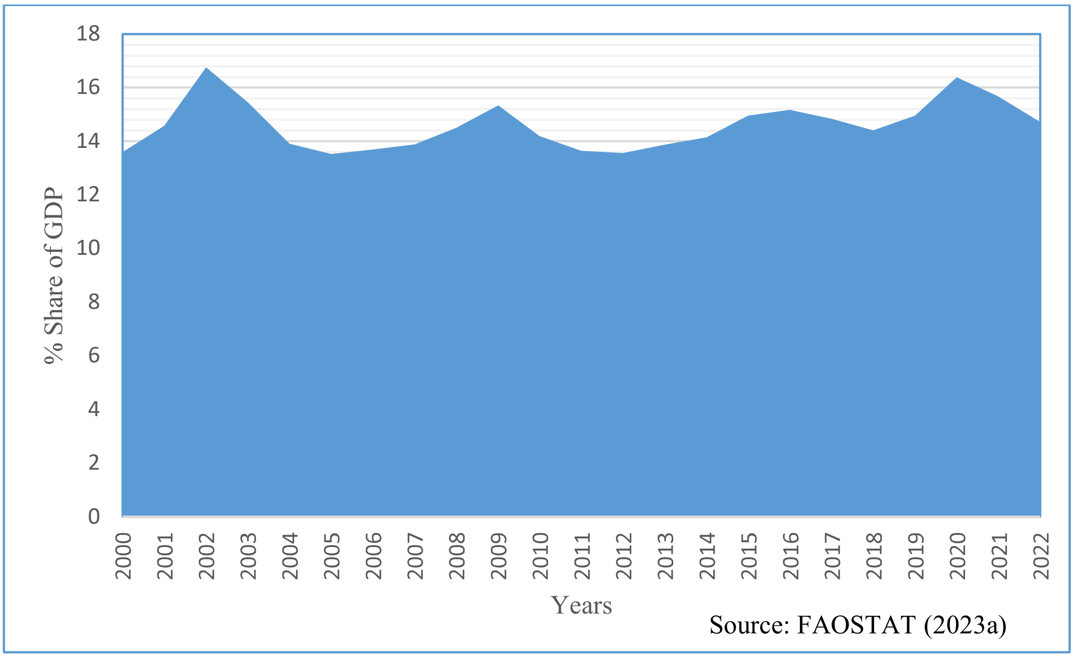
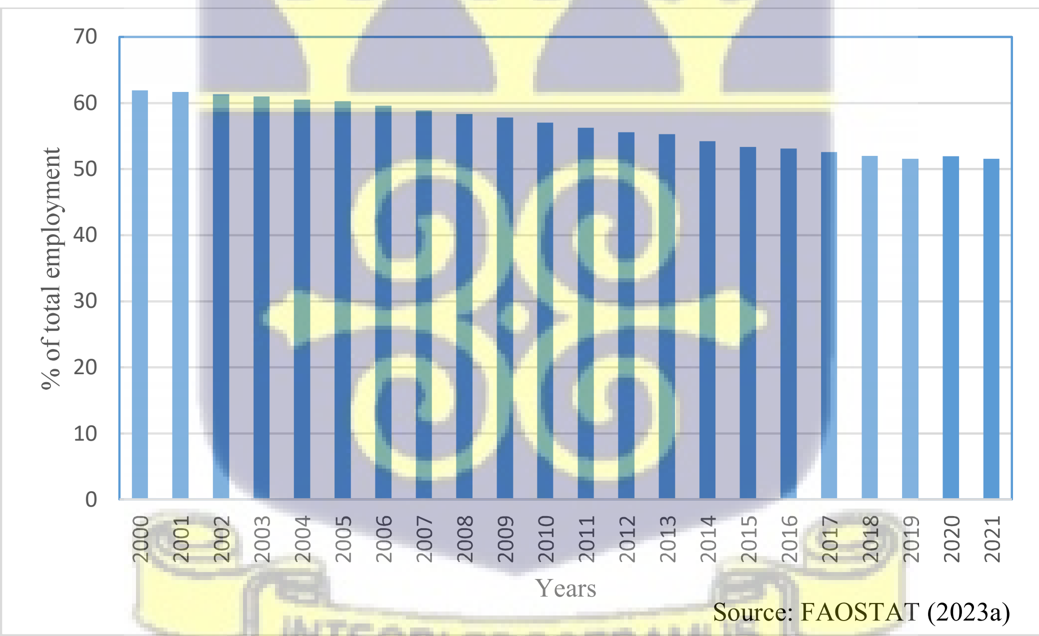


Figure 2.3: Agriculture Share of Total Employment

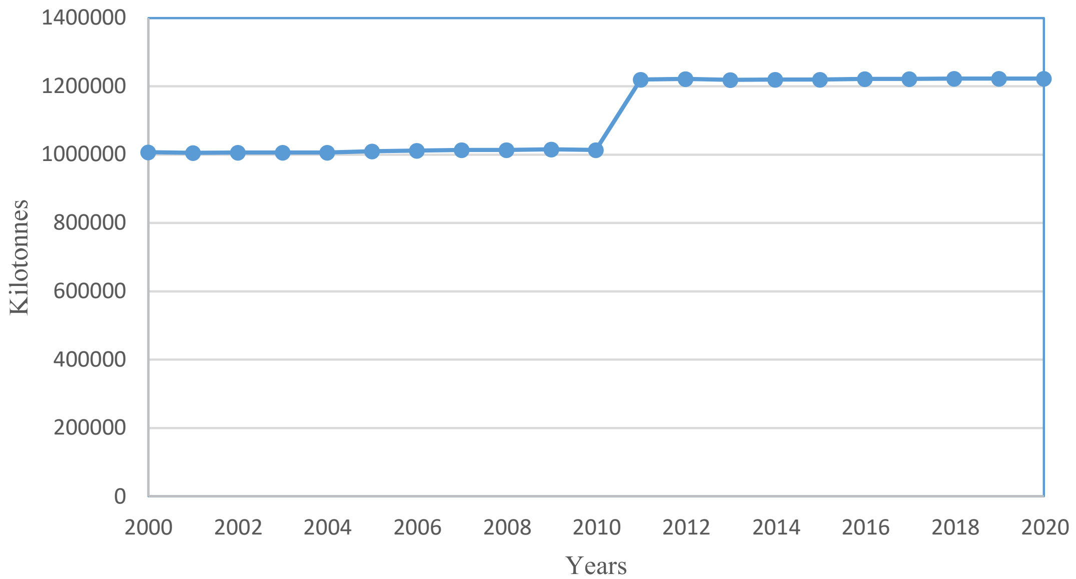


2.3 Environmental Impact of Agriculture in Africa

Agricultural activities worldwide have gathered increasing attention due to their substantial environmental implications, particularly in the context of greenhouse gas emissions. The sector's significant contributions to carbon dioxide, methane, and nitrous oxide emissions have underscored its role as a notable source of atmospheric pollutants. Carbon dioxide emissions arise from the extensive use of fossil fuels in mechanised farming and land-use changes. In contrast, methane emissions primarily result from livestock rearing, rice cultivation and environmentally unfriendly on-farm practices. On the other hand, nitrous oxide emissions predominantly stem from the application of synthetic fertilisers and other agricultural practices. Particularly in Africa, these emissions collectively contribute to the region's overall environmental footprint, which, contrary to assertions, exhibits relatively higher rates compared to other regions. Figures 2.4, 2.5, and 2.6 illustrate the increasing trend in agricultural greenhouse gas emissions, specifically carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4) emissions. The surge in CO_2 emissions between 2010 and 2012 could be attributed to environmentally unsustainable agricultural production practices, including deforestation, land degradation, changes in land preparation techniques such as biomass burning, and energy use by machinery.

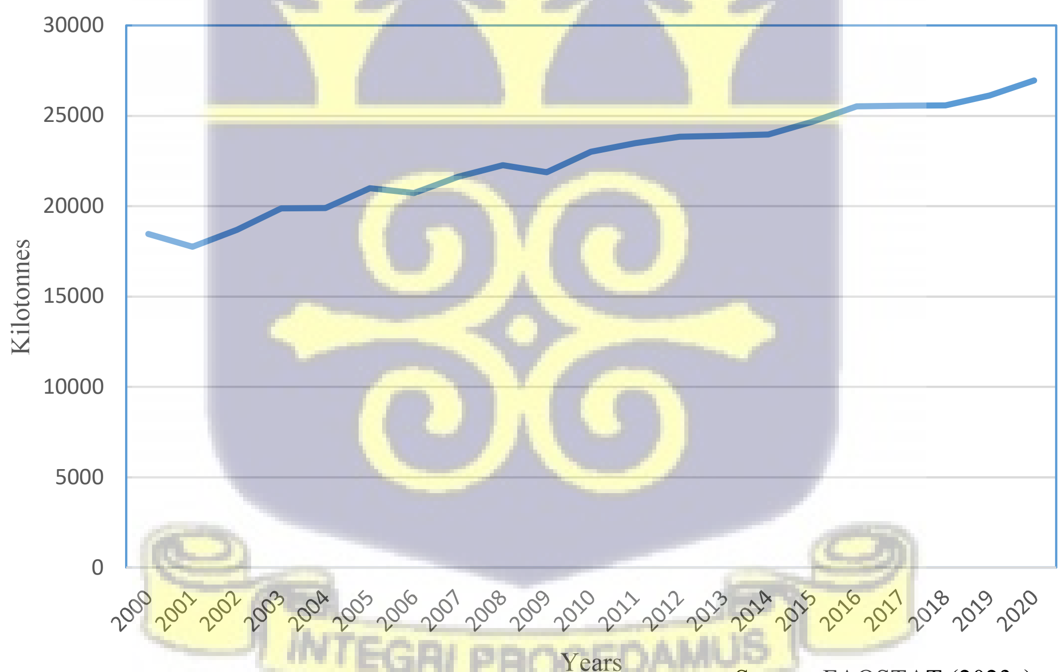
The above statistics have prompted discussions on strategies for sustainable agricultural development, emissions mitigation, and enhanced environmental stewardship. Addressing the environmental impact of agricultural pollutants in Africa is imperative for promoting ecological resilience and long-term agricultural productivity.

Figure 2.4: Carbon Dioxide Emissions



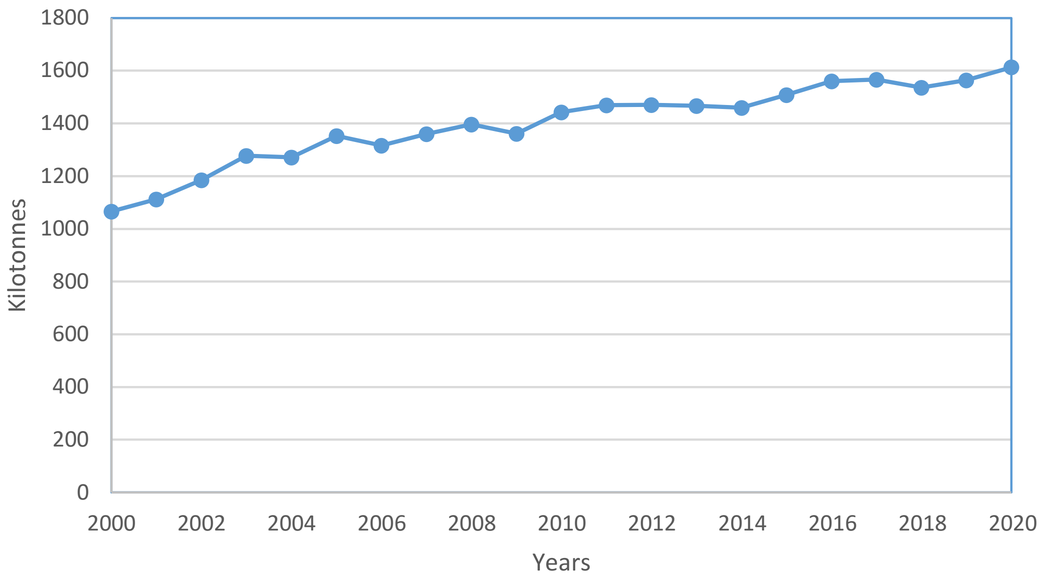
Source: FAOSTAT (2023a)

Figure 2.5: Methane Gas Emissions



Source: FAOSTAT (2023a)

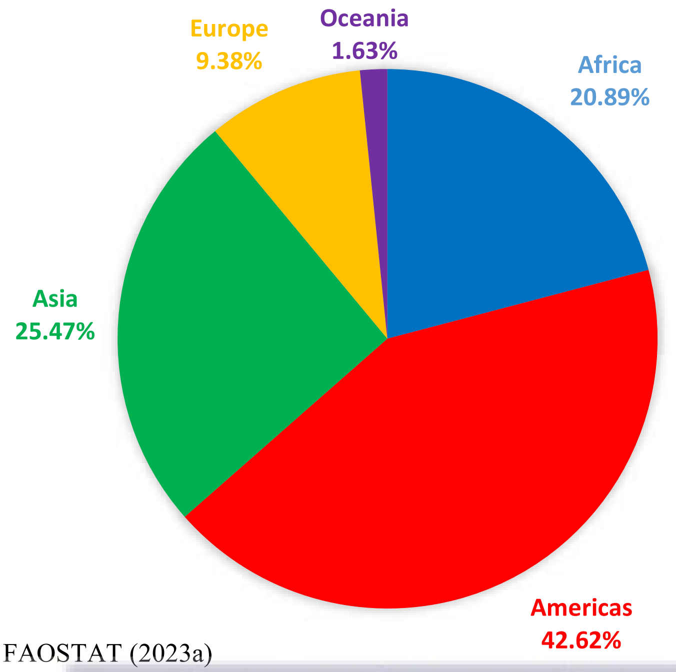
Figure 2.6: Nitrous Oxide Emissions



Source: FAOSTAT (2023a)

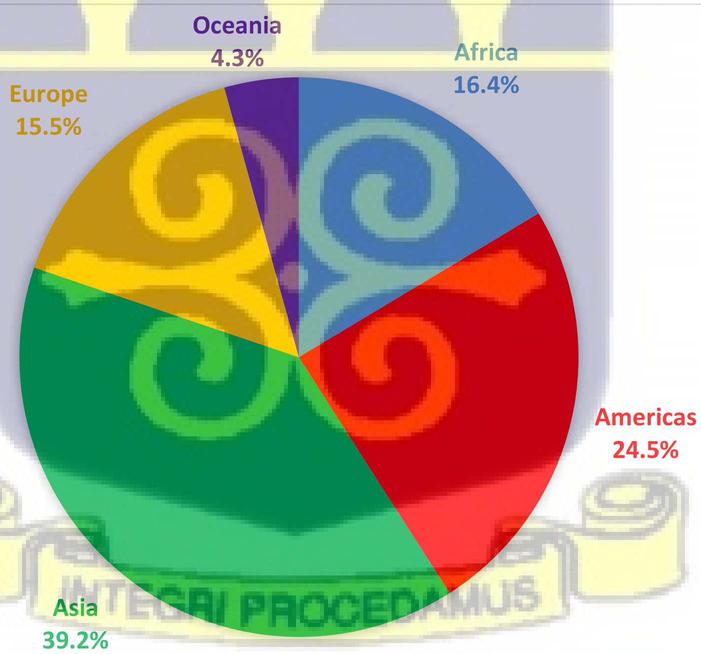
The pie charts below (see Figures 2.7, 2.8, and 2.9) also visualise Africa's contributions to global agricultural greenhouse gas emissions between 1990 and 2020. The data shows that Africa's emissions in all three primary agricultural emissions only lag behind Asia and the Americas, in sharp contrast to the supposed low contribution of African countries to global agriculture greenhouse emissions. This further reinforces the proactive effort towards climate-smart agriculture productivity in Africa.

Figure 2.7: Share of Agriculture CO_2 Emissions by Continent



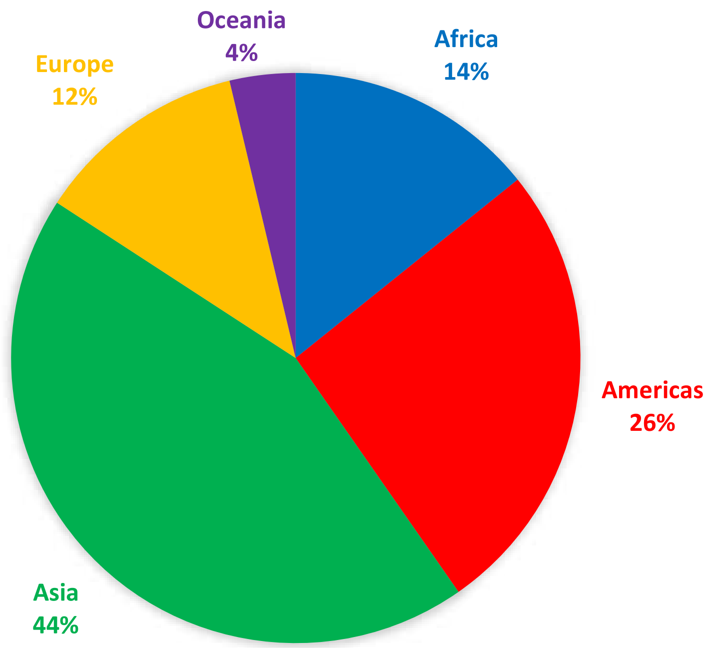
Source: FAOSTAT (2023a)

Figure 2.8: Share of Agriculture N_2O Emissions by Continent



Source: FAOSTAT (2023a)

Figure 2.9: Share of Agriculture CH_4 Emissions by Continent



Source: FAOSTAT (2023a)

2.4 Climate Impact on Agricultural Production in Africa

Empirical estimates indicate that climate change has contributed to a 34% reduction in total agricultural productivity growth in Africa since 1961, surpassing any other continent (Ortiz-Bobea et al., 2021). This impact has immediate implications for food security, first for the farmer and then the general population at large, most especially because the farmer must wait for the supposed ideal planting time, which is increasing and becoming elusive, just as the incomes of farmers (Antwi-Agyei et al., 2018). The phenomenon also has negative consequences for migration and a labour supply shortage for agricultural productivity in the source location.

The high vulnerability of Africa's agricultural production system is partly due to the over-reliance on rain as the primary source of water for growing crops and the application of ineffective farming methods to entirely different current growing conditions. Abrams (2018) estimates that about 95% of Africa's agricultural land depends on rainwater for food production and other risk factors. Given the high uncertainties surrounding weather conditions and highly unpredictable rainfall patterns in recent times, such practices cannot yield the desired outcomes.

Further negative impacts of unsustainable and dwindling agricultural production will lead to hikes in food prices and associated effects on hunger, mainly for people in African countries. An economic-wide loss of 23.5% of the gross domestic product (GDP) of countries in Sub-Saharan Africa alone has been projected by Rehdanz and Maddison (2005) if global warming continues at the current alarming rate. The African Climate Policy Centre (ACPC) also projects that worsening climate change situations could result in up to 15% loss of GDP per capita growth for some countries by the year 2050, with broad implications on incomes and quality of life (Baarsch et al., 2020).

2.5 Financial Investments in Agriculture in Africa

2.5.1 Public Commitment to Financing Agriculture

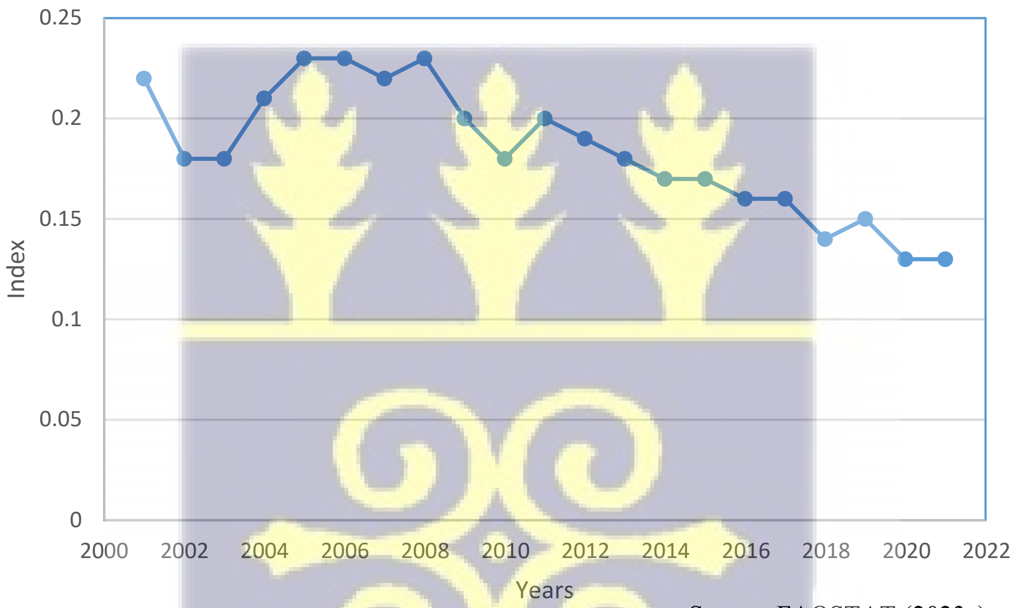
Despite agriculture's significant role in African countries' economies, the sector still needs to be better financed, notably by central governments. In this thesis, we utilised a unique dataset, the agricultural orientation index (AOI), for government expenditure to measure real public sector fiscal commitment to the agricultural sector. It is also an accurate measure of the extent to which much investment goes into agriculture as a matter of priority relative to its contribution to the economy of Africa. A value greater than 1 indicates that the agriculture sector receives a higher share of government expenditure than its economic value, indicating that agriculture is highly prioritised. On the other hand, an index lower than 1 signifies a lower commitment and priority. From Figure 2.10, we observe that the highest AOI score of 0.23 was recorded in 2005, 2006, and 2008, indicating that there needs to be more commitment to financial investments in agriculture in Africa. This revelation is in sharp contrast to the immense contribution of the sector to GDP, employment, poverty alleviation and social welfare.

AOI is a Sustainable Development Goal 2 (SDG 2) target and indicator; the data clearly shows that Africa needs more commitment to financing and investing in agriculture to end hunger and promote food security, falling way behind in meeting SDG 2 by the target year of 2030. The share of government expenditure in agriculture (see Figure 2.11) further highlights the levels of investment priorities of African governments in agriculture. Both graphs show a downward trend, signifying a worrying and alarming future for food security, hunger, and economic catastrophe, with their adverse ripple effect on socio-cultural vices. The seeming disregard for the agriculture sector is evident in the recent Malabo progress review report towards the 2025 target.

The Malabo Declaration is the most encompassing documented intention by African countries to transform their agricultural systems for sustained economic growth and the social well-being of citizens. The broad goal of the Declaration is to increase annual growth in agricultural GDP by 6%, allocate at least 10% of public expenditures to the agricultural sector, and ensure its overall efficiency and effectiveness (African Union, 2022). Central among these pledges, in line with this study, is the commitment to enhancing investment finance in agriculture, which has pass-through effects on ending hunger, halving poverty, fostering agricultural resilience against climate change, and improving cross-country trade in agricultural commodities by 2025. From the current 2021 biennial progress report on the commitments, only Rwanda attained a score of 7.46 out of 10, a little above the minimum threshold of 7.28 for a country to be classified as on course to meet the set targets by 2025 (African Union, 2022).

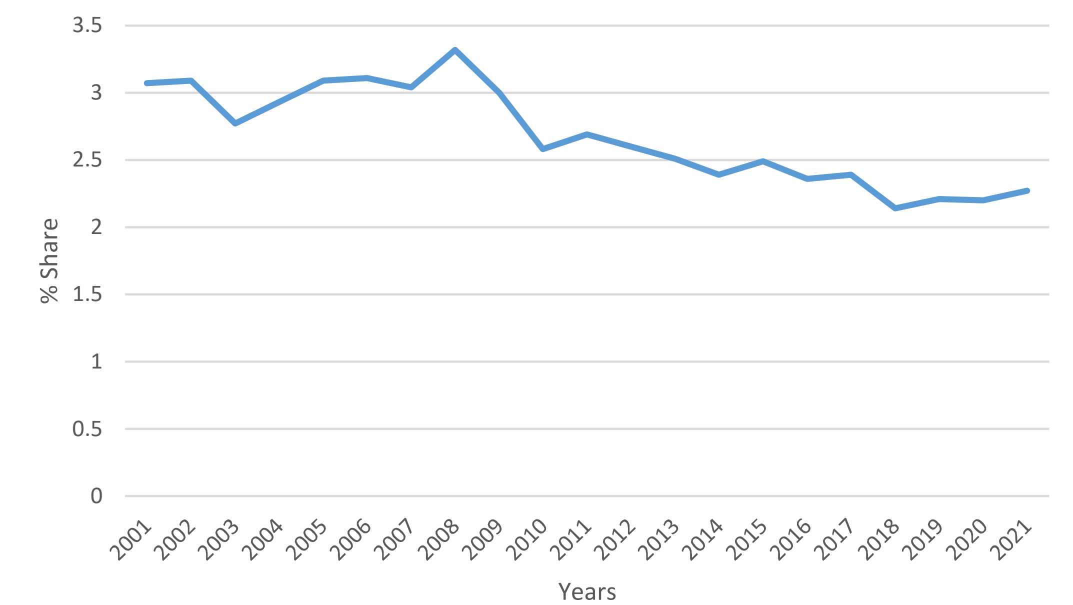
With the Declaration fast approaching its target year, the outcome of the review report and the stylised facts provided in this study show an overall downward spiral of the needed financial investments to transform agriculture in Africa. The data indicate that the share of the 10% commitment is below the target as evidenced by the meagre 2.27% average expenditure share of all government expenditure: the empirical reasons for this underperformance remain a question. Therefore, it is unsurprising that Africa continues to witness persistent food insecurity coupled with hunger and poverty, with recent food price volatilities.

Figure 2.10: Agricultural Orientation Index



Source: FAOSTAT (2023a)

Figure 2.11: Agriculture Share of Government Expenditures

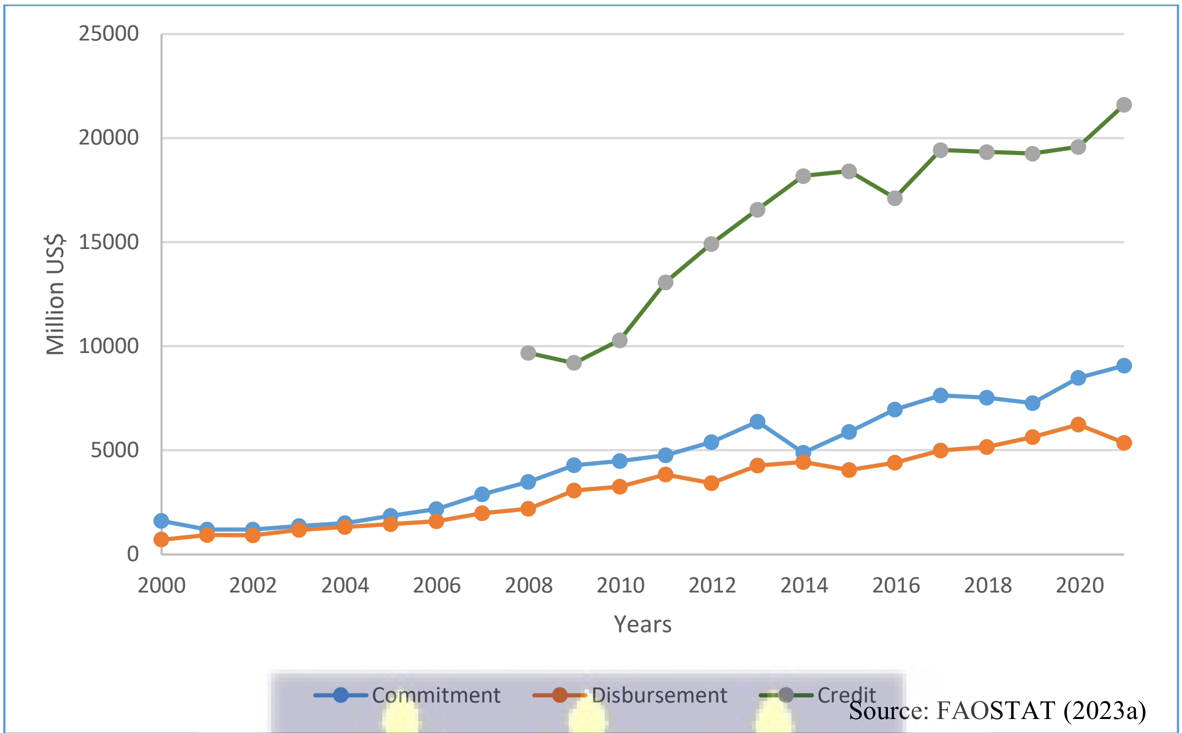


Source: FAOSTAT (2023)

2. 5.2 Private Sector Funding and Development flows to Agriculture in Africa

Private sector funding and development flows have contributed significantly to Africa's agriculture. Data from FAOSTAT (2023a), as shown in Figure 2.12, indicates that credit to the sector is vital as it supports public and donor funding. As observed, domestic credit far exceeds aid disbursement and still possesses exceptional growth potential. Therefore, domestic private financing is crucial as public sector financing and investments keep dwindling over the years. More importantly, the gap between funding commitment and actual disbursement has widened since 2000. In recent times, the data shows a wider deviation of the two. As the commitments increase, the actual disbursements fall further below, as depicted in Figure 2.12 below. This calls for renewed funding strategies for agriculture in Africa.

Figure 2.12: Development flows and Credit to Agriculture in Africa



Source: FAOSTAT (2023a)

2.6 Agricultural Policies and Reforms in Africa: A Historical Context

Agriculture in Africa has undergone several transformations, from pre-colonial era practices through colonial-led reforms and policies to post-independence advancements. In this section, we examine the historical evolution of agricultural policies and reforms, their rationales, implementation, and impacts in Africa.

Pre-colonial Africa featured sophisticated agricultural systems that ensured local food security, manufacturing, and trade, where farmers integrated export and subsistence crops, demonstrating advanced land use (Bjornlund et al., 2020). Customary land tenure systems, governed by traditional rules, vested control in kinship groups through unsatisfactory arrangements, with rights often based on first occupation and labour investment (Brace & Migot-Adholla, 1994). These systems evolved, with increasing population density and commercialisation leading to shorter fallow periods and more individualised household land holdings, sometimes even land sales (Brace & Migot-Adholla, 1994). Notwithstanding, community members often retained secondary rights (e.g., grazing on stubble) and access to common resources, revealing adaptable and responsive agricultural foundations in Africa (Brace & Migot-Adholla, 1994), which were mainly labour-intensive, relying heavily on family labour (Bjornlund et al., 2020).

The colonial era fundamentally reshaped African agriculture, driven by European industrial demands (van Beusekom, 2021). From the 1920s, colonial governments intensified intervention to control cash crop production (e.g., cotton, peanuts, coffee, cocoa) for export (van Beusekom, 2021). Typical examples of European-led agricultural schemes include: The Gezira Scheme (Sudan), the Office du Niger (French Soudan), the Tanganyika Groundnut Scheme, the Compagnie Générale des Oléagineux Tropicaux (CGOT, Senegal) (van Beusekom, 2021). This reorientation often suppressed indigenous food crops, alienated fertile lands, and restricted market access for local farmers, leading to significant food insecurity (Mureii et al., 2021). For instance, during the colonial era, Kenyan Nandi farmers were compelled to cultivate non-local crops, such as maize, tea, and coffee, often incurring debt and facing food shortages (Mureii et al., 2021). Colonial policies, despite being framed as development, primarily served European extraction, undermining indigenous food security and creating economic vulnerability (Mureii et al., 2021).

Colonial planners, believing in European scientific superiority, sought radical agricultural transformations, pushing for intensive plough agriculture and strict crop rotations (van Beusekom, 2021). These intrusive interventions, especially by the 1940s and 1950s, fuelled anti-colonial movements (van Beusekom, 2021). However, African farmers actively resisted or selectively adopted new practices, often prioritising their food security and local market opportunities, notably when export crop terms of trade declined (Bjornlund et al., 2020).

Colonial rule also involved selective infrastructure investment (e.g., railroads) concentrated in profitable export areas, neglecting other regions or relegating them to labour reserves (van Beusekom, 2021). This created profound and enduring regional disparities, hindering the development of diversified local economies. The colonial emphasis on exports over food security, land alienation, and uneven development established a legacy of vulnerability that continues to challenge post-independence development (van Beusekom, 2021).

Following independence in the 1960s, African nations pursued rapid growth, with Sub-Saharan Africa achieving an average annual economic growth of 3.4% and agricultural growth of 3% between 1961 and 1980 (Heidhues & Obare, 2011). Many adopted import substitution industrialisation to replace imports with domestic production, aiming for self-sufficiency and industrialisation through state-led development, nationalisation, and protectionist policies (Heidhues & Obare, 2011). Despite initial modest agricultural growth, the overall trend for Sub-Saharan Africa was one of decline in per capita production, contrasting with other developing regions (Bjornlund et al., 2020).

Economic growth slowed in the 1970s and stagnated in the 1980s, with overall output declining by 1980 (Mureii et al., 2021). During this period, import substitution policies often disadvantaged the agricultural sector, resulting in declining incomes in export-oriented agriculture and an increased reliance on food imports (Mureii et al., 2021). This stagnation stemmed from internal policy flaws, including resource mismanagement, faulty exchange rates, excessive state intervention, and corruption, which were compounded by external factors such as economic crises and declining terms of trade for agricultural exports (van Beusekom, 2021).

Africa's severe economic crisis in the 1970s led to the widespread implementation of Structural Adjustment Programs (SAPs) in the 1980s and 1990s, primarily imposed by the World Bank and IMF (Heidhues & Obare, 2011). SAPs advocated for reduced government intervention, market liberalisation, free trade, and currency exchange (Heidhues & Obare, 2011). Key elements included macroeconomic stabilisation, private sector promotion, budget deficit control, privatisation of public enterprises, elimination of subsidies, and cuts to social services. For agriculture, reforms focused on opening up processing and marketing to competition and removing export taxes (Ataman & Anil, 2011). In the short term, some reforms yielded positive responses in agricultural output, although these were often not sustained in the face of subsequent shocks (Ataman & Anil, 2011). In South Africa, for instance, reforms made the agricultural sector "leaner" but "poorer" in real terms, despite some net income growth due to declining expenditures (Rooye et al., 1996).

SAPs faced significant criticism for neglecting the social dimension and institutional weaknesses of developing countries (Rooye et al., 1996). They were widely perceived as having failed in Africa, resulting in increased food imports and chronic balance of payment deficits (Ataman & Anil, 2011). Critisms, however, remain of international partners who subsidise their farmers while dictating liberalisation in Africa, creating an uncompetitive business environment in agriculture.

The early 2000s marked a shift toward African-led agricultural development with the adoption of the Comprehensive Africa Agriculture Development Programme (CAADP) by the African Union in the 2003 Maputo Declaration (African Union, 2022). CAADP is Africa's policy framework for agricultural transformation, aiming for wealth creation, food security, nutrition, and overall economic growth and prosperity (African Union Development Agency, 2018).

Key targets and evolutions include (African Union Development Agency, 2018):

- Maputo Declaration (2003): Called for a 6% annual agricultural growth rate and a minimum of 10% of national budgets allocated to agriculture.
- Malabo Declaration (2014): Renewed commitment to CAADP, setting 2025 goals to increase agricultural finance, eradicate hunger, halve poverty, reduce malnutrition, triple intra-African trade, and enhance climate resilience. Targets included doubling productivity, halving post-harvest losses, and reducing stunting to 10%.
- Kampala Declaration (2026-2035): Emphasises sustainable food production, agro-industrialisation, and investment. Targets include a 45% increase in agrifood output, 50% reduction in post-harvest losses, tripling intra-African trade, zero hunger by 2035, and significant reductions in malnutrition.

African agriculture continues to face persistent challenges despite policy shifts. A key issue is inefficiencies in production in smallholder agriculture, despite over $2 billion annually in research (Wollburg et al., n.d.). Climate resilience and adaptation are increasingly central to African agricultural policy, requiring proactive, comprehensive climate-smart practices and integrated risk management.

The history of African agricultural policies reveals a complex interplay of internal dynamics and external influences, from pre-colonial self-sufficiency to colonial extraction, post-independence state control, and market-oriented reforms. A persistent tension between food security and export orientation, coupled with external policy imposition, has often led to mixed results and persistent challenges like stagnant productivity and widespread poverty.

The current African-led CAADP framework marks a significant shift towards self-determination and a comprehensive understanding of agricultural transformation, setting ambitious targets for investment, productivity, and resilience. However, significant implementation gaps, particularly in budget allocation, and the paradox of research investment without widespread productivity gains, highlight systemic failures. Addressing food insecurity and rural poverty requires integrated, systemic policy responses that account for market access, infrastructure, climate vulnerability, and social inequalities.

Moving forward, sustainable agricultural transformation demands consistent political will, increased domestic investment, and effective implementation of comprehensive strategies. A holistic approach addressing productivity, climate resilience, market access, post-harvest losses, and human capital development is essential. Engaging the private sector through enabling policies and innovative financing will be critical. The path forward lies in strengthening African ownership, fostering genuine multi-stakeholder collaboration, and designing policies with a deep understanding of local contexts and the needs of diverse farming communities, grounded in fulfilled financial commitments.

2.7 Agricultural Financing Models in Africa

Across Africa, agriculture is vital but persistently underfunded. Innovative credit guarantee schemes have emerged to address this, reducing risks and encouraging investment. These initiatives, such as the Ghana Incentive-Based Risk-Sharing System for Agricultural Lending (GIRSAL), aim to change the perception of agriculture as a risky venture by offering guarantees, technical support, and innovative financing options. They are unlocking the potential of agri-SMEs and supporting sustainable development. This overview highlights key programmes across Africa focused on risk mitigation, capacity building, and value chain enhancement.

Launched in 2019 by the Government of Ghana with support from the Bank of Ghana and the African Development Bank (AfDB), GIRSAL is a non-banking financial institution established to promote agricultural lending by reducing risks for financial institutions. It provides credit guarantees covering up to 70% of loan losses, offers technical assistance to banks and agribusinesses, and advocates for policy changes. Current data indicate that GIRSAL has guaranteed loans worth over GHS 1.57 billion to 158 agribusinesses (www.girsal.com). Its focus includes export-oriented value chains such as chilli pepper and, recently, sesame.

Nigeria Incentive-Based Risk Sharing System for Agricultural Lending (NIRSAL) is established and owned by the Central Bank of Nigeria. It mirrors GIRSAL's risk-sharing approach but operates on a broader scale with five pillars: risk-sharing, insurance, technical assistance, bank rating, and bank incentives (www.nirsal.com). With USD 500 million in seed capital, NIRSAL provides guarantees covering up to 75% of loan losses, aiming to increase agricultural lending. NIRSAL's technical assistance has enhanced banks' capacity to assess agricultural loans. At the same time, its focus on value chain financing has supported crops such as rice and maize, reducing Nigeria's reliance on food imports. It has so far facilitated over N211 billion for agriculture and agribusiness from banks and other financing sources. It has over 1.9 million agriculture insurance subscribers, as well as more than 200,000 beneficiaries of technical assistance to actors in the value chain (www.nirsal.com)

The Kilimo Biashara scheme, a collaboration between the Alliance for a Green Revolution in Africa (AGRA), Equity Bank, and the Government of Kenya, was a four-year pilot programme designed to provide affordable credit to smallholder farmers and agribusinesses based on a cash-guaranteed fund supplied by AGRA. It offered loans at a reduced interest rate of 10% per annum (covering the guaranteed portion of the loan) through Equity Bank, supported by credit guarantees and capacity-building initiatives aimed at enhancing financial literacy and loan management (www.agra.org). This initiative aimed to de-risk Equity Bank's credit lending activities with agricultural value chain players, thereby bridging the gap in financial access and disbursement. The programme faced initial capital injection challenges from funding partners (specifically, IFAD), which resulted in a lower percentage of the credit guarantee.

In South Africa, AGRA partners with Equity Bank and Standard Bank to implement credit guarantee and risk-sharing facilities that leverage public capital into private lending (www.mfw4a.org). These facilities, which multiply committed capital by up to ten times, encourage banks to finance agricultural MSMEs. South Africa's relatively developed financial infrastructure boosts the effectiveness of these programmes, which have increased lending to agriculture compared to other sub-Saharan countries. The focus on rural MSMEs and export-oriented crops has supported job creation and economic diversification. Other similar risk-based lending programs can be found in Sierra Leone, Rwanda, and other African countries, with varied implementation guidelines and scopes.

The Africa Fertiliser Financing Mechanism (AFFM) and the Africa Fertiliser Trade Credit Guarantee Programme (AFTCGP), implemented by the African Development Bank and the African Fertiliser and Agribusiness Partnership (AFAP), are complementary initiatives designed to unlock access to affordable fertilisers and boost agricultural productivity across Africa. Hosted by the African Development Bank, the AFFM supports Africa's target of 50 kg of nutrients per hectare by deploying innovative financial solutions, notably three credit guarantee models: Working Capital Credit Guarantees, Portfolio Credit Guarantees, and Trade Credit Guarantees, to share up to 50% of loan risks with financial institutions and suppliers (www. afdb. org). These models target private importers, wholesalers, distributors, and agro-dealers, with initial rollouts in Nigeria and Tanzania backed by $ 4 million in guarantees and covering strategic crops such as rice, millet, cocoa, coffee, cowpea, maize, cotton, soybean, horticultural crops, wheat, palm oil, cassava, and sorghum (www. afdb. org).

The AFTCGP, led by AFAP with support from the Bill & Melinda Gates Foundation, USAID (via AGRA), the U. S. International Development Finance Corporation, and AFFM, builds on AFAP's successful trade credit guarantee record, which has leveraged guarantee funds by 13 times with default rates below 1% (www.afap-partnership.org). Initially operating in Ghana, Kenya, Mozambique, Tanzania, Uganda, and Zambia, the AFTCGP offers a non-bank partial guarantee (50% risk-sharing) to fertiliser suppliers, enabling them to extend 30–60 days of fertiliser credit to hub agro-dealers and key agricultural SMEs with established retail networks just before planting seasons. This strategy improves timely fertiliser availability, broadens market access, reduces suppliers' stockholding and default risks, and enhances storage capacity through hub facilities. The revolving credit model allows recycling 3–5 times per planting season, boosting sales turnover and farmer access. Both initiatives include technical assistance, business capacity building, and policy support to strengthen input value chains, creating scalable models that increase smallholder productivity, foster agribusiness development, and promote food security across Africa.

These programmes share key features with GIRSAL, including credit guarantees, technical assistance, and a focus on value chain financing. However, their scope and effectiveness vary. Nigeria's NIRSAL, with its multi-pillar approach and significant seed capital, is the most comprehensive, closely resembling GIRSAL but operating on a larger scale. Kenya's Kilimo Biashara prioritises low-interest loans, while South Africa's AGRA facilities benefit from a robust financial sector. Smaller programmes in Sierra Leone and Rwanda are more donor-driven with limited scope, whereas multi-country initiatives like AFTCGP target specific niches (e.g., fertiliser access or regional MSMEs). Uganda's use of Crop Receipts introduces an innovative pre-harvest financing model, setting it apart from guarantee-focused programmes.

Collectively, these programmes have increased agricultural lending across Africa, although their impact varies. Despite achievements, they face significant challenges. Limited financial infrastructure in many sub-Saharan countries hampers scale, except in South Africa.

High interest rates and low financial literacy among farmers remain barriers. Inconsistent policy environments and donor dependence in smaller programmes (e.g., Sierra Leone, Rwanda) limit sustainability. Moreover, while guarantees reduce risk, they do not eliminate it entirely, and some financial institutions remain cautious due to potential credit losses. Nonetheless, agricultural credit guarantee programmes in Africa, exemplified by GIRSAL, NIRSAL, Kilimo Biashara, and others, represent a transformative approach to closing the financing gap in agriculture. By mitigating risks, enhancing financial institutions' capacity, and promoting innovative financing models, these initiatives have increased lending, supported job creation, and boosted export potential. As African nations pursue agricultural transformation, these programmes offer valuable lessons and scalable models to unlock the sector's potential, aligning with broader goals of food security, economic resilience, and sustainable development.

2.8 The Future of Agriculture in Africa

Africa's agricultural resource endowments make the continent a potential food basket for the entire world. Despite this economic advantage, the continent remains food-insecure and vulnerable. For the necessary transformative change to happen, deliberate commitment and the right policies will be required. Understandably, this will require a delicate interplay of choices amid scarce resources and opportunities.

As the continent strives to achieve food security, economic growth, and sustainable development, several key trends are shaping the future of agriculture globally. Adopting advanced technologies, including precision agriculture, sustainable production practices, and digital platforms, is fast evolving and promises to enhance productivity, reduce resource waste, and bolster resilience in the face of climate variability. Collaborations between governments, the private sector, and development partners are driving investment in agricultural production, infrastructure, research, and capacity-building, laying the groundwork for the complete modernisation of Agriculture in Africa. It is noteworthy that actual financial investments from African governments and donor agencies may be more encouraging, but they fall short of the required investment needs. As evident from the stylised facts presented in the discussions above, African states must stay committed to the Malabo declaration, private sector funding must continue its upward trajectory, and development partners must honour their pledges by closing the gap between funding commitments and actual disbursement.

Additionally, the vulnerability of agricultural production to climate change necessitates proactive measures to ensure long-term, sustainable production. However, this will hinge on robust adaptation strategies involving innovation, value chain development, and the promotion of inclusive policies that empower smallholder farmers. With these in place, African agriculture has the potential to emerge as a dynamic force driving economic growth, improving livelihoods, enhancing global food security, and fostering overall socio-economic transformation in the decades to come.

CHAPTER THREE

AGRICULTURAL GREEN EFFICIENCY IN AFRICA: A SLACKS-BASED MEASURE DATA ENVELOPMENT ANALYSIS WITH UNDESIRABLE OUTPUTS

Abstract

In this chapter, we examined the green efficiency of agricultural productivity in Africa by employing the slacks-based measure data envelopment analysis with undesirable outputs approach, covering 48 African countries from 2000 to 2019. The data were mainly from the Food and Agriculture Organisation's statistical database. The findings reveal that, on average, Africa exhibits green inefficiency in agricultural productivity, with an estimated average green efficiency score of 66%. The analysis identified the primary sources of inefficiency as unsustainable input intensification, including excessive usage of arable land, labour, fertiliser, irrigation water, and pesticides. The optimal operational input combinations required to achieve green efficiency and avoid resource misallocation were also estimated. The chapter further discovers that, on average, an estimated output value of US$6.29 billion is required to achieve optimal green efficiency. This chapter presents a more comprehensive and environmentally robust assessment of agricultural green efficiency in Africa. It also unveils the empirical direction for optimum investment in production inputs and environmentally adequate emission targets for agricultural productivity. The chapter concludes with policy recommendations to address the identified inefficiencies and promote sustainable agricultural practices.

3.1 Introduction

Africa's abundant natural resources have significantly positioned the continent to contribute to global agricultural production and food security. The agricultural sector is the backbone of many African economies, providing employment opportunities for the youth. For instance, in Sierra Leone alone, agriculture accounted for approximately 59.5% of the country's GDP in 2020 (World Bank Data, 2022). Despite these favourable conditions, Africa continues to grapple with food insecurity, importing about $43 billion worth of food annually, while a significant portion of its population faces extreme poverty and hunger (World Bank, 2022). These challenges directly impede the achievement of the United Nations Sustainable Development Goals 1 (No Poverty) and 2 (Zero Hunger).

Apart from limited financial resources allocated to agricultural productivity growth, unfavourable climatic conditions exacerbate the difficulties faced by smallholder farmers (FAO & WHO, 2017). The resulting impact on agricultural outputs severely affects incomes and overall livelihoods. Increased pest attacks, resistance, prolonged droughts, erratic rainfall patterns, and declining soil fertility are all outcomes of the current environmental situation (Musango & Peter, 2007; Ortiz-Bobea et al., 2021). These factors further deteriorate the economic well-being of farmers (Yoshida et al., 2014). Hence, there is a need for a shift towards CSA to improve output and provide resilience to production with minimal or no environmental damage (Morkunas & Balezentis, 2022).

Numerous pathways have been proposed for achieving agricultural green production, including conservation agriculture, sustainable intensification, transgenic crops, organic agriculture, and agroecological systems (Koohafkan et al., 2012). However, Africa has predominantly adopted an input-intensive approach to increase agricultural output, resulting in environmental unsustainability and on-farm pollution (Burke et al., 2022; Clay & Zimmerer, 2020; Heidenreich et al., 2022; Jayne et al., 2019; FAO & WHO, 2017; Shen et al., 2022). Moreover, excessive use of inputs, such as fertilisers and land, undermines previous gains in agricultural productivity growth, leading to output declines (Burke et al., 2022). Nonetheless, empirical analysis of green-efficient agricultural productivity, considering optimal input-output mixes, is lacking in the African literature, while substantial contributions have been made in other contexts, primarily in Asia (e.g., He et al., 2021; Liu et al., 2022; Shen et al., 2022; Xu et al., 2022).

Although previous studies by Clay and Zimmerer (2020), Jayne et al. (2019), Koch et al. (2019), and Heidenreich et al. (2022) attempted to find sustainable optimal input intensification for agricultural production in Africa, they did not estimate the agricultural green efficiency levels or the required input-output targets for reaching green-efficient agricultural productivity in the respective African countries. These are essential components for sustainable and long-term agricultural productivity. Additionally, Adom and Adams (2020) studied the technical efficiency of agricultural production in Africa, but did not consider agricultural green efficiency. This chapter provides valuable insights to address the green efficiency gaps. Specifically, we employ the Tone (2003) Slacks-Based Measure (SBM) Data Envelopment Analysis (DEA) with undesirable outputs, which provides superior estimates of green efficiency compared to the previous studies in Africa.

The existing literature on agricultural green efficiency predominantly focuses on carbon dioxide emissions from agricultural productivity (Liu et al., 2022; He et al., 2021). However, other equally harmful agricultural-related pollutants are on the rise, often overlooked in agricultural green efficiency research despite their significant environmental threats. Therefore, our study simultaneously considers the three-leading agricultural-related greenhouse gases

(GHGs), carbon dioxide, methane gas, and nitrous oxide emissions, to estimate agricultural green efficiency for a comprehensive environmental analysis.

The objectives of this chapter are threefold.

i. To estimate the levels of agricultural green production efficiency in Africa.
ii. To determine the optimal operational input-output combinations required to achieve green-efficient agricultural productivity and
iii. To identify the sources of green inefficiency in agricultural productivity on the continent.

The remainder of this chapter is structured as follows: Section 3.1 provides a literature review covering sustainable agricultural production, green efficiency estimation methods, and an empirical synopsis. Section 3.2 outlines the methodology employed in this study. Section 3.3 presents the results, and finally, Section 3.4 summarises the findings, draws conclusions, and offers policy recommendations.

3.2 Literature Review

3.2.1 Theoretical Literature

This section presents theoretical literature regarding sustainable agricultural production, known as agricultural green efficiency. We distinctively situate and discuss agricultural green efficiency from climate-smart agriculture and agroecology perspectives.

3.2.1.1 Agricultural Green Production Efficiency

Agricultural green efficiency represents an intersection of environmental sustainability and agricultural productivity, encapsulating the balance between maintaining high agricultural outputs while minimising environmental impacts. The ‘green’ aspect of agricultural efficiency is captured by incorporating undesirable outputs (e.g., greenhouse gas emissions, water pollution) into efficiency measurement models. This approach is increasingly vital as the global population grows and the demand for food intensifies, alongside mounting pressures to preserve natural resources and mitigate climate change (Burke et al., 2022; He et al., 2021; Rahman & Anik, 2020; FAO, 2018). Sustainable agricultural practices thus encourage reusability of resources (FAO, 2018; Xu et al., 2022) that provide production synergies (FAO, 2017), which foster climate resilience (Clay & Zimmerer, 2020; Koohafkan et al., 2012; FAO, 2017) and eventually lead to sustainable and efficient production (He et al., 2021; Liu et al., 2021; Liu et al., 2022; Xu et al., 2022). Two important concepts that align with the sustainable production goal of agriculture green efficiency are climate-smart agriculture (CSA) and agroecology.

3.2.1.2 Climate-Smart Agriculture

Climate-smart agriculture represents an integrated approach to developing agricultural strategies that ensure food security under changing climate conditions while reducing greenhouse gas emissions and enhancing resilience (FAO, 2013). Rooted in sustainable agriculture principles, CSA consists of three essential aspects: 1) sustainably increasing agricultural productivity and incomes, 2) adapting and building resilience to climate change, and 3) reducing and/or removing greenhouse gas emissions where possible (FAO, 2013, p. ix). These pillars have economic, social, and climate change dimensions that are part of the United Nations' sustainable development goals. We can collectively and respectively group them under sustainable productivity, adaptation, and mitigation. It thus sets the pace for specialised policy and investment requirements necessary for sustainable agricultural production to maintain global food security.

The productivity pillar of CSA aims to increase agricultural output and improve farmers' incomes sustainably. This involves enhancing the efficiency and effectiveness of farming practices to ensure that food production can solve the food and nutrition challenges of a fast-growing world population without harming the environment. Productivity in CSA focuses on optimising crop yields through improved farming techniques, high-yield crop varieties, and precision agriculture technologies. These practices enable farmers to produce more food per unit of land, using fewer inputs such as water, fertilisers, and pesticides. These helps maximise resource use efficiency and reduce waste. By reducing resource wastage and increasing productivity, CSA practices enhance the economic viability of farming, particularly for smallholder farmers and improve livelihoods, contributing to development and poverty reduction.

The adaptation pillar of CSA focuses on making agricultural systems more resilient to climate change impacts. This involves developing and implementing practices that help farmers cope with and recover from climate-related stresses such as droughts, floods, pests and disease infestations, and extreme weather conditions. Therefore, CSA calls for developing and using resilient crop varieties and animal breeds to manage climate stresses. Such innovations help farmers adapt to changing climatic conditions. Risk management is another critical aspect of adaptation. It uses weather forecasting, early warning systems, and agricultural insurance to help farmers anticipate and prepare for climate risks, reducing their impact on agricultural production and livelihoods.

The mitigation aspect of CSA aims to reduce or eliminate greenhouse gas (GHG) emissions from agricultural activities. This involves implementing practices that minimise agriculture's carbon footprint while maintaining productivity and resilience. Improved agricultural production practices, such as sustainable land preparation, improved livestock management, and efficient farm nutrient usage, can reduce carbon dioxide, methane gas, and nitrous oxide and significantly lower GHG emissions. These require shifting agricultural production practices and adopting eco-friendly technologies that will help reduce emissions (He et al., 2021; Zhao et al., 2018). The three pillars of CSA are interlinked and mutually reinforcing. Together, they provide a comprehensive framework for transforming agricultural systems to be more sustainable, resilient, and able to overcome the vulnerabilities associated with climate change for a green, efficient future.

Another concept that fits into the broader spectrum of agricultural green efficiency is agroecology.

3.2.1.3 Agroecology

The practice of agroecology, as described by Altieri (1983), emphasises the promotion of sustainable agriculture, biodiversity conservation, ensuring food security, and advocating for social justice. It takes a holistic approach to agricultural production by incorporating ecological processes into agricultural systems and considering social, economic, and environmental aspects.

The concept is keenly debated and still taking shape in approach and practice. It is, however, known and generally accepted that implementation of the basic principles varies across cultures, geographical settings and diverse economic landscapes (Dumont et al., 2021). Dumont et al. (2021) recently proposed a concise framework that aligns the core principles guiding agroecology with ecological and socioeconomic principles. The ecological or environmental tenets include:

1. Recycling of biomass to minimise waste,
2. Biodiversity by enhancing the interaction of species and genetic resources to ensure favourable soil conditions for plant growth,
3. Fostering synergies for beneficial biological interactions,

4. Input use efficiency to minimise losses of energy, water, nutrients and genetic resources,
5. Promoting adaptability by strengthening the resilience of agricultural systems through enhancement of functional biodiversity and,
6. Adaptation to local conditions to ensure context-specific approaches that best suit prevailing environmental conditions and the norms of society.

On the other hand, the socioeconomic principles are supposed to enhance social equity, strengthen local economies, enhance food security, promote cultural diversity, foster farmer autonomy and empowerment, promote participatory approaches, and ensure resilience and adaptability (Dumont et al., 2021).

These principles encompass promoting social equity and justice by empowering smallholders and marginalised communities, ensuring fair labour practices, and advocating for food rights and community control over local food systems. It thus aims to create sustainable livelihoods and strengthen local economies through local consumption and production, integrating traditional knowledge with scientific research and fostering farmer-to-farmer networks. It emphasises the importance of agrobiodiversity and cultural preservation, participatory governance, and policy advocacy to support sustainable practices. Economic diversification and risk management are also crucial in this approach, as they encourage diversified income sources and implement tools to manage climate change risks and market volatility. These principles ensure that agroecology contributes to environmental sustainability while fostering social justice, economic resilience, and the well-being of farming communities.

Following the ecological and socioeconomic principles, it is clear that they can be synthesised into the main driving factors of sustainable production, climate resilience (adaptation), and mitigation of harmful environmental impacts, as enshrined in the CSA concept and generally embodied in agricultural green efficiency. Therefore, when production systems are complemented with agroecological practices and other localised farmer innovations using readily available natural resources, the producer's vulnerability to external input shocks is lessened, thereby promoting resource use efficiency while at the same time delivering financial resilience to the farmer (FAO & WHO, 2017; Xu et al., 2022).

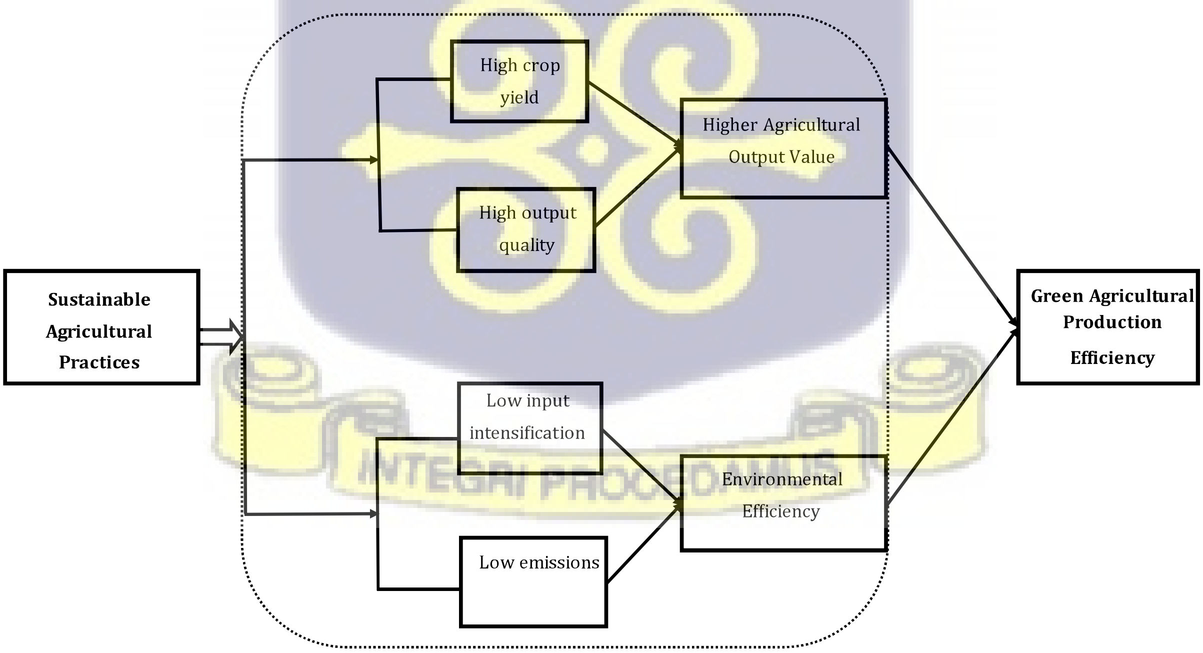
Subsequently, we present a framework, as shown by Figure 3.1 (adopted from Het et al., 2021, with modifications), summarising how sustainable agricultural production practices could lead to higher agricultural output value with minimal environmental damage, resulting in green production aligned with the CSA and agroecology concepts.

Sustainable farming techniques cover a variety of eco-friendly or agroecological methods, including crop rotation, organic farming, and integrated pest management. The goal is to maintain soil health, conserve water, and minimise negative ecosystem impacts. Sustainable agricultural practices are not just about environmental responsibility; they can also significantly increase crop yields. By using nutrient-rich soil, optimising irrigation, and selecting disease-resistant varieties, farmers can enhance productivity. Hence, this leads to higher output value and contributes to economic viability and well-being. The best part? This is achievable through minimal input usage, meaning lower expenditure on production inputs.

Low input intensification, as referred to in Figure 3.1, refers to minimising resource use while maintaining productivity. Thus, the situation where farmers adopt practices such as organic agriculture instead of relying heavily on synthetic fertilisers and pesticides and precision farming to optimise resource use. Low input intensification aims for efficiency and cost-effectiveness. It is worth noting that achieving higher agricultural output value is not just about high crop yield but also resource efficiency, as entailed in the goals of CSA and the core principles of agroecology, which is ultimately about producing more with fewer inputs with high environmental considerations. Sustainable practices are a testament that economic gains and environmental stewardship can go hand in hand. By adopting these practices, farmers can significantly improve their farming methods. These are also possible through feasible local environmental policies and leadership to help address agricultural production-related pollution through sustainable policy directions and actions to minimise adverse environmental impacts while boosting production. These will eventually result in lower agricultural greenhouse gas emissions and better productivity.

Ultimately, all the above will culminate in green agricultural production efficiency, where economic success (higher output value) is achieved through effective input usage and greater environmental responsibility (low emissions/environmental efficiency) and by the efforts of all the agents in the production process. Therefore, green agricultural production efficiency can be achieved when sustainable practices align with efficient resource use.

Figure 3.1: Conceptualising Agriculture Green Efficiency



Source: Adopted from He et al. (2021) with modifications

3.2.1.4 Agriculture Mechanisation: The Classical and Induced Innovation Paradigms

Mechanised agriculture involves the use of machinery and equipment to perform farm tasks (Ruttan & Hayami, 1971). The fundamental understanding of agricultural mechanisation is based on neoclassical economics, which views the adoption of technology as a rational decision aimed at maximising profit by individual farmers. From this perspective, a farmer will invest in machinery if the expected increase in productivity and reduction in labour costs outweigh the capital and operational expenses.

The induced innovation theory significantly enhanced this framework, representing a significant contribution by Ruttan and Hayami (1971). Their work states that technological change in agriculture is not an external, random event but rather a response driven by internal factors to changes in the relative prices and scarcity of production factors, such as land and labour. They argue that in economies where land is abundant and labour is limited and expensive, farmers are encouraged to adopt labour-saving technologies like tractors, combine harvesters, and other farm machinery. Conversely, in economies where labour is abundant but land is scarce, innovation focuses on land-saving technologies, such as high-yielding seed varieties, fertilisers, and irrigation. This theoretical model offers a compelling explanation for the diverse agricultural development paths observed worldwide. However, a key question remains: in Africa, where arable land and labour are abundant, will the induced innovation theory hold? Perhaps not superficially. Due to Africa's youthful workforce and the shift towards youth-led agriculture, innovation and technology-driven farming may seem an attractive option for young people to pursue careers in agriculture.

While the induced innovation model is persuasive, it has faced criticism for its limitations in explaining the complexities of real-world agricultural change. A second significant body of literature, drawing from Marxist and political economy traditions, offers a more critical perspective (Bernstein, 2010). Marxist analysis considers mechanisation as an essential element of capitalist development. According to the Marxist analogy, the introduction of machinery in agriculture is a key method by which capital exerts control over the farming sector. This process results in the displacement of small, independent farmers, the concentration of land into large-scale capitalist enterprises, and the emergence of a landless, wage-earning rural proletariat. Mechanisation, from this perspective, is not a neutral tool but a means of reshaping class relations and deepening social inequality (Bernstein, 2010).

Moreover, a political economy and institutional perspective emphasises the role of government policy, credit markets, and land tenure systems. Binswanger (1986) has argued that machinery adoption is not solely determined by factor prices but is heavily influenced by state-sponsored subsidies, taxes, and access to finance, which often favour large-scale commercial farmers over smallholders. This view highlights that institutional and political forces can either promote or hinder mechanisation in ways not fully captured by purely economic models.

Nevertheless, the rise of precision agriculture and the digital revolution is transforming the theoretical landscape. These new forms of mechanisation, including GPS-guided machinery such as tractors, drones, automated irrigation, and data-driven decision-making, are not merely about replacing manual labour but about optimising resource use and increasing efficiency on a micro-scale. This approach aligns with the perspective of resource use efficiency, which aims to maximise resource utilisation while also safeguarding the environment.

The theoretical literature on mechanised agriculture has evolved from emphasising economic rationality and factor prices to a more complex understanding incorporating social, political, institutional, and environmental aspects. The advent of precision agriculture introduces new challenges and opportunities, necessitating frameworks that recognise the importance of data, information, and new forms of capital in shaping future farming practices. This thesis contributes to the literature by proposing benchmarks that optimise production inputs while safeguarding the environment. In this way, induced innovation aligns with environmental sustainability.

Agroecology and Mechanisation: Similarities and Differences

Although mechanised agriculture and agroecology both aim to improve food production, their fundamental theories and practical methods are pretty different, representing two contrasting ideas of agricultural development. Mechanisation primarily focuses on increasing efficiency through technology, while agroecology adopts a holistic approach centred on the resilience and sustainability of agroecosystems. The primary goal of mechanisation is to maximise yield and profit per unit of labour or land. In contrast, agroecology aims to optimise ecological health and system resilience, while also promoting social fairness. While mechanisation views the farm as a factory, agroecology perceives it as a complex, system-based ecosystem.

The role of technology in mechanisation is to save labour and provide external inputs such as tractors, harvesters, and chemical fertilisers. In agroecology, however, technology functions as a tool, focusing on internal biological processes or organic farming methods such as natural pest control and nutrient cycling. On the social level, mechanisation aims for economic efficiency and market integration, whereas agroecology emphasises social justice, food sovereignty, and community empowerment.

Unlike mechanisation, which relies on scientific inventions often protected by patents, agroecology is transdisciplinary, blending scientific and local traditional knowledge passed down through generations without borders. The ongoing debate between these two paradigms underscores a fundamental tension in modern agriculture, involving trade-offs among efficiency, environmental sustainability, and social equity.

3.2.2 Empirical Review

3.2.2.1 Green Efficiency Estimation Techniques

In the production process of firms, a set of inputs are required for transformation into outputs. While the firm aims to produce marketable goods and services, some unintended (undesirable) outputs accompany the desirable ones. Therefore, the goal of the environmentally-conscious firm would be to limit the undesirable outputs, notably pollutants, as they increase the desirable ones. To estimate green production efficiency, scholars have relied on several Data Envelopment Analysis (DEA) techniques such as Super Efficiency DEA (Li et al., 2013), Directional Distance Functions (DDF) (Rahman & Reza, 2020), undesirable outputs Slacks-based measure (SBM) DEA models (Shen et al., 2022; Xu et al., 2022) and Super-SBM DEA models (Liu et al., 2021).

The undesirable outputs of SBM models follow Tone's (2001) slack-based efficiency measure, while the classical DEA models follow the pioneering work of the Charnes-Cooper-Rhodes (CCR) model (Charnes et al., 1979). In general, DEA models can be classified into two types: radial and non-radial models. The input-oriented radial models are premised on the CCR model and operate with a proportional input reduction (Tone, 2003). The efficiency score is thus measured by assigning an efficiency score to a directional or radial vector of the factors of production (Sueyoshi et al., 2017). Tone (2001) argues that the conventional radial DEA-based models have certain shortcomings despite their significant contributions to efficiency studies in the literature. First, the proportional weighting (reduction or enlargement) of the inputs and outputs can be misleading in the real sense and can only be so in some circumstances. Secondly, omitting the input-output slacks could lead to lapses in the information content of the efficiency scores for the decision-making units (DMUs).

Unlike the radial (input/output-oriented) models, the non-radial (non-oriented SBM) models function by directly operationalising the input and output slacks without assuming proportional input reduction (Tone, 2003). By this, the SBM models have the superior capability to model input excesses (input slacks) and output shortfalls (output slacks) appropriately and effectively better than their radial counterparts (Tone, 2001). The SBM-DEA model also assumes the following (p. 499): Units invariant. In other words, the measure should be invariant with respect to the units of data. Monotone. This means that the measure should be monotone decreasing in each slack in both the input and output. Reference-set dependent. This means that the measure should be determined only by consulting the reference set of the DMU concerned.

Growing environmental concerns to limit global greenhouse gases in all forms and the need for resource use efficiency have gained intensity, and many production units across all production sectors are responding as such. In agricultural production, for instance, the need to reduce emissions of carbon dioxide, nitrous oxide, methane gas and other GHGs while increasing output has resulted in the adoption of CSA practices (Burke et al., 2022; Clay & Zimmerer, 2020). Following environmental considerations, Tone (2001) adjusted the SBM-DEA model to include undesirable outputs to form a new nonparametric SBM-DEA model with undesirable outputs (Tone, 2003). The undesirable outputs SBM model has since become the fundamental DEA approach in recent agricultural green efficiency studies (He et al., 2021; Liu et al., 2021; Shen et al., 2022; Xu et al., 2022) with varied outcomes.

We employed the Tone (2003) nonparametric DEA SBM model with undesirable outputs to measure the agricultural green efficiency of African countries in line with the objective of CSA, which aims at producing more food using relatively fewer inputs in an environmentally sustainable manner. Our approach is similar to earlier studies by Liu et al.

(2021), Shen et al. (2022) and Xu et al. (2022), all in the Chinese context. Despite the considerable contributions of these works, an exhaustive consideration of the significant agricultural greenhouse gases as undesirable outputs in the agricultural green production efficiency literature has yet to be simultaneously examined. Notably, nitrous oxide and methane gas emissions have been studied (see Xu et al., 2022; Zhao et al., 2015 for some attempts). These least-covered gases in the literature could be called the '*forgotten*' greenhouse gases. Another contribution to the literature is simultaneously estimating our efficiency model with these '*forgotten*' gases, including carbon dioxide, as undesirable outputs in Africa.

In instances where two or more DMUs in a DEA efficiency study attain the maximum efficiency score on the production frontier, it is difficult, if not impossible, to know which of them outperforms the other on the frontier. As a remedy, Tone (2002) developed the super-slacks-based measure (S-SBM) model, which can effectively rank and evaluate multiple fully efficient DMUs. Like the earlier efficiency models, the S-SBM is esteemed and applied extensively in DEA studies covering several fields (Li et al., 2013; Li & Shi, 2014; Liu et al., 2021). This thesis uses the non-radial, nonparametric undesirable outputs SBM to estimate agricultural green efficiency scores. The model is discussed in detail in the methodology. In the interim, Table 3.1 briefly outlines related studies in the literature and their respective empirical findings.

Table 3.1: Outline of Empirical Studies in Agricultural Green Efficiency

Author/s	Context	Green Efficiency Estimation Technique	Inputs	Outputs	Outcomes
(Liu et al., 2022)	China	Non-separable undesirable SBM-DEA model	Labour, land, machinery, water, energy, capital, human capital, fertiliser, pesticide, agricultural film.	Desirable: Gross domestic product of primary industry Undesirable: Carbon dioxide emission of the primary industry	• Low overall average green total factor productivity value (0.527) for the 30 provinces in China between 2000-2018
(Xu et al., 2022)	China	Directional global slacks-based inefficiency (DGSBI) measure	Land, labour, chemical fertiliser, pesticide, agricultural machine, irrigation area.	Desirable: Agricultural output Undesirable: Nitrogen surplus Phosphorus surplus	• Existence of high nitrogen and phosphorus nutrient surplus in arable land • Downward trend in green inefficiency over the study period (2000 to 2017)
(He et al., 2021)	China	DDF with non-oriented S-SBM DEA	Fertilisers, pesticides, plastic mulch, energy consumption, irrigation and tillage	Desirable: Agricultural output Undesirable: Carbon dioxide emissions	• Decreasing trend in nationwide low-carbon efficiency between 2000 and 2017
(Chen et al., 2021)	China	Three-stage DEA (SBM-SFA-SBM)	Land, labour, machinery, fertiliser, energy.	Desired: Agricultural output value. Undesirable: Carbon dioxide, non-point source pollution	• Agricultural Green Total Factor Productivity (AGTFP) is lower when undesirable outputs are factored into the model. • Real green TFP scores showed mixed performances (U-shaped in some cases) for 30 Chinese provinces from 2000 to 2017,
(Liu et al., 2021)	China	Super-SBM	Labour, land, mechanical power,	Desirable: agricultural output value	• Overall, AGTFP shows a fluctuating growth trend between 2003 and 2017.

			fertiliser, pesticide, plastic film, and water	Undesirable: agricultural carbon emissions	• Agricultural carbon emissions show an inverted "U" trend caused by fertiliser usage.
(Le et al., 2019)	East Asian countries	Malmquist index and SBM with undesirable output	Land, labour, capital stock, and fertilisers	Desirable: gross agricultural production value Undesirable: carbon dioxide emission	• Taiwan, Japan, and Korea were green efficient over the entire study period between 2002 and 2010 • Thailand was the least green efficient country

3.2.2.2 Gaps in the Existing Literature

This section of the literature review presents the identified gaps in the existing research on agriculture green efficiency. It focuses on sustainable agricultural practices that minimise environmental impact while maintaining productivity. The review covers critical themes, such as green efficiency estimation techniques, the inputs and outputs used, and their respective outcomes based on the empirical literature, as shown in Table 3.1 above.

Several studies in the empirical literature employ different estimation techniques for sustainable productivity, including non-separable SBM-DEA (Liu et al., 2021), DGSBI (Xu et al., 2022), DDF with non-oriented S-SBM DEA (He et al., 2021), Three-stage DEA (Chen et al., 2021), Super-SBM (Liu et al., 2021), and Malmquist index SBM with undesirable output (Le et al., 2019) with varied empirical outcomes. It is important to note that all these studies are in the Asian context with a missing representation from the African context, especially in Agriculture production. Meanwhile, Africa urgently needs to consider comprehensive green agriculture productivity, considering the numerous financial and food security constraints facing the continent. These are only feasible through policy recommendations entrenched in robust empirical studies such as this current chapter.

The inputs employed in the current studies include labour, land, machinery, water, energy, capital, human capital, fertiliser, and pesticide, but with varying input combinations. In sustainable productivity estimation, two outputs are to be considered: desirable and undesirable. The dominant desirable output factor is agriculture output value. However, on the undesirable output side, agricultural carbon emissions have mainly been included in the literature without consideration of other equally harmful agricultural greenhouse gases such as nitrous oxide and methane gas.

Nitrous oxide and methane gas are potent greenhouse gases, so by excluding them from any agricultural green efficiency estimation, such an assessment will overlook a critical component of environmental impact, leading to an incomplete picture of overall efficiency. It could also result in overestimating the efficiency scores, concealing the actual resource use and emissions and consequently misleading policy recommendations. It could also lead to suboptimal resource allocation and ineffective mitigation strategies.

These gaps in the literature demonstrate critical areas needing further exploration to enhance the effectiveness and adoption of green efficiency practices in agriculture. Addressing these gaps will significantly contribute to sustainable agricultural development and the literature. Another significant contribution of this thesis is the development of an agricultural production benchmark that will guide efficient, yet sustainable agricultural production in Africa.

3.3 Methodology

3.3.1 Non-Radial, Nonparametric SBM Model with Undesirable Outputs

Given n number of decision-making units (DMUs) with three factors of production each in a production system, the production factors can be categorised into inputs, good outputs (desirable outputs), and bad outputs (undesirable outputs) such as pollutants in either liquid, gaseous or solid form. These factors can each be represented by a vector: $x \in \mathbb{R}^m, y^g \in \mathbb{R}^{s_1}, y^b \in \mathbb{R}^{s_2}$ in the same order of sequence. The matrices of the vectors (X, Y^g, Y^b) can be written as: $X = [x_1, \dots, x_n] \in \mathbb{R}^{m \times n}$,

$Y^g = [y_1^g, \dots, y_n^g] \in \mathbb{R}^{s_1 \times n}$, $Y^b = [y_1^b, \dots, y_n^b] \in \mathbb{R}^{s_2 \times n}$ where $X > 0, Y^g > 0$ and $Y^b > 0$.

The production possibility set (P) can thus be defined as:

$$P = \{(x, y^g, y^b) | x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda\} \tag{3.1}$$

where $\lambda \in (\mathbb{R}^+)^n$ is the intensity vector, $x \geq X\lambda$ is when the actual level of input exceeds that of the frontier investment, $y^g \leq Y^g\lambda$ means the actual desirable output is less than the desirable output level of the frontier and, $y^b \geq Y^b\lambda$ is when the actual undesirable output exceeds the undesirable output level of the frontier (Li et al., 2013; Tone, 2003).

According to Tone (2003, p.2), a $DMU(x_0, y_0^g, y_0^b)$ is efficient in the presence of undesirable outputs if there is no vector $(x, y^g, y^b) \in P$ such that $x_0 \geq x$, $y_0^g \leq y^g$ and $y_0^b \geq y^b$ with at least one strict inequality. Thus, there are no input excesses and no output shortfalls in any optimal solution.

On this basis, the undesirable output-SBM model (ρ^*) following Tone (2003) can be expressed as follows:

$$\rho^* = min \left[\frac{1 - \frac{1}{m} \sum_{i=1}^{m} \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{r_0}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{r_0}^b} \right)} \right]$$

$s.t.$

$$\begin{aligned} x_0 &= X\lambda + s^-, \\ y_0^g &= Y^g - s^g, \\ y_0^b &= Y^b + s^b, \\ s^- \geq 0, s^g &\geq 0, s^b \geq 0, \lambda \geq 0. \end{aligned} \tag{3.2}$$

where ρ^* is efficiency score of the $DMU(x_0, y_0^g, y_0^b)$ in the SBM model and satisfies the condition $0 < \rho^* \leq 1$; s^-, s^g, s^b are the input slacks, desirable output slacks and undesirable output slacks respectively in the same sequence; $s = (s^-, s^g, s^b)$ represent all the slacks; m is number of input factors; s_1 and $s_2$are desirable and undesirable output slacks respectively; and λ is the intensity vector.

For easy evaluation and linear programming purposes, equation 3.2 could be transformed into a linear one. Tone (2003) relied on the Charnes and Cooper (1962) transformation to arrive at an equivalent linear programme notated by $t, \Lambda, s^-, s^g, s^b$ given by:

$$\tau^* = \min\left[t - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}\right]$$

$s.t.$

$$1 = t + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2}\frac{s_r^b}{y_{r0}^b}\right)$$

$$x_0 t = X\Lambda + s^-,$$

$$y_0^g t = Y^g\Lambda - s^g,$$

$$y_0^b t = Y^b\Lambda + s^b,$$

$$s^- \geq 0, s^g \geq 0, s^b \geq 0, \Lambda \geq 0, t > 0. \tag{3.3}$$

where τ^* is undesirable-outputs SBM efficiency score similar to ρ^* $(i.e. \tau^* = \rho^*)$; Λ is the factor intensity vector, and t is a scalar variable. All the other notations mean the same as in equation (3.2) above.

Tone (2001; 2003) indicates that if an optimal solution exists, a DMU_0 is efficient in the existence/presence of undesirable outputs if and only if $\rho^* or\ \tau^* = 1$. In this case, there will be no slacks in: inputs $(s^{-*} = 0)$, desirable outputs $(s^{g*} = 0)$ and undesirable outputs $(s^{b*} = 0)$. By inference, a DMU_0 with $\rho^* or\ \tau^* < 1$ is environmentally inefficient. However, this can be improved by limiting excesses in inputs and bad outputs while simultaneously supplementing the shortfalls in good outputs. The inputs and outputs used in this study are discussed next. Before then, we outline the superior features of the SBM-DEA model with undesirable outputs over the conventional efficiency models such as the Stochastic Frontier

Analysis (SFA). The SFA is parametric and asuumes proportional weighing of inputs and outputs aside other assumptions such as a correct specification of a functional form which could biase the eventual efficiency scores. The SFA as well omits input-output slacks which are key considerations in this thesis. As a standard feature, the non-parametric SBM-DEA model simultaneously increases good outputs while reducing bad outputs in constructing the efficient frontier, which means it does not require any assignment of input and output weights that could be arbitrary.

3.3.2 Production Inputs and Outputs

Classically, input factors for economic-wide productivity involve labour force and capital stock (Peng et al., 2021; Wang et al., 2021; Day et al., 2019; Ur et al., 2019). However, other input factors, such as fossil fuel energy consumption, are considered for environmental sustainability (Salahuddin et al., 2020; Tansel & Kumar, 2016). In specific sector productivity analysis (for example, agricultural production), other additional specific input factors such as agricultural land, labour, fertilisers, pesticides, rainfall, irrigation water, energy or mechanical power usage, among others, are considered for production depending on the level of technology or mechanisation employed in the farming process (Chen et al., 2008; Liu et al., 2021). On the output side, two outcomes are conceivable: the economic output/s for which the production activity is undertaken, known as desirable outputs, and those that are unplanned but accompany the actual process in the form of by-products or residuals. These are neither wanted nor separable, and so are undesirable. The desired output in agriculture is agricultural output value (Chen et al., 2021; Xu et al., 2022). The undesired outputs are either produced directly by the production system or by using the production technology applied. Agricultural production, in particular, is associated with undesirable pollutants such as carbon dioxide (CO_2), Nitrous Oxide (N_2O), and Methane gas (CH_4) emissions with adverse and undesirable environmental effects (Khan & Tariq, 2021; Sagoff, 2012). An eco-friendly or "green" production system is, therefore, one that utilises little available input resources to produce more beneficial socio-economic outputs with little or no adverse environmental impacts (Xu et al., 2022).

For this reason, the agricultural green production efficiency estimation approach must consider environmental factors equally for inputs and outputs. Table 3.2 details the inputs and outputs used in this study, drawing insights from existing literature as well as the aim of this chapter. The respective descriptions, measurements, and sources of the data have also been given in Table 3.2. Missing data is a significant setback in DEA analysis, with proposed solutions including complete case analysis and the use of dummies, which may lead to biased outcomes (Kuosmanen, 2002). In this chapter, we utilised the mean imputation approach of Raaijmakers (1999) to replace all missing observations, which were very minimal.

The data repository originates from various sources, including national governments and specific agency extrapolations, with metadata provided for transparency, particularly for FAO datasets. Data transmitted from national sources is assessed, checked, and validated. However, since member countries primarily gather the source data and submit the dataset, it is not possible to evaluate the overall accuracy of the dataset submitted by collection agencies. This may raise concerns about data reliability in member countries with limited resources. Nonetheless, data from all sources are widely utilised in the literature and are considered highly reliable. These principles apply to all other data aspects in the subsequent chapters, as they share the same data sources.

Table 3.2: Input and Output Variables

Inputs and Outputs		Definition/Measurement	Data Source
Inputs			
Agricultural Land		Land used for the cultivation of crops and animal husbandry. The total of areas under "Cropland" and "Permanent meadows and pastures." In thousand hectares.	FAOSTAT
Labour		Employment in agriculture (% of total employment) (modelled ILO estimate).	WDI
Energy consumption		Energy use: Value of energy use (thousand terajoules) in agricultural activities. It includes energy from fuel burning and the generation of electricity used in agriculture.	FAOSTAT
Pesticides		Total pesticides (thousand tonnes), covering insecticides, fungicides and bactericides (including seed treatments), herbicides, plant growth regulators, rodenticides, mineral oils, disinfectants and others used per value of agricultural production.	FAOSTAT
Irrigation Water		Annual freshwater withdrawals, agriculture (% of total freshwater withdrawal): Withdrawals for agriculture, irrigation and livestock production.	WDI/FAO AQUASTAT
Rainfall/Precipitation		Average precipitation is the long-term average in depth (over space and time) of annual precipitation in the country. Precipitation is any water that falls from clouds as a liquid or a solid (mm per year).	FAOSTAT
Fertilisers		Fertiliser consumption (kilograms per hectare of arable land): measures the quantity of plant nutrients used per unit of arable land. Fertiliser products cover nitrogenous, potash, and phosphate fertilisers (including ground rock phosphate). Traditional nutrients: animal and plant manures are not included.	WDI/FAOSTAT
Outputs			
Desirable	Gross Agricultural Output	Gross Agricultural Production Value (current thousand US$).	WDI
Undesirable Outputs	Agricultural Carbon dioxide (CO_2) emissions	Energy use (kilotonnes): emissions from energy consumption associated with fuel burning and the generation of electricity used in agriculture.	FAOSTAT
	Agricultural Methane Gas (CH_4) emissions.	Agricultural methane emissions (% of total or metric tons of (CO_2) equivalent): emissions from animals, animal waste, rice production, agricultural waste burning (nonenergy, on-site), and savannah burning.	WDI and FAOSTAT
	Agricultural Nitrous Oxide (N_2O) emissions	Agricultural nitrous oxide emissions (% of total or thousand metric tons of (CO_2) equivalent): emissions produced through fertiliser use (synthetic and animal manure), animal waste management, agricultural waste burning (non-energy, on-site), and savannah burning.	WDI and FAOSTAT

Notes: WDI is World Development Indicators, World Bank; FAOSTAT is Food and Agriculture Organisation Corporate Database; AQUASTAT is FAO global information system on water resources and agricultural water management.

3.4 Empirical Results and Analysis

3.4.1 Descriptive Statistics

The descriptive statistics of the inputs and outputs used in this study are in Table 3.3. The Table shows that, on average, there are over 19.7 million hectares of agricultural arable land under cultivation and animal husbandry. The descriptive statistics also indicate that, on average, 8.7 million terajoules of energy are consumed annually for agricultural purposes, mainly through fuel burning and electricity generation for farming activities. Likewise, over 3.6 million tonnes of pesticides are used per unit of agricultural production over the study period. The summary statistics also indicate that, on average, 48.4% of total African employment is in agriculture. The employment statistic indicates the sector's significant role in providing livelihoods for a greater number of people on the continent. As in the case of Burundi, the data show that the sector provided approximately 92% of the total employment in the country at a point in time during the study period. A more significant percentage (59.8%) of the fresh water in Africa is withdrawn for crop irrigation and livestock production. An average of 937.426 millimetres of precipitation or rainfall provides annual water for production. The average fertiliser consumption is 37.3 kilogrammes per hectare of arable land (about 37.3 kg/2.5 acres). This rate is, however, below the average recommended rate of about 60 kilogrammes per hectare for specific crops such as maize (Essel et al., 2020).

The data further indicate that the average annual agricultural output value in the selected countries is about US$5.7 billion. However, estimates suggest that production must grow by at least 50% more to meet food demands by 2050 (FAO, 2017). From Table 3.3, it is evident that Africa's contribution to agricultural-related GHG emissions is quite substantial at annual average rates of 6,499.9 kilotonnes, 8,834.5 kilotonnes, and 21,923.6 kilotonnes, respectively, for nitrous oxide, methane gas, and carbon dioxide though relatively low compared to other regions such as Asia, Americas and in some cases, Europe (FAOSTAT, 2022).

Table 3.3: Summary Statistics of Input and Output Variables

Variables	Min	Max	Mean	Std. Dev.
Inputs				
Land (1000 hectare)	1.50	98125	19712.78	20689.99
Energy (1000 Terajoule)	34.24	165055.80	8678.66	20196.98
Pesticides (1000 tonnes)	1	152789.70	3609.23	13877.55
Labour (% of total employment)	0.79	91.76	48.43	23.04
Irrigation (% of total freshwater withdrawal)	0.55	98.11	59.83	28.41
Precipitation (mm per year)	18.10	2526	937.43	609.76
Fertiliser (kilograms per hectare of arable land)	1	816.93	37.27	94.99
Outputs				
Agric Output (1000 US$)	4641	9.41E+07	5693662	9741338
Nitrous Oxide (Kilotonnes)	1	44480	6499.87	7453.13
Methane (Kilotonnes)	1	69130	8834.48	11316.33
Carbon Dioxide (Kilotonnes)	8.79	601790.60	21923.64	69650.90
No. Observations				960

Source: Author's estimations

3.4.2 Agricultural Green Production Efficiency

Table A.3.6 under the appendix provides a broad overview of the agricultural green efficiency scores of 48 African countries over twenty years. The table shows that many countries have been producing below their optimum over the entire study period; hence, agricultural production could be more efficient. While some countries (for example, Algeria, Carbo Verdi, Central Africa Republic, Congo, Democratic Republic of Congo, Lesotho, and Seychelles) achieved total production efficiency multiple times across the study period, others such as Angola, Chad, Egypt, Eritrea, Gabon, Gambia, Kenya, Malawi, Mali, Mauritania, Namibia, Niger, Nigeria, Sierra Leone, Tanzania, and Togo achieved total efficiency in few times within the study period. Notably, a lot of the countries still needed to attain total productive efficiency in any of the years of the study. These include Botswana, Burkina Faso, Cameroon, Cote d'Ivoire, Eswatini, Ethiopia, Uganda, Madagascar, Morocco, Mozambique, Senegal, Ghana, Tunisia, Zambia and Zimbabwe. On average, we found 0.66 agriculture green efficiency score for Africa. This is below the theoretical optimum of 1 indicated by Tone (2003). This inefficiency is consistent with the findings of Liu et al. (2022), who found a 0.53 efficiency score in their study of 30 provinces in China between 2000 and 2018, which is in the Asian context.

The countries' low levels of green agricultural production efficiency suggest that agricultural productivity in Africa is primarily achieved without significant incorporation of climate-smart agricultural (CSA) practices, or the concept of agroecology is not fully implemented. It is also possible that the low levels of green efficiency recorded in the study are due to the incorporation of broader undesirable outputs into our model, similar to the findings of Chen et al. (2021), also in the Asian context. Specifically, China. However, this is a robust outcome since excluding the crucial agricultural pollutants would have led to an overestimation of the efficiency scores of the countries. Meanwhile, adopting superior production practices has improved productivity (FAO, 2017). Another contributory factor to the low levels of green efficiency in Africa is the focus on input intensification rather than improving the efficiency of input usage (FAO, 2017). Apart from the environmental consequences, the agricultural production shortfalls arising from input intensification also impose a substantial financial burden on farmers. Input intensification requires that the farmer spend more on quantities of fertilisers and agrochemicals, acquire more acres of land, and spend on the productive expansion's energy needs, among other sunk costs. This phenomenon could impoverish the farmer more, with broader implications for economic and food security systems.

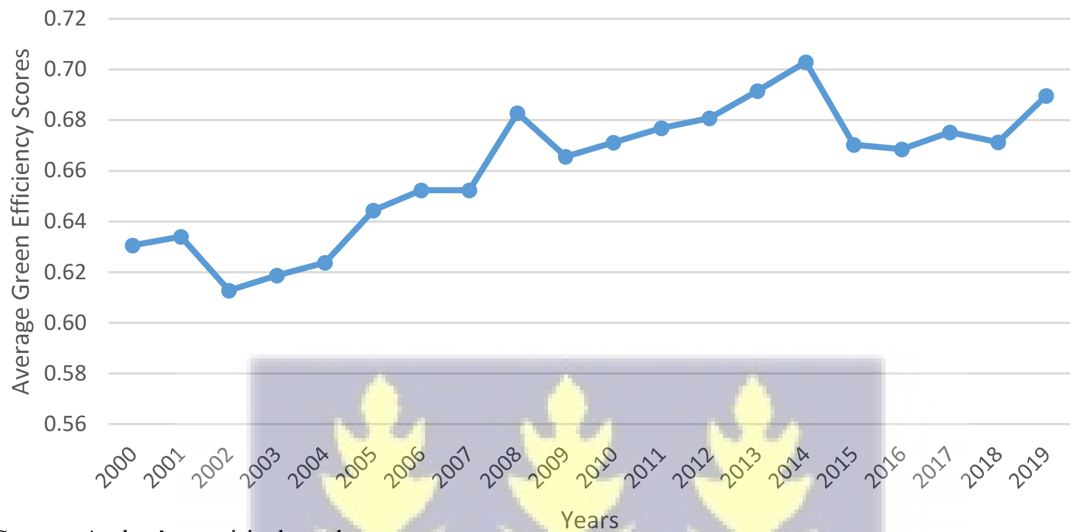
In addition, unsustainable input intensification leads to environmental pollution through land degradation, excessive freshwater withdrawal, nitrous oxide pollution from excessive use of fertilisers, and other emissions from environmentally unfriendly and unsustainable farming practices. This practice is against the theoretical basis of CSA and agroecology. The associated financial costs owing to the input intensification phenomenon would negatively impact the farmers' socio-economic lives. Xu et al. (2022) noted that excessive use of soil nutrients results in high residues and low efficiency scores. Nonetheless, demand for agricultural production inputs is projected to increase enormously by 2050, mainly in low-income countries (FAO, 2017).

An increasing demand for food worldwide puts equal pressure on production systems to meet global food needs. Africa's agricultural production requires significant improvements to meet the current need to grow more with less or no adverse environmental impacts. Coupled with current climatic adversaries and uncertainties, the need for CSA has become inevitable. However, technology adoption and CSA production do not come at a lean cost. They are usually expensive and unaffordable, far beyond the means of smallholder farmers who form the more significant portion of agricultural producers in Africa.

Notwithstanding the below-optimal green efficiencies in production, there appears to be some overall progress over the years, as shown in Figure 3.2, contrary to the downward trend in green efficiency reported by He et al. (2021) and Xu et al. (2022) in the Chinese cases. However, Africa's overall average agricultural green efficiency score is 0.66, meaning Africa is green-inefficient in agricultural productivity. Notwithstanding, the best performers include Algeria, Carbo Verdi, Central African Republic, Congo Republic, Democratic Republic of Congo, Lesotho, and Seychelles.

The need for sustainably efficient agricultural production will require the precise deployment of agricultural inputs to produce outputs at the desired optimal level. To ascertain the exact input-output requirements for each country studied, the study projected the targets for each set of inputs and outputs. The targets in SBM DEA studies are the input-output values/levels that will make inefficient agricultural producers sustainable (Aparicio et al., 2007; Tone, 2003). The targets are discussed next.

Figure 3.2: Trend of Agriculture Green Efficiency in Africa (Average)



Source: Author's empirical results

3.4.3 Operational Input-Output Targets for Green Efficiency

Table 3.4 presents the practical targets for all inefficient countries to become sustainably efficient in their operations. For efficient and sustainable agricultural production in Africa, an average of only 3.51 million hectares of arable land is necessary based on each country's input and output targets. This area is below the average of 19.7 million hectares currently under cultivation. The target outcome reinforces the need for ease in land intensification to improve output in congruence with the theoretical underpinnings of CSA and agroecology. Similarly, only about 2.92 million terajoules of energy and 1.37 million tonnes of pesticides per output value will be sufficient for green, efficient production compared to the current averages of 8.7 million terajoules and 3.6 million tonnes, respectively. If these lower input targets are achieved, it will substantially reduce production costs and GHG emissions and enhance ecovitality. The input targets for water, labour, and fertiliser usage for effective green production are below the current actual values. Compared to the current average of 59.82%, only 29.68% of irrigation water is required to meet efficient crop and livestock production levels. Also, employing just about 34.01% of the labour force will be enough for efficient production compared to the current average of 48.43%. The result highlights the labour-intensive nature of agricultural production in Africa and the urgent need for mechanisation and CSA production through technological adoption.

Though Africa's average fertiliser usage rate is relatively below the recommended global average, the current average consumption volume (37.3 kilograms per hectare of arable land) is excessive relative to the actual output. Operationally, the required average target is 21.97 kilogrammes per hectare relative to the output. The high excess rates could be attributable to poor application practices and low proficiency in fertiliser usage. The lower required levels have both socio-economic and environmental gains. Economically, it will relieve farmers of high fertiliser expenditures and enhance their disposable income. Environmentally, it will lower nitrous oxide emissions for cleaner production (Xu et al., 2022). Knowledge acquisition and training on the practical application of fertilisers for maximum output results will thus be required.

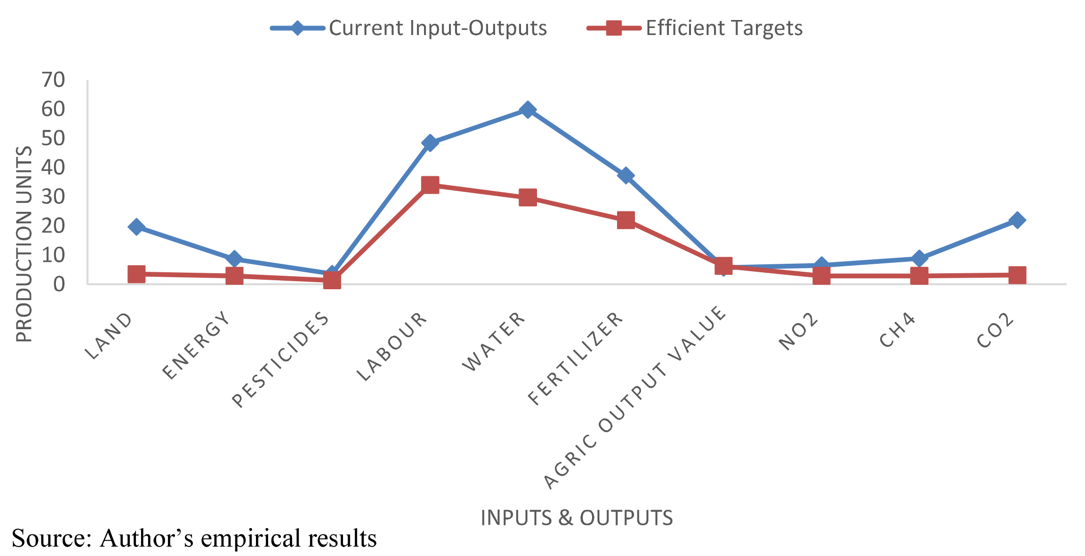
In order to achieve maximum green efficiency in agricultural production, African countries need to observe pollution limits of 2.89, 2.90, and 3.17 thousand kilotonnes in nitrous oxide, methane gas, and carbon dioxide, respectively. Figure 3.3 represents the current input and output volumes against the projected green, efficient targets. From the graph, all the inputs and undesirable outputs require drastic reduction and improved output value to achieve green efficiency in agricultural production. Agriculture must generate an estimated average gross output value of US$6.29 billion to achieve green-efficient African production.

Table 3.4: Average Input-Output Targets

	Average Input Targets							Average Output Targets			
DMU	Land	Energy	Pest.	Labour	Irrigate	Preci.	Fert.	Output	NO2	CH4	CO2
Algeria	4.40	3.75	3.33	14.51	57.75	1.95	14.50	7.12	3.47	3.58	2.61
Angola	4.18	2.92	0.75	35.91	15.87	3.00	2.07	6.74	3.46	3.39	4.08
Benin	3.56	3.18	2.30	36.68	32.32	2.92	3.17	6.56	3.06	3.10	3.63
Botswana	1.76	2.45	0.88	13.32	6.33	2.62	8.06	4.97	1.18	1.14	2.07
Burk. Faso	3.55	2.69	0.39	31.33	7.08	2.87	3.06	6.18	2.81	2.73	3.49
Burundi	3.28	2.39	1.71	66.84	54.35	2.96	1.79	6.22	2.95	2.87	3.21
C. Verdi	1.89	2.51	0.71	16.98	92.31	2.36	5.00	5.31	1.80	1.74	1.34
Cameroon	3.91	2.99	0.84	32.40	23.02	2.83	3.59	6.66	3.12	3.07	3.63
C. Africa Rep.	3.71	1.76	1.36	72.36	0.56	3.13	0.12	5.90	3.92	3.97	4.15
Chad	4.43	2.39	1.25	67.22	51.80	2.51	20.35	6.59	3.97	4.12	4.23
Comoros	2.12	1.75	0.10	44.90	47.00	2.95	12.70	4.73	1.64	2.28	1.82
Congo	3.84	2.56	0.37	36.95	5.27	3.22	2.38	6.21	3.11	3.01	3.84
Cote d'Ivoire	4.06	3.04	0.81	31.48	18.64	2.83	3.64	6.79	3.26	3.20	3.83
D. Rep. Congo	4.44	3.56	3.48	69.33	10.87	3.19	0.63	7.01	4.10	4.09	5.66
Djibouti	3.23	2.30	1.99	32.39	15.79	2.34	2.40	5.75	2.40	2.67	1.01
Egypt	3.56	4.59	3.67	19.90	77.51	1.26	396.78	7.34	3.69	3.74	3.30
Eritrea	3.48	2.43	0.93	45.03	21.50	2.58	1.95	5.87	2.82	2.93	2.58
Eswatini	2.66	3.11	1.71	14.20	56.35	2.56	8.28	5.99	2.00	2.03	2.11
Ethiopia	4.13	3.29	1.41	30.57	29.31	2.49	4.53	6.96	3.31	3.28	3.73
Gabon	2.88	2.62	0.80	25.36	8.35	3.24	4.63	5.72	2.16	2.07	3.03
Gambia	2.49	2.45	1.83	23.95	19.60	2.75	3.96	5.30	1.94	2.15	1.94
Ghana	4.06	3.31	1.35	27.08	36.12	2.50	5.27	6.93	3.17	3.16	3.48
Guinea	4.00	2.65	0.18	37.12	4.89	3.21	0.62	6.28	3.23	3.14	3.93
G. Bissau	2.47	2.44	0.57	23.40	10.13	3.05	6.85	5.43	1.83	1.85	2.61
Kenya	4.18	3.18	1.46	36.55	29.10	2.63	6.30	6.92	3.51	3.53	3.65
Lesotho	3.36	2.75	0.83	51.04	8.68	2.89	2.00	5.72	2.76	2.93	1.76
Libya	4.19	4.16	3.16	20.77	83.01	1.75	19.78	7.45	3.07	3.15	2.83
Madagascar	3.99	2.72	0.12	35.65	4.47	3.17	1.37	6.46	3.21	3.11	3.94
Malawi	3.65	2.94	1.52	42.35	34.34	2.92	7.01	6.64	3.08	3.04	3.51
Mali	4.14	2.91	0.41	47.38	44.51	2.44	9.10	6.57	3.47	3.53	3.19
Mauritania	4.06	3.20	1.06	31.36	45.10	1.96	8.64	6.68	3.11	3.21	2.96
Mauritius	1.95	2.98	2.66	8.07	59.52	3.16	196.27	5.59	1.94	1.34	1.87
Morocco	4.07	3.41	1.62	25.05	43.65	1.94	6.00	6.99	3.16	3.17	3.28
Mozambique	4.01	2.73	0.24	36.64	5.29	3.01	1.69	6.52	3.26	3.17	3.98
Namibia	2.99	2.68	0.81	24.81	15.57	2.45	3.87	5.61	2.30	2.30	2.92
Niger	4.26	2.80	1.26	63.41	62.88	2.18	0.28	6.36	3.60	3.76	3.16
Nigeria	4.70	4.13	4.10	39.80	41.51	2.94	6.28	7.72	4.17	4.30	4.48
Rwanda	3.26	2.63	2.00	62.20	50.40	2.93	2.27	6.37	2.97	3.00	3.09
Senegal	3.31	2.66	0.41	28.04	5.76	2.68	3.72	6.06	2.58	2.51	3.32
Seychelles	0.38	2.41	1.28	2.71	6.84	3.37	182.71	4.08	0.10	0.10	1.19
Sierra Leon	3.54	2.69	1.21	41.94	15.26	3.18	8.82	6.37	2.89	2.90	3.50
S. Africa	4.64	4.52	4.08	6.20	58.80	2.51	47.86	7.18	3.83	3.89	3.59
Tanzania	4.13	2.90	0.51	38.34	13.75	2.93	2.94	6.63	3.41	3.35	4.04
Togo	3.40	2.72	0.99	32.47	17.15	2.91	2.77	6.11	2.71	2.69	3.06
Tunisia	3.20	3.62	2.54	12.71	62.35	2.19	10.16	6.54	2.29	2.37	2.32
Uganda	4.03	2.73	0.16	36.56	4.49	3.07	1.28	6.50	3.25	3.15	4.00
Zambia	3.60	2.70	0.25	30.20	4.73	3.01	3.26	6.31	2.86	2.76	3.64
Zimbabwe	3.42	2.68	0.31	28.84	4.89	2.82	3.63	6.17	2.68	2.59	3.48

Source: Author's estimation

Figure 3.3: Average Input-Output Targets



Source: Author's empirical results

3.4.4 Input and Output Slacks

The slacks in undesirable SBM DEA estimation indicate the excesses in inputs and bad outputs and the underperformances or shortfalls associated with good outputs. Table 3.5 shows summary statistics of the slack results of all the variables used in this study for the selected African countries.

Minimising redundancy in inputs and outputs to the estimated targets is essential to improve sustainable agricultural efficiency. This includes reducing excessive land intensification by 0.34 million hectares, decreasing energy consumption by 0.36 million terajoules, cutting pesticide usage by 1.08 million tonnes per output value, and reducing labour intensification by over 14.43%. Additionally, it is essential to reduce excess water usage by 30.14%. There is very little excess precipitation, about 0.11mm on average. Excessive fertiliser consumption must be reduced extensively by up to 15.30 kilograms per hectare of arable land in line with Burke et al. (2022) regarding excessive fertiliser usage in agricultural production in Africa. Total emissions must also be reduced by 0.49 (thousand kilotonnes) to achieve total green agricultural production efficiency in Africa. By implication, the main drivers of inefficiency in agricultural green production in Africa are excess land usage, excessive pesticide usage, labour-intensive farming, water wastage, overusage of chemical fertilisers, and agricultural pollution, which are associated with economic consequences for farmers. The consequences are twofold: extra burdens on farmer incomes arising from the need to increase farm input expenditure and, secondly, the overall finances of these countries to increase funding and importation of inputs for agricultural production. This comes from the tight budgets and high constraints on funding for African agricultural production. The phenomenon further deepens input dependency and exposes African countries to high systemic shocks to the agricultural supply market.

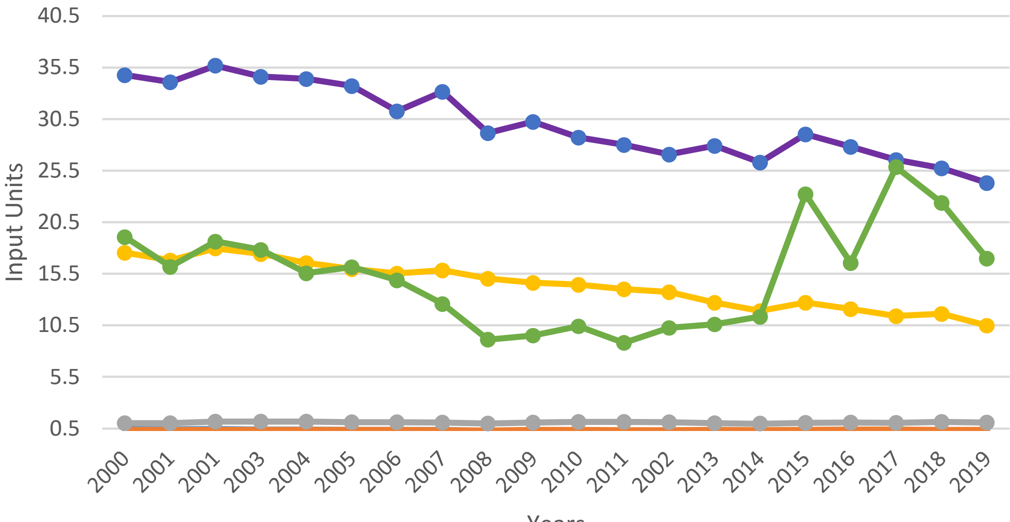
Figures 3.4 and 3.5 show the average trend in the input and undesirable output excesses. The graphs show that though the trends in the input excesses are gradually reducing, their high excessive rates must cause worry. The undesirable outputs equally show lagging progress in their decline.

Table 3.5: Average Input-output Slacks

	Average Input Slacks							Average Output Slacks			
Country	Land	Energy	Pesticides	Labour	Irrigation	Precipit-ation	Fertlizer	Output	NO2	CH4	CO2
Algeria	0.21	0.04	0.30	0.04	2.52	0.00	2.14	0.00	0.19	0.18	0.01
Angola	0.53	0.36	0.85	9.28	10.94	0.00	4.01	0.00	0.77	0.84	0.44
Benin	0.00	0.16	1.27	7.21	1.87	0.10	5.46	0.00	0.26	0.32	0.42
Botswana	2.65	0.85	0.35	8.95	31.60	0.00	41.92	0.00	2.35	2.45	2.54
Burk. Faso	0.51	0.54	1.95	19.51	45.40	0.00	9.30	0.01	1.08	1.32	0.36
Burundi	0.00	0.00	0.45	21.71	22.16	0.14	5.52	0.00	0.12	0.06	0.35
C. Verdi	0.00	0.01	0.00	0.28	0.02	0.00	0.00	0.00	0.03	0.01	0.01
Cameroon	0.07	0.17	2.66	22.79	46.40	0.37	6.33	0.00	0.63	0.79	0.97
C. Africa Rep.	0.00	0.02	0.00	0.63	0.01	0.00	0.08	0.03	0.02	0.01	0.00
Chad	0.26	0.00	0.37	10.64	25.19	0.00	9.65	0.00	0.25	0.35	0.05
Comoros	0.00	0.11	0.00	1.39	0.00	0.00	0.00	0.00	0.02	0.01	0.01
Congo	0.18	0.00	0.05	0.69	0.61	0.00	0.98	0.03	0.09	0.06	0.13
Cote d'Ivoire	0.25	0.72	1.16	15.46	25.56	0.29	24.61	0.00	0.22	0.30	0.62
D. Rep. Congo	0.00	0.00	0.00	0.05	0.00	0.00	0.20	0.00	0.01	0.01	0.00
Djibouti	0.00	0.02	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.02
Egypt	0.00	0.36	0.26	8.19	7.33	0.00	123.07	0.00	0.48	0.46	0.41
Eritrea	0.40	0.00	0.52	21.51	69.46	0.01	1.81	0.03	0.36	0.52	0.26
Eswatini	0.42	0.00	1.48	2.02	38.34	0.59	8.92	0.00	0.58	0.75	0.48
Ethiopia	0.42	0.46	1.97	42.95	62.41	0.44	16.55	0.00	1.22	1.44	0.84
Gabon	0.45	0.40	2.30	9.84	21.51	0.02	11.36	0.00	0.34	0.21	0.63
Gambia	0.26	0.03	0.91	7.53	19.93	0.18	1.27	0.08	0.58	0.72	0.80
Ghana	0.07	0.49	1.63	19.77	34.78	0.57	12.77	0.00	0.45	0.51	0.43
Guinea	0.16	0.71	2.33	29.59	46.54	0.01	1.76	0.04	0.44	0.82	0.13
G. Bissua	0.40	0.00	1.33	41.38	66.98	0.15	18.15	0.00	1.00	1.16	0.57
Kenya	0.26	0.45	1.74	20.97	39.44	0.19	24.59	0.00	0.61	0.82	0.07
Lesotho	0.00	0.12	0.46	0.09	0.00	0.00	0.00	0.00	0.00	0.01	0.01
Libya	0.00	0.06	0.02	0.58	0.00	0.00	6.42	0.00	0.01	0.00	0.06
Madagascar	0.62	0.49	2.25	37.31	91.80	0.01	4.16	0.06	0.69	1.07	0.33
Malawi	0.07	0.10	1.24	36.43	52.02	0.15	24.56	0.00	0.29	0.23	0.41
Mali	0.47	0.02	0.62	20.67	53.44	0.01	8.68	0.00	0.53	0.66	0.01
Mauritania	0.54	0.34	0.16	4.69	46.13	0.00	14.36	0.00	0.33	0.54	0.00
Mauritius	0.01	0.00	0.24	0.67	5.76	0.15	70.56	0.00	0.14	0.00	0.14
Morroco	0.41	1.19	2.52	15.45	37.99	0.60	52.86	0.00	0.68	0.66	0.11
Mozambique	0.58	0.36	2.38	39.66	68.71	0.00	3.56	0.00	0.68	0.78	0.72
Namibia	1.60	1.32	0.94	2.84	54.22	0.00	5.21	0.25	1.24	1.35	1.13
Niger	0.38	0.05	0.12	11.58	16.23	0.00	0.17	0.05	0.29	0.37	0.00
Nigeria	0.13	0.34	0.65	1.76	5.53	0.12	3.03	0.00	0.23	0.28	0.21
Rwanda	0.00	0.00	0.74	15.36	7.48	0.15	3.96	0.00	0.16	0.15	0.34
Senegal	0.64	1.04	2.33	10.37	87.22	0.16	8.01	0.05	1.07	1.28	0.32
Seychelles	0.00	0.04	0.00	0.62	0.00	0.00	60.46	0.00	0.18	0.00	0.05
S. Leon	0.03	0.06	1.68	21.50	6.81	0.23	21.18	0.00	0.17	0.44	0.05
S. Africa	0.34	0.40	0.35	0.03	2.64	0.19	12.92	0.00	0.34	0.34	0.49
Tanzania	0.44	0.55	0.69	33.64	75.60	0.10	4.86	0.03	0.87	1.12	0.70
Togo	0.16	0.32	1.65	10.17	20.74	0.16	2.71	0.01	0.39	0.41	0.05
Tunisia	0.79	0.68	0.75	4.55	17.92	0.12	33.85	0.00	1.07	0.99	0.78
Uganda	0.11	0.81	1.79	32.93	33.37	0.00	0.58	0.00	0.71	0.93	0.26
Zambia	0.77	1.48	3.27	32.58	68.55	0.00	35.06	0.00	1.27	1.25	0.73
Zzimbabwe	0.79	1.50	3.14	36.24	75.74	0.00	26.94	0.00	1.01	1.23	0.60
Average*	**0.34**	**0.36**	**1.08**	**14.43**	**30.14**	**0.11**	**15.30**	**0.01**	**0.51**	**0.59**	**0.38**

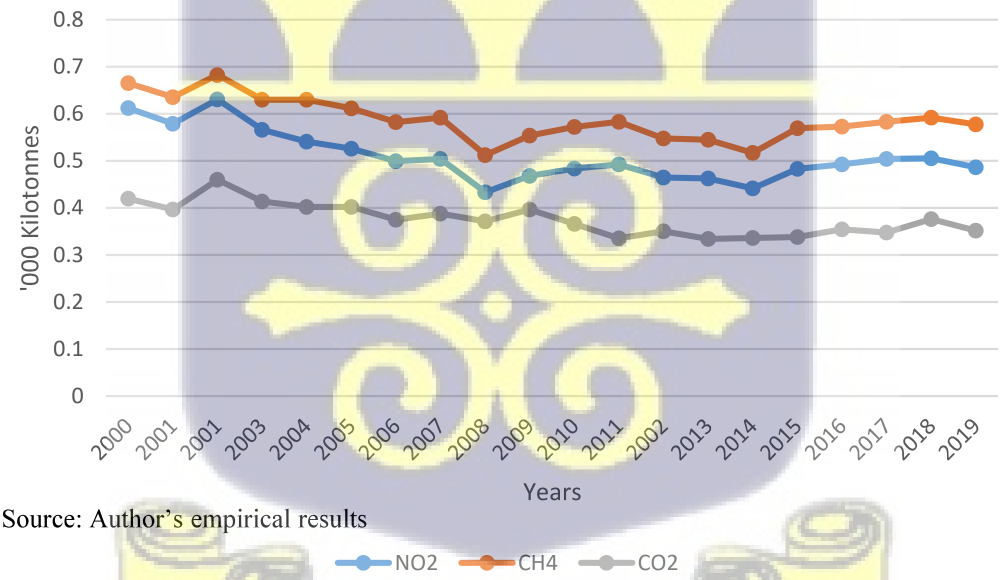
Notes: * overall average slacks were calculated from country specific overall slacks across the coutnries over the study period.

Figure 3.4: Trend of Average Input Slacks



Source: Author's empirical results

Figure 3.5: Trend of Average Undesirable Output Slacks



Source: Author's empirical results

3.5 Summary, Conclusion and Recommendations

Using the SBM-DEA model for nonparametric undesirable outputs, the chapter analysed the green efficiency of agricultural production in Africa. The results revealed that, on the whole, agricultural production in Africa is green inefficient at an average efficiency rate of 66%. The inefficiencies are caused by highly unsustainable input intensification involving land, labour, fertiliser, water and pesticides. For instance, we found that despite Africa's generally low fertiliser application adoption rate, the current 37.3% average application rate per hectare of arable land does not correspond with the output value produced, leading to production inefficiencies and wastage. To realise the full benefits, fertiliser application wastage must be cut by up to 15.30 kilograms per hectare of arable land. Equally, 0.34 million hectares of land, 0.36 million terajoules of energy consumption, 1.08 million tonnes of pesticide usage per value of output, 14.43% of labour, and 30.14% of freshwater usage excesses must be reduced for sustainable and efficient production in Africa. These will go a long way to improving the production shortfalls, saving costs, and improving eco-vitality.

The estimated targets also indicated that, on average, considerably low levels are actually needed to achieve green efficiency. This further underscores the need to adopt CSA and agroecology in agricultural production due to their substantial cost-saving and environmental protection potential. Agricultural production emissions (carbon dioxide, nitrous oxide, and methane gas) must be reduced for environmental efficiency. Nonetheless, an estimated annual average of US$6.29 billion worth of agricultural output is required for African countries to be green-efficient in agricultural production.

Given our findings, the following policy formulation and recommendations are made. 1) Agroecological practices must be a prime priority of African countries as a less expensive avenue for promoting higher agricultural output value and enhancing environmental efficiency for green agricultural production efficiency. 2) Targeted farmer education on effective and sustainable input usage must accompany all governmental input usage drives to reduce all GHG emissions from agricultural input usage. 3) Sustainable farm management practices must be incorporated into agricultural extension services to reduce on-farm pollution practices. 4) All concerned stakeholders should also prioritise sustainable agricultural mechanisation to enhance the agricultural productive capacity of African countries.

CHAPTER FOUR

AGRICULTURAL GREEN EFFICIENCY IN AFRICA: THE ROLES OF FINANCIAL INVESTMENTS AND AGRI-ENVIRONMENTAL FISCAL POLICIES

Abstract

This chapter examines the roles of financial investments and agri-environmental fiscal policies in enhancing agricultural green efficiency in 48 African countries from 2000 to 2019. The study uses a two-stage analysis. Firstly, it employs slacks-based measure data envelopment analysis to generate agricultural green efficiency scores. Then, the fractional heteroskedasticity probit regression model is applied to identify factors influencing green efficiency. The results show that financial investments in agricultural technological innovation and prudent capital expenditure significantly improve green efficiency. Additionally, aid to agriculture and effective agri-environmental fiscal policies play crucial roles, while urbanisation threatens green efficiency. This study provides valuable insights into how financial investments influence climate-smart agriculture and the importance of environmentally oriented fiscal policies in achieving sustainable agricultural practices.

4.1 Introduction

Every country worldwide is diligently working to ensure sufficient food production to meet the needs of its population and the demands of other necessities. In Africa, the agricultural sector remains the largest employer and cornerstone of the economy (World Bank Data, 2022). As the global population continues to proliferate, there is an urgent need to increase the food supply to meet the escalating demand for food, especially in Africa, due to the continent's unique food challenges. However, agricultural production in Africa has been severely affected by adverse environmental conditions, primarily due to recent climate change (Ortiz-Bobea et al., 2021). This phenomenon has led to severe drought, extreme heat, flooding, erratic rainfall patterns, and increased pest infestation, resulting in substantial economic and social costs.

It is argued that Africa and other least-developed countries bear the most significant costs associated with climate change, with the projected annual loss and damage for Africa estimated to be US$201 billion if no action is taken (Kray et al., 2022). Unpreparedness and the inadequate adoption of effective strategies have contributed to these challenges (Martey et al., 2020). To address the growing food demand-supply gap caused by the rapidly expanding population and unfavourable production conditions, there is a pressing need to significantly increase agricultural production by adopting coping strategies to deliver the required output efficiently and with minimal environmental damage. Two pathways have been proposed to explain this phenomenon: climate adaptation and mitigation. While adaptation aims to manage current and anticipated future climate uncertainties, mitigation aims to prevent further environmental pollution and promote eco-vitality. These pathways are encompassed by climate-smart agriculture (CSA), which entails efficiently increasing agricultural production, improving climate resilience, and minimising negative externalities (FAO, 2013; Morkunas & Balezentis, 2022). Achieving these three core CSA areas necessitates shifting production focus towards green production efficiency. However, attempts to address this in Africa comprehensively have not been sufficiently extensive.

Contrary to the prevailing belief that Africa contributes minimally to global greenhouse gas (GHG) emissions, current data on global agricultural emissions, particularly carbon dioxide, nitrous oxide, and methane gas, indicate that Africa falls below the Americas and Asia in terms of total emissions (FAOSTAT, 2022). These emissions are predominantly driven by ineffective and environmentally unfriendly farming practices, resulting in low output and a high pollution footprint. For instance, approximately 95% of Africa's food production relies on rainfall (Abrams, 2018), and input usage does not always correspond to the actual output in some cases (Burke et al., 2022). Budget constraints are the primary challenge for Africa's agricultural underperformance amid environmental adversities. It is estimated that an annual total cost of US$150 billion is required to address these environmental challenges and provide resilient production capabilities (Chapagain et al., 2020, p. 4). These costs are considered substantial in the budgets of most African countries. Although Africa has received significant funding from various CSA sources, the effectiveness and efficiency of these initiatives on productivity have been mixed, unsatisfactory, or questioned (Savvidou et al., 2021). The growing financing gap necessitates an urgent and innovative approach to financing sustainable agriculture, as further borrowing could exacerbate the already high debt burden in African countries (Savvidou et al., 2021).

This chapter presents comprehensive alternatives to promote sustainable agricultural production practices in Africa, drawing inspiration from He et al. (2021) and Liu et al. (2021) in an Asian context, specifically China. Although some recent studies (Aye et al., 2018; Heidenreich et al., 2022) have covered the African context, the ability and superiority of their approaches in generating robust and pure green efficiency outcomes are limited compared to the application of the Tone (2003) slacks-based measure (SBM) with undesirable outputs employed in our study for Africa. Furthermore, studies that utilised two-stage DEA used debatable second-stage regression methods (see He et al., 2021, for instance), for which we propose a more suitable approach. Theoretically, DEA scores are bounded between 0 and 1 (0–100%), representing a fractional or proportional relationship. Therefore, any second-stage approach that fails to account for this issue yields misleading outcomes. Additionally, the DEA data-generation process (DGP) is not based on censoring (McDonald, 2009; Wulff, 2019). Instead, it can be described as a normalising DGP (Ramalho et al., 2010). Consequently, any second-stage regression that treats bounded DEA scores naively as censored and applies a censored model in the second stage also produces misleading outcomes (Amore & Murtinu, 2021; Banker & Natarajan, 2008; Villadsen & Wulff, 2021). To address these concerns, this study employs an alternate econometric approach, fractional regression, deemed most appropriate for two-stage DEA analysis.

In addition to the influential factors of agricultural green efficiency identified in the literature, we provide evidence using an unexplored dataset from the Socioeconomic Data and Applications Centre (SEDAC) (Wendling et al., 2020) to estimate how prudent agri-environmental government fiscal policies affect sustainable agricultural production in Africa. We also demonstrate that implementing these fiscal policies positively influences the impact of climate financing and investment on sustainable agricultural production in Africa. This study highlights the positive role of development assistance and the detrimental effects of poor economic well-being and urbanisation in shaping green agricultural productivity in Africa. Moreover, this study reveals that agricultural productivity can be significantly enhanced without resorting to high yet inefficient and environmentally unsustainable input intensification. The remainder of the chapter is structured as follows: the next section discusses the relevant literature, followed by a description of the methodology employed in the study.

The empirical results are then presented and discussed. Finally, conclusions are drawn, and recommendations are provided to inform policy decisions.

4.2 Literature Review

4.2.1 Theoretical Review

Production in all sectors, particularly agricultural production, is most affected by unfavourable environmental conditions. Many of these factors are believed to be human-induced. Therefore, for ecological conservation and adaptation, environmental stewardship and favourable externalities management play pivotal roles in sustainable and green production. It has long been asserted that sustainable productivity is anchored in technological innovation in the production process. In this chapter, green production is in the context of CSA. All of these lie in goal nine (9) of the United Nations Sustainable Development Goal (SDG) of sustainable output through innovation. The theoretical foundation of this chapter is anchored on the theory of environmental stewardship of Bennett et al. (2018) and Porter's (1991) concept of innovation for green production through production policies.

The principle of environmental stewardship underscores the need to responsibly utilise and oversee natural resources to guarantee their viability for future generations. This involves implementing methods that safeguard and improve the environment while sustaining agricultural productivity and livelihoods. Though several opinions have been expressed on the concept, the most encompassing one is that proposed by Bennett et al. (2018). The authors view the concept as "*the actions taken by individuals, groups or networks of actors, with various motivations and levels of capacity, to protect, care for or responsibly use the environment in pursuit of environmental and social outcomes in diverse social-ecological contexts*" (p. 599). Prudent environmental stewardship results in positive environmental production outcomes (Bodin, 2017). Notwithstanding, one of the major hindrances to current environmental actions is the availability of resources in various forms, including social, cultural, financial, physical, human, and institutional capital (Bennett et al., 2018). This is essential for meaningful actions aimed at preserving the environment. In some instances, environmental stewardship is thought to depend on steward motivation (Bennett et al., 2018). Thus, motivation is the driving force of steward actions, whether intrinsic or extrinsic (Cetas & Yasué, 2017). All these have economic and social ramifications.

Farmers, like all rational economic agents, can choose to adjust or vary their production methods as necessary to increase production output. This may include drastic changes in fertiliser utilisation decisions without necessarily considering environmental consequences (Hou et al., 2022). The negative externality of this production decision arises from residues from fertilisers, especially nitrogen-based ones, which cause nitrous oxide (N_2O) pollution.

Although using fertilisers in agricultural production may improve yield, their incorrect usage and application will result in inefficiencies and cause fertiliser pollution in the form of GHG emissions, underground water pollution, and deterioration of soil health (Hou et al., 2022). Excessive application of other synthetic farm inputs, particularly insecticides (pesticides, fungicides, herbicides, bactericides, etc.), among other on-farm practices, also has negative environmental consequences. For instance, farming practices, such as slash-and-burn (bush burning), emit large amounts of carbon dioxide (CO_2) into the atmosphere. Indiscriminate exposure of on-farm organic matter, such as poultry droppings, cow dung, and other plants, also emits high methane gas (CH4) levels into the atmosphere. These are all against the fundamental environmental stewardship principles of sustainable resource management, biodiversity conservation, and pollution reduction. This is a call for sustainable environmental stewardship from stakeholders such as farmers to protect the environment without compromising their production outputs.

For effective environmental regulation, fiscal policies in the form of environmental taxes and other regulatory policies have been proposed to address the growing negative externalities arising from agricultural productivity (Tol, 2009). This aligns with the "narrow" version of Porter's (1991) hypothesis, which posits that flexible environmental policy instruments, such as pollution charges or other production regulations, give production units a greater incentive to innovate than rigid or authoritarian regulations (Peng et al., 2021). This idea implies that stringent and appropriately crafted environmental regulations can encourage farmers and agribusinesses to innovate in the context of agricultural production, leading to increased efficiency, reduced waste, and potentially greater profitability. In particular, implementing regulations that promote efficient irrigation methods and limit the types and quantities of chemicals used in agriculture can provide substantial advantages. Policies to control greenhouse gas emissions, regulate waste disposal, and promote soil conservation in farming practices are also essential.

Though the benefits of regulatory-driven innovation are enormous, such as cost savings and yield increases, implementing such policies could pose tremendous economic challenges to farmers in Africa. These farmers are primarily impoverished and have a low financial capacity to adapt. Highly informalised and unregulated farm ventures in Africa could be another bottleneck, emphasising the role of flexible environmental regulations in promoting innovation within specific sectors, including agriculture.

Nonetheless, given the growing environmental impacts of agricultural production, some forms of environmental regulation and agri-environmental policies can offer remedies (DeBoe, 2020). This is the fundamental basis of Porter's (1991) hypothesis, which suggests that strict production regulations can potentially spiral innovation for producing more resource-efficient and valuable products in an environmentally sustainable ('*green*') way.

Per cost theory, strict regulation forcing compliance and the need to innovate will impose additional costs and expenditure burdens on the producer. However, the “strong form” of the three variants of the hypothesis suggests that well-designed and implemented regulations may encourage innovation that provides higher economic compensation (a better financial position) than the cost of compliance (Peng et al., 2021). This might mean strictly enforcing eco-friendly farming techniques, resource optimisation, or energy-efficient processes for agriculture. Once again, the applicability of this strict enforcement will be intensely dependent on the availability of resources for the enforcing agency to carry out its mandate and for the complying farmers to have the means to adopt.

Finally, the “weak” version of Porter’s hypothesis postulates that environmental regulation partly encourages environmental innovation in production (Van Leeuwen, 2017). This plays a pivotal role in promoting green output and growth and forms an integral part of the environmental sustainability agenda. This suggests that while environmental regulations can drive innovation, these innovations might only partially offset compliance costs. However, these regulations still play a crucial role in promoting sustainable practices and improving resource efficiency. Successful implementation of these innovations requires supportive policies, education, and investment to ensure that the benefits are maximised and the costs are minimised.

4.2.2 Empirical Review

Several two-stage DEA techniques have been employed in empirical literature to arrive at efficiency estimates, green efficiency scores, and their influencing factors in diverse economic sectors, including agricultural production. Several scholars have also adopted various approaches to generate green efficiency scores in the first stage, including the DDF (Rahman & Anik, 2020), SBM, DDF DEA models (Färe & Grosskopf, 2010), as well as super-SBM DEA techniques (Liu et al., 2021). Nevertheless, slack-based models with undesirable outputs (Tone, 2003) offer superior environmental efficiency scores because they can estimate excess input and output shortfalls for operational and practical production considerations.

The econometric estimation technique employed by several studies in the two-stage DEA analysis is the Tobit model. This is the same for all agriculturally focused two-stage DEA studies in the literature (Liu et al., 2021; Rahman & Anik, 2020). However, this approach is of academic concern to several scholars (Amore & Murtinu, 2021; Banker & Natarajan, 2008; Villadsen & Wulff, 2021). As discussed in the introduction, applying inappropriate estimation techniques to model DEA scores as dependent variables can lead to disproportionate and misleading outcomes (Villadsen & Wulff, 2021). For instance, Liu (2018) reported that technological innovation in agriculture, output value, and adjustments in the industrial structure promote agricultural total factor productivity in China. In some cases, crop specialisation and farm size influence agricultural green efficiency and substantial investments in research and development (Rahman & Anik, 2020). The general agricultural economic development level, as well as the degree of regional opening-up, also have an influential impact on green total factor productivity (Liu et al., 2021). We can hence hypothesise that:

H1: Investments in technological innovation positively influence agricultural green efficiency in developing economies.

Socioeconomic factors are crucial to many smallholder farmers' agricultural decisions and practices. Urbanisation has been observed as one of the factors that reduce green efficiency in agricultural production in underdeveloped contexts (Liu et al., 2022; Chiarini & Marzano, 2019). This is possible if labour shortages and the consequent inability of smallholder farmers to substitute their production approaches technically hinder production output. Highlighting production techniques, farmers may resort to environmentally unfriendly practices, such as fertiliser use, to increase production. This has long been found to have external consequences through environmental pollution in the form of nitrous oxide (Bai et al., 2020; Gu et al., 2018). Inefficient fertiliser use may lead to significant economic losses for farmers. We can thus hypothesise that:

H2: Sustainable farming practices will have a significant positive influence on green efficiency.

Oueslati et al. (2019) suggest that urbanisation presents opportunities for agricultural producers at the rural-urban fringe through the emergence of a new customer base that provides opportunities for higher-value crops. This may only be possible for peri-urban farmers, and is not necessarily applicable to rural farmers, many of whom are in developing countries. In providing a more nuanced synthesis, Oueslati et al. (2019) provided evidence that increasing population density increases agricultural productivity at the rural-urban fringe. In contrast, increasing urban fragmentation may have a detrimental effect on agricultural productivity at low levels of fragmentation. There appears to be some suggestive evidence of the adverse impact of urban population growth on agricultural green efficiency. This phenomenon leads to the loss of agricultural land to nonagricultural sectors, with potential causes of land disputes and negative externalities (Beckers et al., 2020). We therefore hypothesise that:

H3: Urban population growth has negative consequences on sustainable agriculture productivity.

Empirical findings show that, in cases where separate lands are used for cultivation following conversion, the newly cultivated lands are less productive than the previous ones (Andrade et al., 2022). Additional negative pressures on sustainable agricultural production also arise when the youth population migrates, leaving older people to produce (Beckers et al., 2020). Environmentally oriented government policies and controls have been shown to offer socioeconomic and ecological responses (Bennett et al., 2018; Solarin et al., 2017). Hence, we hypothesise that:

H4: Environmentally sustainable fiscal policies lead to sustainable agricultural productivity.

4.2.3 Gaps in the Existing Literature

This literature review section aims to identify gaps in existing research on applying two-stage DEA in agriculture. Two-stage DEA is a technique used to evaluate the efficiency of decision-making units by considering both the production process and subsequent influencing factors. The review covers vital themes such as methodologies, geographic focus, and integration of environmental and socioeconomic factors in the literature.

Numerous researchers have employed different methods to calculate eco-friendly performance scores initially. These methods include the DDF (Rahman & Anik, 2020), SBM, DDF DEA models (Färe & Grosskopf, 2010), and super-SBM DEA techniques (Liu et al., 2021). However, slack-based models considering undesirable outputs (Tone, 2003) provide better environmental efficiency scores as they can assess excess input and output deficiencies for practical production considerations. However, despite its numerous advantages, this topic is lacking in the empirical literature.

The literature has focused on censored models in the second stage of analysis of green efficiency's influencing factors (see He et al., 2021, for example). Notwithstanding, DEA scores are theoretically bounded between 0 and 1, representing a fractional relationship and cannot be censored (Amore & Murtinu, 2021). So, any second-stage approach that fails to account for this will lead to misleading outcomes. Again, the DEA data-generation process is not based on censoring but can be described as a normalising process (Ramalho et al., 2010). The suitable approach is to treat the scores in their theoretical frame as fractional scores. Therefore, this thesis chapter aims to bridge the gap by applying the appropriate econometric approach to model the DEA scores for robust estimates.

Contextually, two-stage green efficiency studies have been focused mainly on the Asian context (see He et al., 2021; Liu et al., 2021). Though some scholars have studied the African phenomenon (Aye et al., 2018; Heidenreich et al., 2022), the approaches adopted in both stages of these studies are not superior to the Tone (2003) approach and the fractional response econometric model applied to the second-stage analysis.

The influencing factors of agriculture's green efficiency have focused on social and economic variables. However, no variables relating to environmental governmental fiscal policies in the context of agriculture have been explored. We bridge this gap by using an unexplored dataset from the Socioeconomic Data and Applications Centre (SEDAC) (Wendling et al., 2020).

4.3 Methodology

4.3.1 The slacks-based measure data envelopment analysis

The methodological approach adopted in this study consisted of two stages. First, we generate agricultural green efficiency (GE) using slacks-based measure data envelopment analysis (SBM-DEA) with an undesirable output model (Tone, 2003).

The Tone (2003) non-radial SBM-DEA model is robust to its radial counterparts in two distinct ways: the non-proportional weighting of the inputs and outputs provides an accuracy of scores, and the efficiency scores obtained from the model provide us with complete information on the excesses (slacks) in inputs and undesirable outputs as well as the output shortfalls of the DMUs' good outputs (Tone, 2001). This is vital for resource use efficiency and sustainable output growth within the scope of climate-smart agricultural productivity. The Tone (2003) SBM-DEA model with undesirable outputs has been applied in several studies (Shen et al., 2022; Xu et al., 2022).

The model can be specified as:

$$\Pi = min\left[\frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r_0}^g}+\sum_{r=1}^{s_2}\frac{s_r^b}{y_{r_0}^b}\right)}\right]$$

$s.t.$

$$x_0 = X\Lambda + s^-,$$

$$y_0^g = Y^g - s^g,$$

$$y_0^b = Y^b + s^b,$$

$$s^- \geq 0, s^g \geq 0, s^b \geq 0, \Lambda \geq 0. \qquad (4.1)$$

where Π is the green efficiency score of the decision-making unit (DMU), Tone (2003), which is the individual country in our case. Π is theoretically bounded between zero and one, where a score of one indicates green efficiency and a score below one suggests inefficiency. X and Y are the input and output factors, respectively. s^-, s^g, s^b are the input slacks, desirable output slacks, and undesirable output slacks, respectively; m is the number of input factors; s_1 and s_2 are desirable and undesirable output slacks, respectively; and Λ is the factor intensity vector. Y^g and Y^b are desirable and undesirable outputs, respectively.

4.3.2 Fractional Response Model

At the second stage of our study, we utilised the Π scores generated from the SBM-DEA with undesirable outputs model in equation (4.1) as the regressand. We regressed the variables of interest on it. Fractional regression models (FRMs) are quasi-maximum likelihood estimators (QMLE) in the family of generalised estimation equations (GEE) modelled on the conditional mean of the covariates using either the probit, logit, or heteroskedastic probit model as the link function or functional form (Papke & Wooldridge, 2008; Wulff, 2019). An important and significant feature of FRMs is that they do not require knowledge of the distribution of the model to achieve consistency in parameter estimates (Dorta, 2016). However, they require the correct conditional mean specification (Ramalho et al., 2010). Detailed justification of the use of this model in this current chapter was provided in sections 4.1 and 4.2.3.

We can write the unobserved effects panel FRM model as (Papke & Wooldridge, 2008):

$$E(GE_{it}|\omega_{it}, \psi_{it}, \Theta_{it}, \Gamma_{it}, E_{it}, c_{it}) =$$

$$\mathrm{G}(\beta_0 + \beta_1\omega_{it} + \beta_2\psi_{it} + \beta_3\Theta_{it} + \beta_4\Gamma_{it} + \beta_5 Env_{it} + c_{it}) \tag{4.2}$$

where GE_{it} is agricultural green efficiency for country i at time t; $\omega_{it}, \psi_{it}, \Theta_{it}, \Gamma_{it}$, are 1×2 vectors of regressors representing financial investments, development flows, socioeconomic factors, and agri-environmental fiscal policies, respectively; and Env_{it} represents environmental management performance by country i at time t. β_0 is a varying or random intercept, $\beta_1, \ldots, \beta_5$ are the respective coefficients. $\mathrm{G}(\cdot)$ is the specified link function or functional form used to model the equation, and c_{it} is the unobserved time-invariant heterogeneity effect. c_{it} can further be decomposed or modelled as $c_{it} = \vartheta_i + \theta_t + \mu_{it}$ where ϑ_i is the country-specific effect, θt is the time effect, and μ_{it} is the random error term.

The nonlinear estimation of the FRM's parameters in (4.2) follows the Bernoulli log-likelihood function procedure proposed by Papke and Wooldridge (1996, p. 621) in its general cross-sectional form as

$$l_i(\beta) \equiv Y_i \log[G(X_i\beta)] + (1 - Y_i)\log[1 - G(X_i\beta)] \tag{4.3}$$

and the for $\hat{\beta}$ is obtained through a maximising problem given as:

$$\hat{\beta} \equiv \max_{\beta} \sum_{i=1}^{N} l_i(\beta) \tag{4.4}$$

(Papke & Wooldridge, 1996, p. 622). l_i is the Bernoulli log-likelihood function and N is the sample size.

According to Papke and Wooldridge (1996), $\hat{\beta}$ is consistent and asymptotically normal if the functional form of Equation (4.2) is correctly specified. For this study, we used the heteroskedasticity probit model (HPM) as the nonlinear functional form [G(·)] because it is best suited to Equation (4.2), following the RESET procedure suggested by Papke and Wooldridge (1996, 2008). This was also a remedy for heteroscedasticity in the data. The binary link function is also meant to satisfy the boundary condition of $0 \leq GE_{it} \leq 1$. The HPM functional form [G(·)] can be expressed as

$$\Phi[X'_{it}\beta / \exp{(Z_{it}\lambda)}] \tag{4.5}$$

where Φ is the cumulative density function (CDF) of the standard normal distribution, X_{it} is the set of all explanatory variables, Z is the covariate used to model the variance, and λ is its associated coefficient to be estimated in (4.5).

From Equation (4.2), we can write the unobserved empirical fractional HPM as

$$E(GE_{it}|\omega_{it},\psi_{it},\Theta_{it},\Gamma_{it},Env_{it},c_{it})$$
$$= G(\beta_1\omega'_{it}+\beta_2\psi'_{it} + \beta_3\Theta'_{it}+\beta_4\Gamma'_{it}+\beta_5Env_{it} + \vartheta_i + \theta_t + \mu_{it}) \qquad (4.6)$$

The regressors with vectors can be written as follows:

$$\omega'_{it} = \begin{bmatrix} Ino \\ Exp \end{bmatrix}$$

$$\psi'_{it} = \begin{bmatrix} Aid \\ MFin \end{bmatrix}$$

$$\Theta'_{it} = \begin{bmatrix} Urb \\ PGDP \end{bmatrix}$$

$$\Gamma'_{it} = \begin{bmatrix} CO_2Pol \\ CH_4Pol \end{bmatrix}$$

To incorporate the interaction effects, we can write equation (4.6) as follows:

$$E(GE_{it}|\omega_{it},\psi_{it},\Theta_{it},\Gamma_{it},Env_{it},COFin_{it},CHFin_{it},c_{it})$$
$$= G(\beta_1\omega'_{it}+\beta_2\psi'_{it} + \beta_3\Theta'_{it}+\beta_4\Gamma'_{it}+\beta_5Env_{it}+\beta_6COFin_{it}+\beta_7CHFin_{it} + \vartheta_i$$
$$+ \theta_t + \mu_{it}) \qquad (4.7)$$

where $COFin_{it}$ and $CHFin_{it}$ are the interaction terms between CO_2Pol and $MFin_{it}$ and then CH_4Pol and $MFin_{it}$, respectively.

The acronyms in the equations are interpreted as follows: Ino is agricultural research and development (R&D) expenditure as a proxy for innovation in agriculture, Exp is government budget expenditure on agriculture, Aid is agricultural aid from development partners, $MFin$ is development flows to agriculture for climate mitigation (climate mitigation financing), Urb is urbanisation, $PGDP$ is per capita gross domestic product as a proxy for economic well-being, CO_2Pol is government fiscal policy on carbon dioxide emissions, and

CH_4Pol is government fiscal policy on methane gas emissions. Also, $\beta_1 = [\beta_1', \beta_1'']$, $\beta_2 = [\beta_2', \beta_2'']$, $\beta_3 = [\beta_3', \beta_3'']$, $\beta_4 = [\beta_4', \beta_4'']$, $\beta_5 = [\beta_5', \beta_5'']$, $\beta_6 = [\beta_6', \beta_6'']$, and $\beta_7 = [\beta_7', \beta_7'']$.

4.3.3 Data and Variables

Data were sourced from diverse statistical databases. The first-stage analysis follows the data used in chapter three of the thesis (see Table 3.2). However, the variables used in the second stage of this chapter are shown in Table 4.1. Due to missing data in some of the series, we estimated the second stage regression model based on complete case analysis. The choice of the variables were driven by the key objectives of the chapter with theoretical foundations in the literature.

Table 4.1: Second Stage Regression Variables

Variable	Definition & Measurement	Source(s)
Agricultural Technological Innovation (***Ino)***	Agriculture Research Spending (R&D Expenditure): Agricultural research and development expenditure (in millions of US Dollars at 2011 constant value).	ASTI (IFPRI) & FOASTAT
Agricultural aid (***Aid***)	Development flows to Agriculture (millions of US$): The value of direct development aid from all donors (donor countries) and disbursed to a recipient country for *all agricultural purposes only*.	FAOSTAT
Climate Mitigation Financing (***MFin***)	Development flows to Agriculture (millions of US$): The value of direct development aid from all donors (donor countries) and disbursed to a recipient country for *environmental protection purposes only*.	FAOSTAT
Agric Expenditure (***Exp***)	Government budget expenditure on agriculture (millions of US$).	FAOSTAT
Agri-environmental fiscal policies ($\boldsymbol{CO_2Pol}$) & ($\boldsymbol{CH_4Pol}$)	CO_2 Intensity Trend/Ecosystem Vitality: It indicates the contribution of governments policy considerations on sustainability (reducing CO_2). It is adjusted for economic trends to isolate change due to policy rather than economic fluctuation.	SEDAC
	Methane (CH_4) Intensity Trend: It is calculated as the average annual rate of increase or decrease in raw methane emissions. It shows governments policy commitment in reducing methane gas emissions. It adjusted for economic trends to isolate change due to policy rather than economic fluctuation.	SEDAC
Environmental Performance (***Env***)	Sustainable Nitrogen Management Index (SNMI): It balances efficient application of nitrogen fertiliser with maximum crop yields as a measure of the environmental performance of agricultural production. It is a measure of agricultural drivers of environmental damage.	SEDAC
Urbanisation (***Urb***)	Sum of people living in urban areas as defined by national statistical offices.	WDI
Per capita GDP (***PGDP***)	GDP per capita (at 2015 constant value in US$). It's used as a measure of economic well-being.	WDI

NOTES: Agricultural Science and Technology Indicators (ASTI), International Food Policy Research Institute (IFPRI), Environmental Performance Indicators (EPI), World Development Indicators (WDI), Socioeconomic Data and Applications Center (SEDAC). Food and Agricultural Organisation Statistics (FAOSTAT).

4.4 Empirical Results

4.4.1 Summary Statistics of First Stage Analysis

The initial phase of our empirical analysis involved generating agricultural green efficiency (GE) scores using the SBM-DEA model with undesirable output. These scores, representing each country during the observation period, were the dependent variables in the subsequent analyses. The descriptive statistics for the variables in the initial analysis are presented in Table 4.2. It can be observed from the Table that the average arable land used in African agriculture was 19.7 million hectares. In contrast, the energy consumption in farming amounted to 8.7 million terajoules on average. On average, 3.6 million tonnes of pesticides are used in agricultural production, with potential environmental and food safety concerns. The data also suggest that agriculture contributes significantly to employment, averaging 48.4%, and sometimes reaching 92%. The average freshwater withdrawal rate for irrigation was 59.8%. The annual precipitation in Africa is approximately 937 mm, and fertiliser usage is 37.3 kilograms per hectare of arable land on average. Two outputs are presented in this chapter: Desirable and undesirable. The desirable output (agricultural output value) was approximately US$5.7 billion on average. Turning to the undesirable outputs (emissions), average annual emissions of 6,499.9 kilotonnes of nitrous oxide, 8,834.5 kilotonnes of methane, and 21,923.6 kilotonnes of carbon dioxide were recorded. These emissions pose environmental sustainability challenges for agricultural production and affect the ecological footprint.

Table 4. 2: Summary Statistics of Input-Output Variables

Variables	Min	Max	Mean	Std. Dev.
Inputs				
Land (‘000 hectare)	1.5	98125	19712.78	20689.99
Energy (‘000 Terajoule)	34.2445	165055.8	8678.662	20196.98
Pesticides (‘000 tonnes)	1	152789.7	3609.234	13877.55
Labour (% of total employment)	0.793201	91.76	48.43494	23.0394
Irrigation (% of total freshwater withdrawal)	0.5517241	98.11369	59.82595	28.40512
Precipitation (average mm per year)	18.1	2526	937.426	609.7603
Fertiliser (kilograms per hectare of arable land)	1	816.9333	37.26835	94.99437
Outputs				
Agric Output (‘000 US$)	4641	9.41E+07	5693662	9741338
Nitrous Oxide (Kilotonnes)	1	44480	6499.865	7453.131
Methane (Kilotonnes)	1	69130	8834.479	11316.33
Carbon Dioxide (Kilotonnes)	8.7872	601790.6	21923.64	69650.9

Source: Author’s estimations

4.4.2 Influencing Factors of Agricultural Green Efficiency

4.4.2.1 Descriptive statistics of GE Influencing Factors

Table 4.3 summarises the data for the second stage of our study on the determinants of GE. The average GE score from the SBM-DEA model is 71.65%, indicating suboptimal green efficiency in African agricultural production. The average annual agricultural R&D expenditure (*Ino*) is USD$60.5 million on average. General agricultural aid (*Aid*) and financing for climate risk mitigation in agriculture (*MFin*) average USD$51.5 million and USD$11.4 million, respectively. Climate financing lags agricultural financing, underscoring the need for increased climate-related funding. Policy wise, there was an average of 50.1% commitment to addressing climate change through policies on methane gas emissions (CH_4Pol), while commitments to reducing carbon dioxide emissions (CO_2Pol) were below average at 33.2%. The effective use of nitrogen-based fertilisers for sustainable environmental management (*Env*) averaged 42.05%, suggesting inadequate application for optimising crop yields and contributing to environmental pollution.

Government investment in general agriculture (*Exp*) averages US$9.8 million, and the urban population averages 8.1 million (*Urb*). With a significant portion of Africa's food produced by rural smallholder farmers, increasing urbanisation may stress rural food production systems. The average GDP per capita (*PGDP*) is US$2,280.

Table 4.3: Summary Statistics of Green Efficiency Influencing Factors

Variable	Mean	Std. Dev.	Min	Max
GE	.7165	.2133	.3275	1
Ino (‘000,000)	60.4782	98.2738	.2	541
CH_4Pol	50.1717	29.7153	0	100
CO_2Pol	33.2316	21.6535	0	100
MFin (‘000,000)	11.3697	16.5099	.0016	178.3272
Aid (‘000,000)	51.5309	74.0761	0	633.684
Env	42.0508	18.1376	0	100
Exp	9,780,793	17,624.43	871,558	99,117,380
Urb	8,096,713	1.27e+07	40,917	1.03e+08
PGDP	2,280.1	2789.256	258.6288	16,989.96

Source: Author’s estimation

Notes: GE is agricultural green efficiency. Ino is agricultural research and development (R&D) expenditure as a proxy for innovation, Exp is government budget expenditure on agriculture, Aid is agricultural aid from development partners, $MFin$ is development flows to agriculture for climate mitigation (climate mitigation financing), Urb is urbanisation, $PGDP$ is per capita gross domestic product as a proxy for economic well-being, CO_2Pol is government fiscal policy on decoupling carbon dioxide emissions, and CH_4Pol is government fiscal policy on decoupling methane gas emissions.

4.4.2.2 Data Characteristics and Diagnostics

As a preliminary step, we examined the nature of the data to ensure that the analysis was accurate, consistent, and reliable. This involved investigating the presence of outliers and assessing the slope heterogeneity. The Billor et al. (2000) BACON algorithm detected no significant outliers at the 15% and 30% percentiles, as shown in Table 4.4. Subsequently, we employed the Pesaran and

Yamagata (2008) test for slope heterogeneity, which indicated rejection of the null hypothesis, signifying slope heterogeneity across cross-sectional units. We applied the RESET procedure to the functional form, leading to a fractional heteroscedasticity probit model selection. Analysing the long-run equilibrium relationship, the Kao panel data cointegration test (Kao, 1999) confirms the cointegration among all panels. Multicollinearity checks using the conditional index (CI) (Belsley et al., 1991) demonstrated a CI of 11.51, below the recommended limit of 30, suggesting no significant multicollinearity issues. Heteroscedasticity was addressed using a fractional heteroscedasticity model that provides robust estimates and standard errors. Serial correlation was detected using Wooldridge's (2002) test, and its impact was mitigated using the fractional heteroscedasticity probit model with corrected and bootstrapped standard errors, as suggested by Papke and Wooldridge (2008). The bootstrap-based conditional moment (CM) test indicated non-normality in the residuals, which is a common concern in Tobit models. However, this did not affect our estimates' consistency in the fractional regression case, because the functional form of the model was correctly specified following Papke and Wooldridge (1996, 2008).

To test for the presence or otherwise of endogeneity in our data, we relied on the Wald test of exogeneity following the estimation of a fractional instrumental variable probit model. In separate regressions, we instrumented climate financing, innovation, development flows, and agri-environmental fiscal policies. The respective results from the Wald tests are shown in Table 4.4. The outcome of the tests for all the estimations failed to reject the null hypothesis of exogeneity at the 5% alpha level. We also evaluated the robustness of our model by estimating the logit and probit models (models 1 & 2 respectively) as base models. As can be observed from the results of models 1 and 2, the sensitivity of their outcomes is not very high compared to the desired model (model 3). Hence, our estimator, the fractional heteroscedasticity probit, is robust.

Table 4.4: Data Characteristics

Statistical Test	Test Statistic/P-value
BACON outliers at 15% & 30% percentiles	0
Slope Homogeneity	-5.809 (0.000)
Cointegration	
Modified Dickey-Fuller test	-3.0653 (0.0011)
Unadjusted modified Dickey-Fuller test	-5.0811 (0.0000)
Serial dependence	19.866 (0.0001)
Multicollinearity (CI)	11.51
Heteroskedasticity ($LR\chi^2$)	242.59 (0.0000)
Normality of residuals (CM test)	111.42 (0.0000)
Wald test of exogeneity ($athrho = 0$): χ^2	0.01(0.94); 0.23(0.6); 0.14(33); 0.3(0.585)

Source: Author's estimations.

Notes: The Number of observations for all the tests was 324. BACON is Blocked Adaptive Computationally Efficient Outlier Nomination. Values in parentheses are p-values. CI is a conditional Index, and LR is the likelihood-ratio. LM is the Lagrange Multiplier. CM is Conditional Moment. *athrho* is the correlation between the error terms of the structural equations.

4.4.3 Empirical Results, Analysis and Discussion of GE Influencing Factors

4.4.3.1 Financial Investments

Many direct domestic agricultural investments in Africa are derived from government budget allocations for specialised programmes or routine agricultural expenses. Data on private sector funding are sparse and limited. If funding is supplied in the form of credit, it is not encouraging because of the several high-risk factors associated with agricultural production in Africa. The empirical results in Table 4.5 suggest that government investment in the agricultural sector significantly drives agricultural green efficiency in Africa, at the 1% alpha level. Agriculture makes a tremendous contribution to employment, livelihoods, and the overall GDP of African countries. From Model 3a, it can be observed that, a one-unit reasonable increase in the log of government expenditure can increase the average agricultural green efficiency by 0.0577 at the

5% alpha level. This recalls commitments to the 2014 Malabo Declaration targets set by African Union member countries to meet key agricultural development goals, such as ending hunger, enhancing the resilience of livelihoods and production systems, and reducing poverty through agriculture by 2025 (African Union, 2014). According to the Malabo Declaration, African countries must commit at least 10% of their public budgets to finance and invest in agriculture. Although current investments are significant for sustainable agricultural production efficiency, they seem insufficient given the fast-approaching Malabo targets and the ongoing issues of hunger, poverty, and weak climate resilience in Africa's farming systems, which appear far from resolved. Increased expenditures on agricultural technologies and other CSA production techniques will significantly reduce production inefficiencies that bedevil African agriculture (Clay & Zimmerer, 2020) while addressing food security.

Innovation in agriculture, including the development of climate-adaptive crop varieties, modern mechanisation, digitisation, and the deployment of resource-use efficient technologies in agricultural production (Liu et al., 2021), has been widely accepted as a means to adapt to the increasingly unfavourable climate conditions affecting agricultural productivity globally. However, this requires a significant financial investment in R&D. This has been proven to provide positive outcomes for farm productivity and financial performance in the long term (Peng et al., 2021). Our empirical results indicate that investments in agricultural technological innovation significantly and positively influence sustainable agricultural productivity in Africa at the 1% alpha level. From Model 3a in Table 4.5, a one-unit increase in investment in agricultural innovation results in an average improvement in the green efficiency productivity proportion of 0.0725 at the 1% alpha level in support of H1 that investments in technological innovation positively influence agricultural green efficiency in developing economies. The results are also consistent with Porter's (1991) concept of innovation as a driver of sustainable production. Studies (see Liu et al., 2021; Peng et al., 2021) have reported similar results in the Chinese context. Localising adaptive innovation strategies is critical for providing suitable solutions to location-specific climate shocks. Investments in agricultural innovation must involve strengthening proven indigenous agroecological practices as a means of mitigating and adapting to improve the resilience capacity of farmers, particularly at the rural level.

4.4.3.2 Development Flows

Development flows from multilateral, bilateral, and other donor agencies have been a significant source of financing for most climate action in Africa, including mitigation and adaptation. Evidence from the literature suggests that a substantial proportion of all financial commitments are not honoured. The results in Table 4.5 indicate that although agricultural climate mitigation financing positively influences sustainable agricultural productivity, it is not statistically significant. Several factors could account for this, including possible mismanagement of resources, poor implementation, and corruption. As our empirical evidence shows, one possible effective remedy is to channel funding through well-formulated, de-risked, and tested fiscal policies as an indirect means of implementing the intended sustainable agricultural projects at the 5% alpha level. Although statistical interpretations of the average marginal effects (AMEs) for the interaction terms are not straightforward, they are essential for practical and policy considerations. Similar to Umbadda and Elgizouli (2013), our findings indicate that robust and well-implemented agri-environmental fiscal policies and reforms positively and significantly drive agricultural financing intention.

Aid to agriculture has also been a significant avenue for funding agriculture in Africa because of the widening budget constraints in African countries and the constant need for additional financial support for specific projects. Despite the complexities associated with its effectiveness, it offers significant support for sustainable agricultural production in Africa (Umbadda & Elgizouli, 2013). Our empirical results also prove that aid significantly contributes to sustainable agricultural production efficiency in Africa at the 1% alpha level. Hence, from Model 3a, an additional increase in foreign funding results in an average proportional improvement of 0.066 in African agricultural green efficiency. Earlier findings also showed that agricultural aid has a significant influence on agricultural growth (Kaya et al., 2012). Agricultural aid has been reported to be ineffective in the past because of several factors, including poor regulatory and institutional quality in the recipient country and the unavailability of other good enablers such as physical infrastructure and financial systems (Ssozi et al., 2019). Nonetheless, improvements in agricultural aid effectiveness may be associated with renewed and past declarations and action plans.

4.4.3.3 Socio-Economic Factors

The empirical findings show that urbanisation significantly threatens sustainable agricultural production in Africa at the 1% alpha level (Table 4.5). Specifically, a one-unit increase in the log of the urban population results in an average decrease in the proportion of agricultural green efficiency by 0.0955 as shown in Model 3a. this outcome is consistent with our H3 that urban population growth has negative consequences on sustainable agriculture productivity. Liu et al. (2022) and Chiarini and Marzano (2019) have reported comparable outcomes. Several factors may have accounted for our empirical results. First, losing a healthy and youthful labour force at the source location could hinder productivity. Notably, agricultural production relies heavily on labour-intensive and low technical (technological) substitution or innovation. Second, the ageing farmer population in Africa, coupled with dwindling succession rates in the farming profession (unattractiveness to youth), further aggravated by low technological adoption rates, has reduced the marginal productivity of labour (Beckers et al., 2020). Third, agricultural land is converted into non-agricultural production. This has increased land competition and reduced the land size for cultivation (Oueslati et al., 2019; Beckers et al., 2020). Fourth, growing climatic shocks in the form of unfavourable weather patterns and conditions resulting in distorted cropping cycles and poor yields have been mentioned as causative factors forcing rural youth to migrate to urban centres for better and more reliable means of employment.

The prosperity of people's economic activities is reflected in their well-being. Agriculture contributes an average of 48.4% of the total employment in Africa. It is the largest employer in some African countries, providing almost 92% of the total employment. These smallholder farmers, mostly rural dwellers, contribute the most to overall agricultural output in Africa. However, the results suggest that this has not led to significant improvements in the well-being of these farmers, as shown by the insignificant impact of the economic well-being indicator (PGDP) on sustainable agricultural productivity in Africa. However, statistical insignificance offers essential economic significance and insight. Farmers cannot invest in efficient and sustainable agricultural production owing to their poor financial status. This further highlights the poor living standards of most African agriculturists and their inability to adapt effectively and sustainably to changing trends in agricultural production. Overall, farmers' improved personal income has been linked to enhanced sustainable productivity at an optimal level (Gu et al., 2018; Hou et al., 2022). It is also possible that other non-agricultural incomes could significantly influence production efficiency in Africa (Hou et al., 2022).

4.4.3.4 Agri-environmental Fiscal Policy Effects

Since the Paris Agreement on climate change, countries that signed the treaty have pledged and continuously communicated their desire to institute programmes and policies to reduce GHG emissions in their nations to ensure environmental sustainability. This has remained rhetorical and engraved in negotiations, mostly without actual implementation, mainly because of the financing challenges and fiscal commitments. Even in countries where climate policies have been formulated, especially in Africa, implementation has often been problematic. Through the support of the African Development Bank (AfDB), standardised climate policies in the form of nationally determined contributions (NDCs) have since been developed as a step towards climate action in Africa (AfDB, 2019). As representative NDCs may be, they are in their early stages and difficult to appraise.

Notwithstanding, as a robust and factual measure of the performance of government fiscal policies on climate action and environmental stewardship, we tested the CO_2 and CH_4 intensity variables specific to each African country over the study period as proxies for fiscal policy reforms to ascertain their effects of these fiscal policies on sustainable agricultural production in Africa. The empirical findings in Table 4.5 Model 3a indicate that a one-unit increase in CO_2 and CH_4 fiscal policy-related interventions results in an average improvement in the green efficiency proportion of agricultural productivity of 0.0836 and 0.01516 at the 1% and 5% alpha levels, respectively which is consistent with H4: Environmentally sustainable fiscal policies lead to sustainable agriculture productivity and the environmental stewardship theory.

. However, CH_4 policy commitments were ineffective in the interactive-effects model (Model 4a in Table 4.5). These mixed results are understandable given the relatively low global attention paid to methane gas emission management despite their significant impact on global warming. Notably, environmental stewardship actions have positive social, economic, and ecological effects (Bennett et al., 2018). This could also be explained by improved environmental regulatory implementation and control (Solarin et al., 2017). It is important to note that the success of climate-focused fiscal policies can be significantly enhanced if complemented by the provision of financial, cultural, social, physical, human, and institutional capital (Bennett et al., 2018). As can be observed from Model 4a, the combined impact of effective environmental fiscal policies and climate financing has significant effects on green agriculture efficiency in Africa. Model 4b produced similar outcomes but with lower marginal effects.

4.4.3.5 Environmental Management Efficiency

Chemical fertilisers, in general, and nitrogen-based fertilisers, in particular, account for nitrous oxide emissions if not managed appropriately. Their residual effects are detrimental to the environment and lead to economic losses for farmers owing to inefficient application. It can be observed from the empirical results in Table 4.5, Model 3a, that high environmental performance emanating from nitrogen-based fertiliser use efficiency positively results in higher, greener and more efficient agricultural production at the 1% alpha level. Thus, a one-unit improvement in agricultural environmental management efficiency will likely lead to an average increase of 0.0330 in green agricultural production efficiency consistent with H2: Sustainable farming practices will have positive significant influence on green efficiency. This finding is also consistent with the environmental stewardship theory. Earlier studies (Bai et al, 2020; Gu et al., 2018) have also provided further insights into how efficient nitrogen fertiliser use could help reduce future carbon sinks and soil health degradation and contamination, including underground water sources. Therefore, the sustainable application of nitrogen-based fertilisers to agricultural productivity in

Africa will reduce environmental pollution while providing socio-economic benefits to farmers through high yields.

Table 4.5: Second-Stage Fractional Regression Results

	Main Effects				Interaction Effects		
	(1)	(2)	(3)	(3a)	(4)	(4a)	(4b)
Ino	0.33662***	0.22441***	0.1703***	0.07245***	0.24492***	0.08472***	0.00812***
	[0.06363]	[0.04218]	[0.05529]	[0.01689]	[0.05566]	[0.01659]	[0.00017]
LExp	0.26319***	0.16241***	0.13567**	0.05772**	0.16204***	0.05605***	0.04984**
	[0.08467]	[0.05207]	[0.05231]	[0.02069]	[0.05582]	[0.01878]	[0.21158]
Aid	0.33628***	0.23598***	0.15514**	0.06600***	0.15281**	0.05285**	0.00085***
	[0.09089]	[0.06035]	[0.07353]	[0.02426]	[0.07107]	[0.02349]	[0.00024]
Mfin	0.09981	0.03534	0.04844	0.01533	0.15104***	0.05128***	
	[0.34417]	[0.20788]	[0.03187]	[0.09017]	[0.04390]	[0.01744]	
LUrb	-0.44635***	-0.26927***	-0.22450***	-0.09551***	-0.30578***	-0.10564***	-0.09374***
	[0.07736]	[0.04606]	[0.0574]	[0.01830]	[0.05599]	[0.01624]	[0.01782]
LPGDP	0.05574	0.03763	0.01247	0.00531	0.0366123	0.12664	0.00265
	[0.08418]	[0.05200]	[0.05261]	[0.02208]	[0.05652]	[0.01929]	[0.01883]
CO2Pol	0.08516***	0.05264***	0.04315***	0.01836***	0.08056***	0.27865***	
	[0.02295]	[0.01404]	[0.01536]	[0.00534]	[0.02131]	[0.06290]	
CH4Pol	0.05489**	0.03095**	0.03564***	0.01516**	0.01436	0.04966	
	[0.02087]	[0.01228]	[0.01110]	[0.00590]	[0.01709]	[0.06056]	
Env	0.13102***	0.08030***	0.07756***	0.03299***	0.08502***	0.02941***	0.00500***
	[0.03090]	[0.01898]	[0.01720]	[0.00857]	[0.01919]	[0.00722]	[0.00030]
CO2Pol*Mfin					0.02585*	0.08941**	0.00500***
					[0.01397]	[0.04404]	[0.00020]
CH4Pol*Mfin					0.16670**	0.05770**	0.00309***
					0.08377	[0.02647]	[0.00069]
Cons	6.38472***	3.88377***	3.16515***		4.55420***		
	[1.16542]	[0.70811]	[0.92034]		[0.91578]		
N	394	394	394		394		
R-Square	0.2707	0.2724					
PseudoR-Square	0.0432	0.0438	0.043		0.0463		
Chi-Square	100.73***	106.97***	95.86***		112.19***		
lnsigma			0.13214		0.06711		
			[0.00803]		[0.6711]		
RESET 1	0.64289***	1.02294***	1.20057		0.15029		
	[0.17991]	[0.27195]	[3.29196]		[0.59041]		
RESET 2	19.964***	20.226***					
GGOFF	19.931***	20.199***					

NOTES: Source: Author's estimations. Dependent variable is agricultural green efficiency. ***P<0.01, **P<0.05, *P<0.1. Models 1, 2, 3, are logit, probit and heteroskedasticity probit regressions respectiviely. Average marginal effects are reported under models 3a and 4a for the main effect and interation effects respectively. Standard errors are presented in paranthesis and were bootstrapped after 50 replications. RESET 1 is the Ramsey (1969) functional form test procedure and RESET 2 is that of Ramalho et al. (2014). lnsigma is the estimated variance resulting from the heteroskedasticity probit regression. LExp is log of expenditure, LUrb is log of urbanisation, LPGDP is log of per capita GDP. The R square, RESET 2 and GGOFF are estimated from the generalized fractional linear model of Ramalho et al. (2014).

4.5 Post Estimation Model Evaluation

Despite the overall statistical significance of the models in Table 4.5 from the perspective of the chi-square values, the low pseudo-R-squares recorded in our models deserve further investigation. Similar to other two-stage DEA studies, the orientation of the current study is focused on the significant influencing factors of agricultural green efficiency and the magnitude of their average marginal effects (McDonald, 2009, p.794). Moreover, the fit of one-part or fractional models is generally low, as evidenced in the literature (see Ramalho et al., 2010, p. 352; Villadsen & Wulff, 2021, p.330). However, the R^2 produced by Ramalho et al. (2014) fractional generalised linear model showed impressive results, as shown in Table 4.5. Notably, the results from the fractional generalised linear models (GLMs) are almost the same as those produced by the standard QMLE of Papke and Wooldridge (2008).

Notwithstanding, as a way of testing the specification of the functional form of our models, we conducted the Ramsey (1969) and Ramalho et al. (2014) RESET procedures as suggested by Papke and Wooldridge (1996, 2008). This study also employed the generalised goodness of functional form (GGOFF) test by Ramalho et al. (2014) as comparative and robustness measures. These tests are based on the fitted power of the response variable under the null hypothesis that the functional form of the model is specified correctly (Villadsen & Wulff, 2021). This is essential for any QMLE to produce consistent estimates (Ramalho et al., 2010). The results in Table 4.5 show that RESET 1 and 2, as well as the GGOFF tests for the logit model (Model 1) and probit model (Model 2), are all significant at the 1% alpha level, indicating a rejection of the null hypothesis and the conclusion that these link functions are not appropriate functional forms to fit the model. RESET 1 results from the heteroskedasticity probit model (Model 3); however, indicates acceptance of the null hypothesis at the 1% alpha level, hence, the correct specification of the functional form of Model 3. Thus, we can infer that our estimates are consistent with the heteroscedasticity probit link function.

All subsequent interpretations and average marginal and interaction effects in the chapter were estimated based on the heteroscedasticity probit functional form, as shown in Models 3, 3a, 4, and 4a in Table 4.5. The insignificance of the estimated statistic arising from modelling the variance (lnsigma) at the 5% alpha level also indicates that the heterogeneity of the heteroskedasticity probit is consistently modelled.

4.6 Potential Unintended Consequences or Negative Externalities of Green Efficiency Policies

Green efficiency policies aim to increase agricultural productivity while minimising environmental impacts. However, these policies can lead to unintended consequences and negative externalities, which are side effects or costs imposed on farmers and/or third parties not directly involved in the policy implementation. These include higher costs for smallholder farmers, displacement of traditional farming methods, environmental trade-offs, implementation hurdles, and policy resistance. Nevertheless, strategies to address these issues are also feasible.

4.6.1 Increased Costs for Smallholder Farmers

Green efficiency policies often promote eco-friendly technologies, such as shade-net farming (e.g., GIRSAL's chilli pepper project) or organic fertilisers, which require significant upfront investments or specialised training. In Africa, where smallholder farmers constitute 80% of farms in sub-Saharan Africa, these costs can be prohibitive, especially for those with limited access to credit programmes like GIRSAL or NIRSAL. Such high costs may limit smallholder participation, potentially undermining the aims of inclusive agricultural growth initiatives. For example, policies promoting water-efficient irrigation under specific programmes may result in higher yields but could also increase costs for smallholders, reducing adoption rates among resource-poor farmers. Smallholders may face financial strain or be excluded from adopting environmentally friendly practices, which can result in reduced competitiveness. This externalises economic costs onto these farmers, who might resort to high-interest informal loans or abandon farming altogether, worsening rural poverty and income inequality.

4.6.2 Possible Displacement of Traditional Farming Practices

Green efficiency policies often prioritise modern, sustainable techniques (e.g., precision agriculture, monoculture for export crops) over traditional methods, which hold cultural importance and are adapted to local conditions. In Africa, traditional practices such as mixed cropping and the use of local seeds enhance resilience to environmental variability. The erosion of indigenous knowledge can reduce biodiversity and disrupt local ecosystems, externalising costs onto communities reliant on traditional methods for food security. This can also alienate farmers, diminishing their trust in financing programmes that promote modern technologies. For instance, programmes like GIRSAL's sesame project for export markets may inadvertently sideline traditional crops, impacting local food systems. Balancing modern and traditional practices within financing programmes to mitigate this externality warrants careful consideration.

4.6.3 Environmental Trade-Offs

While green efficiency policies seek to reduce impacts such as greenhouse gas emissions, they may shift environmental burdens elsewhere. For example, promoting monoculture for land use efficiency (e.g., NIRSAL's focus on rice production) can degrade soil fertility or increase pest vulnerability, requiring more chemical inputs over time. Soil degradation or biodiversity loss can harm neighbouring ecosystems or future productivity, externalising costs onto other farmers or regions. These trade-offs may negate the environmental benefits of green financing initiatives.

4.6.4 Implementation Challenges and Policy Resistance

Green efficiency policies may encounter resistance from farmers, financial institutions, or local communities due to their complexity, lack of awareness, or misalignment with local needs. For instance, banks may hesitate to finance unproven green technologies despite guarantees from programmes like GIRSAL. Uneven adoption can externalise costs onto regions or farmers unable to access benefits, increasing regional disparities and undermining programme effectiveness. Stakeholder resistance can also influence the scalability of such initiatives.

However, some mitigation strategies are practical. Providing financial support through subsidies or microfinance can make green technologies more accessible to smallholders, promoting inclusivity. Encouraging the integration of modern and traditional practices helps preserve biodiversity and resilience, as seen in mixed cropping systems. Implementing environmental monitoring through regular assessments of soil health, water use, and biodiversity can detect trade-offs early, ensuring sustainability. Adopting inclusive financing models that prioritise marginalised groups, diversifying markets to support both export and staple crops, and increasing awareness with training programmes can reduce resistance and promote adoption. Leveraging technical assistance models available across Africa will also be beneficial.

4.7 Summary, Conclusion and Recommendations

Agriculture is an integral part of Africa's economy, but it faces many challenges. However, there are several growth opportunities. In this chapter, we examined how efficiently African countries use their agricultural resources in an environmentally friendly manner and the factors that influence these outcomes. We found that a one-unit increase in targeted investments in agricultural innovation can result in an average improvement of 7.25% in green efficiency at the 1% alpha level. Similarly, fiscal policies that promote environmental sustainability could have up to 9.88% impact on green efficiency. In comparison, a one-unit increase in prudent government fiscal spending on agriculture can have a 5.77% positive impact on green efficiency. However, urbanisation is a threat to agricultural productivity, whereas climate change financing is only adequate if it is used sustainably.

Our findings suggest that strategically prioritising innovation, efficiently allocating financial resources, developing sustainable fiscal policies, and adopting sustainable operational practices in African agriculture can significantly enhance productivity and sustainability, ultimately contributing to Africa's economic development and environmental conservation. These efforts are essential for the appropriate stakeholders to address the continent's unique food challenges amid a fast-growing urban population and leverage its potential for sustainable growth in the agricultural sector and overall economic prosperity and resilience. Future research can explore machine learning approaches to ascertain the influencing factors of agriculture green efficiency. Future studies could also explore artificial intelligence and smart farming in transforming sustainable agriculture.

CHAPTER FIVE

THE DYNAMICS OF AGRICULTURAL OUTPUT, PRIVATE CAPITAL, FOOD PRICE ANOMALIES AND SUSTAINABLE AGRICULTURE IN AFRICA

Abstract

In this chapter, we conducted an in-depth study on the interconnections between agricultural output value, domestic credit, foreign direct investments (FDI) in agriculture, food price anomalies, and sustainable agriculture practices in 48 African countries for 20 years. Using the GMM-panel vector autoregressive econometric approach, we estimated our specified endogenous model and found significant interdependence among all the variables. The study revealed a one-way transmission effect of agricultural output value on domestic credit, FDI, and sustainable agriculture. At the same time, food price anomalies were found to have a reverse causal effect on agricultural output. Additionally, we observed a bidirectional causality between FDI and domestic credit, as well as between FDI and sustainable agriculture. Two-way causality also exists between price anomalies and output value. The impulse response function results showed a positive delayed response of domestic credit and FDI following a shock to the agricultural output value, though more pronounced for domestic credit, persisting into the longer term. Further, there was a lagged but relatively positive response of sustainable production to FDI shocks. We observe high domestic credit and FDI forecast innovations on the agricultural output value. This chapter provides distinct and resounding evidence in the literature concerning the complexities between the variables discussed and a robust test of the pollution hallo hypothesis using a sustainable data set in the field of agriculture.

5.1 Introduction

Agriculture provides the foundation for all African economies. It contributed 14.7% to the overall GDP in 2022 (FAOSTAT, 2023a) and provided 51.57% of the total employment across the continent, with an overall gross output value of US$288.38 billion in 2021 (FAOSTAT, 2023a). Despite these substantial economic contributions of the sector, it receives little financial and investment commitment, particularly public funding, as evidenced by the declining agricultural orientation index, which is at an all-time low (0.13) (FAOSTAT, 2023a) and the current abysmal performance of African countries concerning the Malabo 2025 targets. The under-investments and commitments have culminated in low productivity, low incomes for farmers, especially smallholders, and high vulnerability to market dynamics and environmental and external geopolitical shocks. As a direct consequence, Africa faces high levels of hunger, food insecurity, and malnutrition (FAO, 2017), notwithstanding its locational and natural resource advantages as a potential world food basket. The realities are evident in the current alarming state of the continent towards achieving the 2030 Sustainable Development Goal 2 (SDG 2) targets of the United Nations (UN) to end hunger, ensure food security, enhance nutrition, encourage sustainable agriculture, and limit extreme food price anomaly.

The context of this study is imperative for several reasons. From the evidence thus far, the goals of inclusive and sustainable economic growth, poverty reduction, and rural development in Africa will remain elusive if the sector's dynamics of production and financing remain on the current trajectory. Moreover, as climate change and environmental shocks become more negatively impactful on agriculture productivity in Africa than any other continent (Ortiz-Bobea et al., 2021), understanding the intricacies of efficient agricultural financing and investment for a climate-resilient sector in Africa remains crucial. Rising greenhouse gas emissions from overall food systems (30% of total) (World Bank, 2023) with an equally increasing rate from Africa's share of agricultural activities (FAOSTAT, 2023a) are a growing concern that deserves attention. According to the World Bank (2022), the sector requires an annual investment of at least US$80 billion to address current production needs relating to adaptation and mitigation. In Africa, agriculture is predominantly government-funded (Binswanger et al., 2000). However, current data show a declining trend in the total expenditure share of governments at a rate of 2.27% as of 2021 (FAOSTAT, 2023a), far below the 10% lower-bound investment threshold set by African countries to enable them to meet the Malabo 2015 targets by 2025.

Although the sector receives substantial development assistance for several agricultural purposes (Savvidou et al., 2021; Ssozi, 2018), such funding is insufficient, mainly due to a growing gap between committed and disbursed amounts (FAOSTAT, 2023a). Disbursements have further dwindled recently due to several external global shocks and uncertainties. Private sector involvement in bridging the funding gap has long been an option. Nonetheless, it is challenging due to high-risk prevalence, moral hazard situations, and other credit requirements that pose difficulties for farmers to fulfil (Daum & Birner, 2020).

Despite these challenges, private capital remains essential to close the funding gap. The empirical literature has explored this avenue, focusing mainly on domestic private credit access (e.g., Assouto & Houngbeme, 2023; Diamoutene & Jatoe, 2021). Nevertheless, access does not always translate to actual funding. For studies that even concentrate on actual credit extended to the sector, the data on credit is aggregated for the entire private sector (see Ngong & Fonchamnyo, 2022), which can lead to the loss of valuable and specific insights peculiar to agriculture.

Another meaningful way to close the funding gap is through foreign direct investment (FDI) in agriculture. Various studies (see Edeh et al. (2020), Kubik (2023) and Nyiwul & Koirala (2022)) have explored the potential and relevance of FDI to agriculture from different angles, perspectives, and contexts. Kubik (2023), for instance, focused only on the food and beverages sub-sector of agriculture. Some studies also use aggregated data on FDI to the entire economy (e.g., Ali et al., 2023; Udemba, 2020) in probing the influence of FDI on agriculture, which can lead to misleading findings. Therefore, this chapter examines the agriculture sector comprehensively with specific, disaggregated FDI data to ensure accuracy.

The connections among agricultural output, sustainability, private capital, and price anomaly are complex and have yet to be explored fully in the literature. While some studies, such as Nyiwul and Koirala (2022), have examined factors like output value added and FDI, the paper did not include other essential aspects like sustainability, domestic credit to agriculture, and price anomaly. Ali et al. (2023) attempted to address these interconnections in a recent study, but their approach needed to capture these relationships' dynamic nature fully. The empirical discussions of Ali et al. (2023) produced conflicting conclusions regarding the pollution halo and haven hypothesis, contradicting the reported outcomes.

Ensuring stability in food prices is crucial to achieving SDG 2. C, which aims to end hunger. However, previous research on the relationship between price anomalies in agriculture has focused mainly on its impact on economic growth (e.g., Addison et al., 2016; Magrini et al., 2017; Anderson & Brückner, 2011). The effects of price anomalies on output and food security have been explored less (Nyiwul & Koirala, 2022). As a contribution, the study applied a unique dataset in the context of the UN SDG2 to examine how food price anomaly shocks affect agriculture output value.

The quest to increase agricultural output in Africa has led to a rise in chemical fertiliser usage (Clay & Zimmerer, 2020), which has generated growing concern due to its impact on environmental pollution, mainly through nitrous oxide emissions. This potent greenhouse gas significantly contributes to climate change, with a warming potential 300 times greater than carbon dioxide (UNEP, 2023). While nitrous oxide pollution poses a significant environmental hazard, little research has been conducted into its impact on agricultural output. Previous studies by Maaz et al. (2021), Liu et al. (2020), and Zhang et al. (2015) have explored the impact of nitrogen fertiliser use efficiency on output. However, our study takes a unique approach using a unique data set. We utilise the Sustainable Nitrogen Management Index (SNMI), a composite index developed by the Socioeconomic Data and Applications Centre (SEDAC) (Wendling et al., 2020), to assess the sustainability of agricultural practices. This index combines nitrogen fertiliser efficiency and output as a single measure, contributing to SDG 2.4. Our methodological approach also provides a dynamic understanding of the transmission and feedback effects of sustainability and production output value, offering a new perspective on this critical issue.

This study offers significant insights into existing literature. Firstly, we present the dynamic relationships among agricultural output value, domestic capital, foreign capital investments, food price anomalies, and sustainable agriculture, providing a holistic understanding of their interconnectedness. These empirical outcomes are robust to endogeneity, heterogeneity and cross-sectional dependence. Secondly, our study employs disaggregated data, specifically focusing on foreign direct investments in agriculture and credit allocation exclusively within the agriculture sector. Compared to other studies, this approach enhances the accuracy and precision of our analysis, shedding light on previously unexplored aspects of the region's agricultural dynamics. Our innovative empirical evidence demonstrates the impact of foreign direct investment on sustainable farming practices within the pollution halo hypothesis framework. We applied a unique data set on sustainable nitrogen management to achieve this purpose. Our approach distinguishes our empirical evidence and contributes valuable intuitions to promoting sustainable African agriculture practices. Lastly, we employed a specific data indicator aligned with Sustainable Development Goal 2. C to study the dynamics between food price anomalies and agriculture output.

Our findings underscore the dynamic interdependence between these factors, showing their relevance to addressing hunger and food security challenges in Africa. Our study provides a precise and distinct view based on disaggregated data on credit to the agriculture sector. Mahapatra and Jena (2023) adopted a similar approach, but their analysis was limited to cereals in agricultural output. In contrast, our study takes a more comprehensive approach and includes the entire agriculture sector, including fishing and forestry.

The rest of the chapter is organised as follows: relevant literature is reviewed in section two, followed by the methodology in section three. The empirical analysis and discussion of the results are presented in Section 4. Section five concludes, summarises, and offers policy recommendations.

5.2 Literature Review

5.2.1 Theoretical Review

This chapter is founded on four frameworks: Dunning's (1979) eclectic paradigm for understanding FDI driven by value, institutional theory (Meyer & Rowan, 1977) for studying financial institutions' role in agricultural lending, the pollution halo hypothesis for testing private capital's sustainability, and the theory of food price stabilisation (Newbery, 1989) for understanding the connection between agricultural output and price anomalies in the context of SDG 2.

The eclectic paradigm consists of three elements, namely ownership advantage (O), location advantage (L), and internalisation advantage (I), collectively termed OLI (Zhang et al., 2023). However, this study focuses solely on the location advantage aspect of the theory to comprehend how host country-specific characteristics, such as economic or institutional factors, attract FDI, specifically how the production value of the agriculture sector stimulates FDI. According to the theory, countries with higher production values are more likely to attract FDI than those with lower output values. This has some resemblance to the modernisation and dependency theory.

Institutions throughout the entire agriculture value chain play pivotal roles. In this chapter, our attention is on financial institutions as funding agents for agribusinesses. Hence, the applicability of the institutional theory in our study. The theory highlights how organisations' technical and operational interdependencies make them conform to prevailing norms and practices in their external environment by adopting similar structures and practices to gain legitimacy and acceptance in the broader institutional context, even if these practices may not always be the most efficient or rational. In the context of agricultural production, this aligns with the roles played by financial institutions as partners in providing financial support to agricultural actors. Therefore, institutional theory helps us understand how the broader institutional environment shapes financial institutions' decisions to provide agricultural credit to farmers and how the behaviours of a group, in this case, farmers, inform the credit decisions of financial institutions.

Environmental pollution in production is a growing concern due to its contribution to climate change. One contributory factor to the environmental damage has been the environmental intentions of foreign capital inflows to a country in the form of FDI. When FDI improves environmental sustainability in the destination country, it is termed the pollution halo hypothesis (Cole et al., 2008; Emir et al., 2022), and such FDIs are referred to as 'green'. On the contrary, if it leads to environmental pollution in the host country, it forms the pollution haven hypothesis (Cole et al., 2017). Given our objectives, the study focuses on the pollution halo hypothesis. This theory is rooted in the fundamental understanding of economic activity and environmental quality enhancement first identified by Grossman and Krueger (1995) in their seminal paper. Although their original study focused on economic growth in developed and low-income countries, the findings can be extended to include private capital flows to countries and how they influence economic activity in an environmentally sustainable manner.

Foreign firms are more likely to bring superior production technologies to those currently in place domestically (Liu & Kim, 2018; Cole et al., 2008). The technological expertise transfer opportunities provide avenues for domestic producers to learn and upgrade their production processes. There is some evidence to support both the pollution halo and pollution haven hypotheses (Liu & Kim, 2018; Cole et al., 2008). Despite the low dominance of the pollution halo hypothesis, it has received greater acceptance in recent years in the empirical literature (Balsalobre-Lorente et al., 2019; Mert & Caglar, 2020; Ahmad et al., 2021; Emir et al., 2022; Ehigiamusoe et al., 2024).

Ensuring stable food prices is essential in the fight against hunger, particularly in low-income countries. The price stabilisation theory, introduced by Newbery in 1989, proposes minimising fluctuations in food prices in the market. This theory recognises that food prices are susceptible to significant swings due to various factors, including changes in weather conditions, imbalances in production and demand, geopolitical events, and economic shocks. The study focuses on the dynamic interdependencies between production output and food price anomalies, with particular emphasis on the production aspect. The theory emphasises the need to stabilise food prices by making primary food available within the country, given that they constitute a significant portion of consumer expenses. As a remedy, domestic output must counterbalance the source of instability, and safety nets for farmers to enhance production are crucial. Despite this, numerous challenges, especially in Africa, require urgent solutions to achieve food self-sufficiency, given high prices and market exposure.

5.2.2 Empirical Literature

Agricultural foreign direct investment (FDI) has been extensively studied for its potential role in promoting economic growth (Awunyo-Vitor & Sackey, 2018) and its specific impact on enhancing the performance of the agriculture sector (Wang et al., 2021; Wang et al., 2019). Edeh et al. (2020) investigated the influence of foreign direct investment on Nigeria's agricultural sector and found a positive and significant short-term impact on agricultural output. In contrast, Nyiwul and Koirala (2022) identified bidirectional causality between foreign direct investments in agriculture, forestry, and fishing, and value-added, with a positive effect lasting for the medium to long term, particularly up to five years. Kubik (2023) conducted a recent study analysing factors influencing FDI in the food and beverages sector across 49 African countries from 2003 to 2017. The results highlighted a strong correlation between a well-performing and well-capitalised agricultural sector in the host country and increased FDI, particularly from Global North investors. Examining the domestic funding aspect, Diallo et al. (2020) studied the impact of credit access on rice production, revealing that farmers with credit access achieved 37.32% higher rice production than those without credit funding. Similarly, Diamoutene and Jatoe (2021) demonstrated a positive effect of credit on maize production output in Mali. Yadav and Rao (2024) also found significant potential for increased crop productivity among farmer groups with institutional agricultural credit in the Indian context. Hence, we hypothesise that:

H5: Domestic credit to the agriculture sector will significantly improve production output.

Agricultural pollution, primarily from fertiliser residues causing nitrous oxide emissions (Maaz et al., 2021), poses a significant environmental challenge. Empirical evidence supports the view that sustainable fertiliser use can yield environmental benefits and increase agricultural production (Bai et al., 2020; Ren et al., 2022). By implementing more efficient fertiliser practices, farmers can achieve higher crop yields while simultaneously reducing pollution. This approach holds promise for sustainable agriculture, benefiting farmers, consumers, and the environment. Indeed, adaptation to climate change in agriculture necessitates innovation across the entire value chain, from inputs to outputs (Reardon et al., 2019). Implementing innovative technologies requires substantial investments, often resulting in improved output and environmental sustainability; however, it may sometimes lead to reduced output if poorly deployed (Ayisi et al., 2022).

Scholars have explored the causal relationship between environmental sustainability and FDI. Balsalobre-Lorente et al. (2019) investigated FDI's impact on the ecological footprint (EF) in Mexico, Indonesia, Nigeria, and Turkey. The paper found an inverted-U relationship, supporting the pollution haven hypothesis (PHH). The study also validated these countries' environmental Kuznets curve (EKC) hypothesis, suggesting that weaker environmental sustainability standards in host countries contribute to this relationship. Xing and Kolstad (2002) observed that poor environmental regulatory performance in host countries attracts US-based firms, particularly heavy polluters. Tang (2015) further examined the impact of local environmental regulations on different types of FDI activities and found that export-oriented FDI is more sensitive to local environmental regulations than local-market-oriented FDI, indicating firms' varying environmental regulatory compliance based on their market goals. Bao et al. (2011) found evidence supporting the pollution halo hypothesis, showing that FDI reduces environmental pollution in China. Mert and Caglar (2020), Ahmad et al. (2021), and Ehigiamusoe et al. (2024) also provided empirical evidence of the environmental sustainability impact of FDI in support of the pollution halo hypothesis. We thus hypothesise that:

H6: FDI inflows into developing countries will result in sustainable production.

Food price instability poses a significant threat to achieving SDG 2 and impacts agricultural output, economic welfare, and food security. Xie and Wang (2017) investigated the impact of agricultural product price fluctuations on China's grain yield, revealing that variations in grain output are influenced by fluctuations in agricultural product prices, with production changes lagging behind price variation. Magrini et al. (2017) demonstrated that food price variation negatively affects low-income consumers, leading to food insecurity, outweighing any positive impact on net producers. Addison et al. (2016) found that agricultural commodity price shocks asymmetrically affect per capita GDP growth in Sub-Saharan Africa, and Anderson and Brückner (2011) provided empirical evidence of relative price distortions negatively impacting the growth rate of Sub-Saharan African nations, resulting in decreased annual growth of real GDP per capita. Consequently, a reduction in welfare signifies increased poverty and food insecurity. We can therefore hypothesise that:

H7: Significant food price anomalies will negatively impact agricultural output.

5.2.3 Dynamics of Agricultural Output in Africa

There is increasing pressure on agricultural production due to inadequate food self-sufficiency worldwide, which fails to meet the high demand for food (Balezentis et al., 2022). The high demand is exacerbated by prevailing food security issues and current climatic changes affecting production (Beltran-Peña et al., 2020). Agricultural output dynamics in Africa encompass the variations, fluctuations, and changes in output over time. These dynamics are inherently complex across countries, driven by multifaceted factors that challenge the stability and growth of the sector. In the long run, gross agricultural output value (in current terms) in Africa has been growing at a decreasing rate compared to a decade ago (FAOSTAT, 2023a). This growth has not been enough to keep pace with the growing demand for food, which has led to a decline in per capita food production in many African countries and further future decline based on scenario analysis (Defrance et al., 2020).

The underlying dynamics of this phenomenon are vast, but commonalities exist, including climate variability, land fragmentation, market variability, and notable changes in commodity prices, among others. African agriculture is highly susceptible to climate change, characterised by erratic rainfall patterns, prolonged droughts, and unpredictable weather events (Ortiz-Bobea et al., 2021). These climatic variations exert substantial pressure on agricultural systems, leading to fluctuations in productivity and overall output value (Omotoso et al., 2023). The degradation of arable land due to overuse, deforestation, and unsustainable farming practices is another significant source of output variations due to soil erosion and nutrient depletion, hindering productivity.

Agriculture activity has contributed to the environmental menace (Alhassan, 2021). Fluctuations in global commodity prices and access to international markets impact the profitability of agricultural enterprises. Moreover, domestic market dynamics, including price volatility, uncertainties and supply chain disruptions due to external shocks, affect production decisions (Dada et al., 2023).

The causes of the dynamics have been mentioned in the literature, including limited access to production resources, policy orientation, and technological gaps, which have been found to play significant roles (Hermans et al., 2023; Branca et al., 2022). Many smallholder farmers in Africa face challenges accessing critical resources like land, credit, and modern farming techniques for several reasons (Paparrizos et al., 2023). These constraints limit their ability to increase output and adapt to changing environmental conditions. Agriculture output dynamics in Africa are also found to be influenced by the policy and institutional environments, including land tenure systems, trade policies, and government interventions (Paparrizos et al., 2023; Olagunju et al., 2023; Branca et al., 2022; Adem, 2023). Inconsistent policies, government interventions, and unfavourable international market participation policies have led to uncertainty and significantly hindered long-term production planning in Sub-Saharan Africa (Adem, 2023).

A lack of access to modern agricultural technologies and practices is another underlying force in the output dynamics. Investments in modern farming techniques, such as irrigation and climate adaptation services like weather prediction, research and extension services, are needed to bridge these technological gaps (Paparrizos et al., 2023). As a result of the setbacks, agriculture in Africa has largely remained subsistence, characterised by smallholder farming (Clay & Zimmerer, 2020). Although essential for food security, this trajectory is highly susceptible to external shocks and is often characterised by low productivity.

A slowly emerging trajectory from subsistence to commercial agriculture exists (Clay & Zimmerer, 2020; Paparrizos et al., 2023). The shift, however, requires significant financial investments (domestic and foreign) to propel the industry's growth. Therefore, sustainably scaling agriculture in Africa has the potential to enhance productivity and income generation. Addressing these causes and trajectories of the output dynamics will provide the needed resilience, adaptability, and output growth in agricultural production in Africa (Omotoso et al., 2023).

5.2.4 Gaps in the Existing Literature

The empirical literature has explored private sector funding for agriculture, focusing mainly on domestic private credit access (e.g., Assouto & Houngbeme, 2023; Diamoutene & Jatoe, 2021). Nevertheless, access does not always translate to actual funding. For studies that even concentrate on actual credit extended to the sector, the data on credit is aggregated for the entire private sector (see Ngong & Fonchamnyo, 2022), which can lead to the loss of valuable and specific insights peculiar to agriculture. We fill this gap by employing domestic credit data specific to the agriculture sector. This will offer a more precise and accurate picture of the dynamics between domestic credit and agricultural output.

FDI is another source of private capital for funding agriculture, as explored in the literature. Various studies (see Edeh et al. (2020), Kubik (2023) and Nyiwul & Koirala (2022)) have explored the potential and relevance of FDI to agriculture from different angles, perspectives, and contexts. Kubik (2023), for instance, focused only on the food and beverages sub-sector of agriculture. Some studies also use aggregated data on FDI to the entire economy (e.g., Ali et al., 2023; Udemba, 2020) in probing the influence of FDI on agriculture, which can lead to misleading findings. In this current study, however, we employ distinct and specific data on FDI in agriculture to probe its influence on agriculture in Africa.

Scholars have explored the causal relationship between environmental sustainability and FDI. These research directions test either the pollution halo or pollution haven hypotheses. For instance, Balsalobre-Lorente et al. (2019) investigated FDI's impact on the ecological footprint (EF) in Mexico, Indonesia, Nigeria, and Turkey. The paper's findings support the pollution haven hypothesis. Bao et al. (2011) found evidence supporting the pollution halo hypothesis, showing that FDI reduces environmental pollution in China. Mert and Caglar (2020), Ahmad et al. (2021), and Ehigiamusoe et al. (2024) also provided empirical evidence of the environmental sustainability impact of FDI in support of the pollution halo hypothesis. Ali et al.'s (2023) study also yielded conflicting conclusions aside from aggregating their FDI data. There is a need for a more robust and definite study to ascertain the proper direction of FDI to agricultural production in Africa regarding environmental conservation. In this study, we take a unique approach. The study uses the sustainable nitrogen management index to measure eco-vitality in agricultural production, which differs from the existing literature.

Unstable food prices affect both producers and consumers. This is directly under the goals of SDG 2 C in particular. Whereas Xie and Wang (2017) investigated the impact of agricultural product price fluctuations on China's grain yield, and Magrini et al. (2017) investigated the effect of food price variation on low-income consumers in Sub-Saharan Africa, the study focused only on cereal production and not the entire agriculture sector. Addison et al.'s (2016) study on price shocks was also tailored towards per capita GDP growth in Sub-Saharan Africa (see also Anderson and Brückner (2011)). Thus, little attention has been paid to actual food price variations and anomalies, how they impact productivity and their dynamic effects on other essential factors that affect agriculture production in Africa. More importantly, the literature has not explored the specific data dedicated to SDG 2 C to study the phenomenon. The current study incorporates all the above holistically and dynamically using the appropriate econometric approach to provide a concise and consistent account of the effects of food price anomalies and to proffer suggestions to improve food security in Africa.

As discussed above, the literature on the impacts of FDI, domestic credit, sustainability and price distortions on agriculture abounds. What is missing, however, is the distinct measurement of variables specific to agriculture, a holistic examination of the sector, and the application of estimation approaches that do not capture the dynamic interdependence among the key variables under study, which have led to conflicting and inconsistent outcomes.

5.3 Methodology

In this chapter, we employed the vector autoregression (VAR) model in line with the inherent characteristics of our data and the objectives of the chapter. Specifically, we utilise a Panel VAR (PVAR) model, which extends the general VAR models to estimate our variables, considering the panel nature of our data. According to Stock and Watson (2001), a VAR is a linear model with n-equations and n-variables, wherein each variable is explained by its own lagged values, along with current and past values of the remaining variables in a series of multiple regression equations or simultaneous equations. Essentially, VAR models treat all the variables of interest as potentially endogenous (Rafi & Ramachandran, 2018; Grossmann et al., 2014).

PVAR models account for endogeneity and its temporal and cross-sectional dynamics by incorporating the lags of all endogenous variables into the model through its dynamic interdependence feature (Canova & Ciccarelli, 2013). Additionally, PVAR models introduce individual-specific effects to accommodate heterogeneity (Love & Zicchino, 2006) and enable the examination of cross-sectional and time-series dependencies within the dataset. They are vital when theoretical knowledge regarding the relationships between variables is limited, thus aiding in the model specification (Grossmann et al., 2014). The following assumptions underpin the PVAR GMM model (Abrigo & Love, 2016): Errors are serially uncorrelated, instruments are uncorrelated with the errors, and all variables are stationary and endogenous.

Considering a set of countries (N), indexed as $i = 1, \dots, N$ observed over time (in years) as $t = 1, \dots, T$ and drawing insights from Abrigo and Love (2016), we can express the theoretical fixed-effects PVAR model with a lag order, L, as follows:

$$M_{it} = \theta_1 M_{it-1} + \cdots + \theta_L M_{it-L} + \mu_i + \nu_t + \varepsilon_{it} \tag{5.1}$$

where M_{it} is a $K \times 1$ vector of endogenous variables. $M_{it-1}, \dots, M_{it-L}$ are lagged endogenous variables and $\theta_1, \dots, \theta_L$ are $K \times K$ matrix of VAR parameters on M_{it-L} to be estimated. μ_i, ν_t and ε_{it} are $K \times 1$ vectors of dependent variable specific country fixed-effects, time-effects, and idiosyncratic errors, respectively. Considering our variables of interest, we define M_{it} as the transpose of $[OV_{it}\, CREDIT_{it}\, FDI_{it}\, PRICE_{it}\, SNMI_{it}]$. OV_{it} is the agricultural output value of country i at time t. $CREDIT_{it}$ is domestic credit to the agriculture sector of country i at time t. FDI_{it} is foreign direct investment in the agriculture sector of country i at time t. $PRICE_{it}$ is agriculture commodity price anomalies in country i at time t. $SNMI_{it}$ is sustainable nitrogen management index of country i at time t.

With insights from equation (5.1), we can write the PVAR model of order one as follows:

$$M_{it} = \theta_1 M_{it-1} + \mu_i + \nu_t + \varepsilon_{it} \tag{5.2}$$

The estimation of (5.2) was performed using the generalised method of moments (GMM) by instrumenting the lag differences (Abrigo & Love, 2016). In modelling the heterogeneity among countries, the PVAR model may be estimated by either first difference (FD) or forward orthogonal deviations (FOD). In this chapter, we estimated the PVAR GMM model following the FOD approach because, unlike the FD, it helps to preserve the sample size and the orthogonality between the transformed variables and the lagged regressors, thereby reducing bias (Rafi & Ramachandran, 2018). Earlier studies that adopted the FOD approach include Grossmann et al. (2014), Rafi and Ramachandran (2018), and Adarov (2019). The empirical estimation of our PVAR GMM model followed the statistical procedure provided by Abrigo and Love (2016).

5.3.1 Data and Variables

Data for this chapter comprises agricultural output value (OV), domestic credit to agriculture (CREDIT), net foreign direct investments to agriculture (FDI), food price anomalies (PRICE), and the sustainable nitrogen management index (SNMI) as a measure of sustainable agricultural practices. The choice of these variables is founded on the objectives of the chapter and entrenched in the literature. Despite our comprehensive efforts to gather information on all these variables for African countries, obtaining data for each country was challenging, except for SNMI. Consequently, missing data was a challenge that needed to be addressed.

When data sets contain missing observations, one notable option is the complete case analysis, where observations with missing data are deleted. However, this approach leads to a loss of valuable information, a drastic reduction in sample size, and potential biases in inferences (White et al., 2010). Alternative remedies such as mean replacement, regression imputation, and multiple imputations have been applied in various research fields (Leurent et al., 2018). Multiple imputation (MI) is considered the statistically superior technique (Little & Rubin, 2002). MI is a flexible and iterative stochastic approach that handles missing data by generating multiple imputed data sets, reflecting the uncertainty around the actual value of parameters (White et al., 2010). These imputed data sets are then analysed and combined using Rubin's rules (Rubin, 1987).

The MI process consists of three fundamental steps: assessing the pattern of missingness in data, selecting an appropriate imputation model and determining the number of imputations required to produce valid estimates and inferences (Little & Rubin, 2002). The patterns of missingness in the data are classified into three main types: Missing Completely at Random (MCAR), Missing at Random (MAR), and Not Missing at Random (NMAR) (Zhang, 2003). We conclude that the data pattern is MAR based on Little's MCAR test as shown in Table 5.2.

Two widely used approaches for imputation are the Markov chain Monte Carlo (MCMC) procedure and multiple imputations by chained equations (MICE). MCMC draws missing data samples from their posterior distribution based on the assumption of normal distribution (White et al., 2010). Conversely, MICE impute missing values by fitting a chain of regression equations based on observed values (White et al., 2010). The choice between MCMC and MICE is contingent on the missingness pattern of the data. Since our data exhibits non-monotone missingness and MAR based on Little's MCAR test, the MCMC imputation model is deemed appropriate (Zhang, 2003; White et al., 2010). Additionally, the MCMC approach provides reliable estimates even when the underlying multivariate normality assumption is not strictly met, given a relatively large sample size (Lee & Carlin, 2010).

The number of imputations to perform is another crucial consideration. While some suggest three to five imputations for sufficient relative efficiency (Graham et al., 2007), a more significant number of imputations is recommended when the fraction of missing information is high (Graham et al., 2007), as in our case. A sufficiently large number of imputations ensures consistency in standard error estimates and reproducibility in later imputation analyses (Von Hippel, 2020). To determine the optimum number of imputations, we followed Von Hippel's (2020) two-stage criteria, which involves estimating the imputation model with an arbitrary number of imputations and then performing the "*how_many_imputations*" test to ascertain the statistically recommended number. The results of this process have been presented in the empirical section of this chapter. Table 5.1 describes the variables used and their respective sources.

Table 5.1: Variable Definition and Data Sources

Variables	**Definition/Measurement**	**Data Source**
Agriculture Output Value (***OV***)	Gross agricultural production value (Current. Unit of 1000 US$).	WDI
Credit (***CREDIT***)	Private domestic credit to agriculture. Millions of US$.	FAOSTAT
Foreign Direct Investment (***FDI***)	Foreign direct investments (Net inflows) to agriculture. Millions of US$.	FAOSTAT
Price anomalies (***PRICE***)	Indicator of food price anomalies (IFPA): an SDG indicator (target 2.c.1), applied to the consumer food price (Index). Measure of food price variations. $-0.5 \leq IFPAy < 0.5$ *Normal*, $0.5 \leq IFPAy < 1$ *Moderately High*; $IFPAy \geq 1$ *Abnormally High*.	FAOSTAT
Sustainable Nitrogen Management Index (**SNMI**)	It shows the efficiency of nitrogen fertiliser application for maximum crop yields and signifies the environmental performance of agricultural production. It is used as a proxy for sustainable agriculture practices (Index, 0-100).	SEDAC

NOTES: World Development Indicators (WDI), Socioeconomic Data and Applications Center (SEDAC). Food and Agricultural Organisation Statistics (FAOSTAT).

5.3.2 Multiple Imputation

Table 5.2 presents the data. It is clear from Table 5.2 that the data for all the variables, except SNMI, employed were incomplete in the respective databases. The incomplete data necessitated a decision between conducting a complete case analysis or adopting a robust statistical approach to address the missing data issue. The literature contains extensive discussions on the proportion of missingness that ensures accurate imputation outcomes. While some researchers propose a threshold of 50%, Madley-Dowd et al. (2019) suggest that unbiased results can still be achieved even with up to 90% of missing data, given that the imputation model is specified correctly and the data follows the MAR.

To preserve the valuable information in our data and ensure a robust sample, we performed multiple imputations using the MCMC approach to fill in the missing observations through independent random draws from the predictive distribution of the missing values (Madley-Dowd et al., 2019). The imputation process involved generating 188 optimal imputations, which were determined using Von Hippel's (2020) test, as described earlier, to find the number of efficient imputations. We included all the variables in our estimation, as recommended in the literature (Madley-dowd et al., 2019), achieving high relative efficiency rates of up to 0.9967, with FDI recording a high relative efficiency rate of 0.9951 despite having the highest number of missing observations (see Table B.5.8). As a further robustness analysis, we plotted the observed and imputed data set using the quantile plots following Cox (2004) as shown in Figure A.5.3 in the Appendix. From the plots, a vast quantile of the imputed data fits the observed data very well, highlighting the efficiency of the imputation procedure. We also show Kernel density plots of all the variables in their imputed and observed forms (see Figure B.5.4 in Appendix). From the plots, we observe slight variations among the two data sets. These variations are, however, insignificant to create significant distortions in the results. Moreover, other variables could have influenced the possible differences in distributions in the imputation model (Abayomi et al., 2008).

Analysing Table 5.2, we find that the observed mean of OV is US$6.06 billion, while the estimated imputed value is US$5.03 billion. Nigeria stands out as the country with the highest OV value. The output value comprises agricultural production (crop and livestock), fishing, and forestry. For agricultural credit, the observed mean is US$174.4 million, and the estimated mean is US$189.59 million. Concerning FDI, the observed data value is US$30.66 million, and the imputed value closely aligns at US$30.61 million. Despite the FDI variable exhibiting a high missing percentage, the deviation of the imputed value remains within an acceptable range.

We also note a food price anomalies index of -0.2074 and an estimated value of -0.2102. Both values indicate normal food price variation (see Table 5.1 for the classification index). However, the maximum price levels of 6.59 in both samples indicate abnormally high food price variation at specific points during the study period. These descriptive statistics reveal differences between the two data groups, warranting further rigorous statistical examination to better understand their implications.

Before further analysing our results, ensuring that the MAR assumption holds is essential. Thus, the observed data can predict the unobserved data (Li, 2013). This assumption is critical for testing the efficiency and suitability of any imputation model (White, 2010). Abayomi et al. (2008) propose examining the distributions of the observed and imputed data for any variations to assess the MAR assumption. We adopted this approach by plotting the Kernel densities of the observed and imputed variables for each data set, as shown in Figure B.5.4 in Appendix. The plots show that there are only minimal variations for the observed and imputed data.

As a further step to test the MAR assumption of our data, we relied on Little's test of Missing Completely at Random (MCAR) proposed by Li (2013) as an inference to ascertain the MAR assumption. It is important to note that directly testing the MAR assumption is impossible due to the reliance on unavailable information (Li, 2013). The null hypothesis in Little's test is that there are no differences between the means of different missing-value patterns. Therefore, rejecting the null indicates that the data is not MCAR. Based on the test results in Table 5.2, we reject the null at a 1% significance level and conclude that the data meet the MAR missingness assumption.

We conducted a two-sample t-test using Welch's unequal variances t-test approach between the observed and imputed datasets to confirm the MAR assumption further. The test is used to assess the equality of means between two populations. The null hypothesis for this test is that there is no significant statistical difference between the means of the two data groups for each variable. From the test results presented in Table 5.2 and comparing all the empirical t-values with the theoretical t-value of 2.56 at a 99% confidence level, we do not find statistically significant differences in the means of OV, CREDIT, FDI, and PRICE at the 1% significance level. Hence, the imputed data is not statistically different from the observed data, further supporting the MAR assumption.

To assess the efficiency and accuracy of the imputation, we computed the rates of relative efficiency for all the imputed variables, along with within and between variances, as presented in Table B.5.8 under the Appendix. The results indicate high rates of relative efficiency, exceeding 0.99 for all imputed variables, coupled with low within-and-between variances, further validating the imputation process. The study continues with further data investigations after drawing a favourable conclusion on the imputation process.

Table 5.2: Summary Statistics of Observed and Imputed Data

	Observed Data						Imputed Data					
Variables	N	Mean	Min	Max	Std. Deviation	Miss. %	N	Mean	Min	Max	Std. Deviation	Two-sample *t*-test
OV(‘000)	710	6,062.2	4.641	94,100	10,385.9	26	960	5,028.5	4.641	94,094.9	9,135.453	2.115
CREDIT	354	174.14	0.01011	3260.641	347.4174	63.1	960	189.5851	9.6836	3592.891	448.0803	-0.6585
FDI	152	30.6619	-26.12	626.76	65.9699	84.2	960	30.6130	-461.98	626.76	46.7067	0.0088
PRICE	438	-0.2074	-12.29	6.59	0.9797	54.4	960	-0.2102	-12.29	6.59	0.7001	0.0531
SNMI	960	42.0508	0	100	18.1376	0						

Little's MCAR test: Chi-Square = 1143.346, DF = 310, Sig. = .000

Source: Author’s estimations.

Notes: OV is output value, FDI is foreign direct investment, and SNMI is sustainable nitrogen management index. MCAR is missing completely at random. Values reported for the two-sample t-test are estimated t-values.

5.4 Pre-Estimation Data Characteristics

Table 5.3 presents the statistics of the characteristic features of the data. The stationarity test conducted using the Levin, Lin, and Chu test (Levin et al., 2002) showed that all the variables exhibit no unit roots and are stationary at the 1% significance level. The null hypothesis for this test is that the variable under verification has a unit root. We also employed the Kao cointegration test to determine the long-run equilibrium relationship between our variables. The results of the Augmented Dickey-Fuller Test (-3.2343) rejected the null hypothesis of no cointegration, indicating that all the variables are cointegrated at the 1% significance level.

Furthermore, we investigated the presence of endogeneity in our data by estimating an auxiliary fixed effects regression model with repeated but alternated dependent variable regressions of all the variables, treating their respective generated residuals as exogenous. The results of all the regressions indicated that the respective residuals were statistically significant at the 1% significance level, suggesting the presence of endogeneity among the variables.

To verify the existence of cross-sectional dependence in our variables, we conducted the cross-sectional dependence test of the residuals against the null hypothesis of no cross-sectional dependence (correlation) in residuals represented by the Pesaran scaled LM tests (Pesaran, 2004), as shown in Table 5.3. The test suggests the presence of cross-sectional dependence in the residuals of the variables.

Additionally, we assessed the presence of panel cross-sectional heteroskedasticity using the Likelihood Ratio (LR) test of the null hypothesis that residuals are homoscedastic. The LR results presented in Table 5.3 led us to reject the null hypothesis, indicating the presence of heteroskedasticity in the data. As a remedy, we estimated the PVAR standard errors using White's (1980) heteroskedasticity-consistent standard errors.

Considering OV and CREDIT's relatively high standard deviations, we performed their logged transformations in all subsequent analyses, denoted as LNOV and LNCREDIT, respectively.

Table 5.3: Pre-estimation Test Diagnostics

Variable	**Unit Root Tests**	**Endogeneity Tests**
	t-statistic	t-statistic
LNOV	-5.8212***	
LNCREDIT	-9.0593***	29.5249***
FDI	-8.6994***	97.9949***
PRICE	-13.8822***	113.7566***
SNMI	-8.3064***	1.44E+15***
ADF	-3.2343***	
Pesaran scaled LM	30.6986***	
LR Test	638.0308***	

Source: Author's estimation.
Notes: ADF is Augmented Dickey-Fuller Test and it represents the Kao Residual Cointegration Test. The test statistics of the endogeneity test is based on the residuals of the respective variables. *** means significant at 1% significance level. LNOV and LNCREDIT values are the logs of the actuals.

5.5 Moment and Model Selection Criteria

One vital step in estimating the PVAR lies in selecting the optimal lag length and appropriate instruments when employing the GMM estimator for model estimation. Optimal lag selection is imperative for statistical validity and mitigating serial correlation issues in PVAR estimates.

We initially estimated the PVAR model using one instrumental lag to determine the optimal lag length. Subsequently, we conducted model and moment selection criteria tests. However, the identification test indicated that the one instrumental lag failed to meet the requirements. As a result, we systematically increased the instrumental lags, repeating the process until reaching the fourth instrumental lag. We present the results of the final test in Table 5.4. The table includes the coefficient of determination (CoD) as the proportion of variation explained by the panel VAR model (Abrigo & Love, 2016) as well as various selection criteria, such as the Modified Bayesian Information Criterion (MBIC), Modified Akaike Information Criterion (MAIC), and Modified Quasi-likelihood Independence Criterion (MQIC). From Table 5.4, the model with the lowest criterion value is the PVAR model at lag order one, with an MBIC value of -377.153. The results indicate that the PVAR model is efficient at order one.

As the PVAR model is estimated using the GMM estimator, it is essential to ascertain the best instrumentation for modelling the moment condition. To achieve this, we employed lags of all the variables as instruments, ranging from lag 1 to 4. By utilising longer lag lengths for instruments, we aimed to enhance efficiency (Abrigo & Love, 2016). Nonetheless, this approach leads to a loss in observations. To mitigate this issue, we followed the GMM-style estimation procedure proposed by Abrigo and Love (2016) to preserve the information content of the data. Table 5.4 also displays the corresponding Hansen's (1982) J-statistic and associated p-value, which aid in verifying Hansen's overidentification restriction in the GMM estimation. These results show that the restriction is not rejected at the 1% significance level at lag order one with 1 to 4 instrumental lags, indicating the correct specification of our PVAR GMM model.

The dynamic nature of VAR models generally makes it complex to interpret their regression coefficients (Stock and Watson, 2001). Hence, it is customary to focus on reporting and discussing Granger causality results, Impulse Response Functions (IRFs), and Forecast Error Variance Decompositions (FEVD), as they provide more valuable information about the estimated model (Stock & Watson, 2001). However, valid estimation of IRFs and FEVD relies on satisfying the stability condition of the estimated VAR model. Consequently, our empirical discussions and policy implications centred on the Granger causality tests, IRFs, and FEVD results. Nevertheless, the PVAR coefficient estimates are presented in Table C.5.9 in the Appendix.

Table 5.4: Moment and model selection criteria

lag	CoD	J	J p-value	MBIC	MAIC	MQIC
1	0.999845	89.6894	0.118484	-377.153	-60.3106	-184.586
2	0.999908	22.81783	0.999663	-288.41	-77.1822	-160.032
3	0.999907	14.3089	0.956077	-141.305	-35.6911	-77.1162
4	0.999909	.	.	.	.	.

N = 505
Instruments: LNOV, LNCREDIT, FDI, PRICE, SNMI
Instrumental lags: 1 to 4
Sample: 2004 – 2018
Source: Author's estimations.

5.6 PVAR Granger Causality Statistics

In Table 5.5, we can see the Granger-causality statistics for our PVAR model's five variables. The tests show how previous or lag values of an endogenous variable or all endogenous variables can predict another variable treated as exogenous. The test reveals that all variables, namely LNCREDIT, FDI, PRICE, and SNMI, can predict output value at a 1% significance level. However, agricultural lending (LNCREDIT), FDI, and SNMI do not Granger-cause agricultural output value (LNOV) at a 1% significance level. It means that private sector funding does not provide immediate desired outcomes or serve as a push factor for output value. Several reasons could have accounted for this: asymmetries between planned and invested funds, ineffective monitoring of financial allocation to prevent moral hazard situations, poor implementation procedures, misalignments between planned and actual investment executions, or other production hostilities.

On the other hand, the Wald test shows that output value predicts agricultural lending and FDI at a 1% significance level. FDI and sustainable agricultural practices could predict agricultural lending at a 5% significance level. Our findings indicate that private credit to agriculture is determined by output value, indicating a unidirectional causality between agriculture credit and output value. Diallo et al. (2020), Diamoutene and Jatoe (2021), and Yadav and Rao (2024) found similar empirical evidence. Our results also show that agriculture output value is an attraction/pull factor for FDI into the sector. This implies unidirectional causation between FDI and agricultural output value in Africa, suggesting that FDI will flow to where there is value and high performance. The FDI flow direction sometimes is attributable to a well-capitalised sector (Kubik, 2023). Our empirical outcome further supports this view when we discovered that agricultural credit Granger causes FDI to the agricultural, fishing, and forestry sectors, further giving credence to the positioning of domestic financial institutions to offer credit to the sector as a signal for foreign capital investment flows into the domestic economy. This further underscores the relevance of the institutional theory and supports our hypothesis H5: Domestic credit to the agriculture sector will significantly drive production output.

It also reassures multinational firms to rely on domestic financial institutions for credit support if needed during their operations, emphasising the importance of financial institutions and their signalling effect on FDI flows. Our empirical outcome gives us a broader understanding of how the entire financial institutional environment shapes the financial institutions' behaviour and the agents' investment choices within the context of institutional theory.

The data indicates that food price changes significantly impact agricultural production's value. When food prices fluctuate, there is an adjustment in production. The study also shows that the value of agricultural production impacts food prices, indicating a two-way relationship.

Farmers can benefit from favourable price changes by increasing their income from selling higher-priced agricultural products. However, negative price changes can eliminate gains from previous production, especially in low-income countries, highlighting the importance of stabilising food prices, as Newbery's price stabilisation theory (1989) suggests.

Food prices are vulnerable to fluctuations due to various factors, such as changes in weather patterns, production and demand imbalances, geopolitical events, and economic shocks. These factors have significant effects on agriculture production in Africa. Therefore, stabilising food prices is crucial for food security and ending hunger. Domestic production must also counterbalance the sources of instability, and safety nets must be established to support farmers' production. The Granger causality between food price variation and agricultural credit at a 10% significance level highlights the need for these measures. Similar outcomes were observed in the Chinese setting by Xie and Wang (2017). Our empirical findings also support the hypothesis H7 that, significant food price anomalies will negatively impact agricultural output.

Whereas there is an avenue for farmers to take advantage of higher price situations to increase incomes, often, the technology and funding required to produce to meet such pricing windows and stores during bumper seasons are mainly missing (Magrini et al., 2017). Such occasions will favour net food exporters as they gain from price increments. Notwithstanding, since Africa is a net food importer, any slight food price variation has substantial adverse socio-economic effects. Since trade is inevitable, a net exporter will equally be exposed to negative price variations on exported goods. Hence, there is a need for food price stabilisation in the agricultural economy.

From the environmental sustainability angle, the test proves that output value, domestic credit, and FDI Granger cause sustainable agricultural practice at the 1% and 10% significance levels, respectively. The environmental sustainability orientation of multinationals is of great concern to host countries arising from the current climate change crisis. The findings of our study indicate that FDI to agriculture in Africa promotes environmentally sustainable production practices and high environmental standards in line with the pollution halo hypothesis, consistent with Ahmad et al. (2021) and Ehigiamusoe et al. (2024) and also consistent with our hypothesis H6: FDI inflows into developing countries will result in sustainable production. Ren et al. (2022) indicate that larger farms tend to be more environmentally efficient. The current outcome may indicate the size and level of technological sophistication of foreign firms in the agriculture sector in Africa. One benefit of this would be the possible transfer of these sustainably efficient agricultural production technologies and farming knowledge to domestic producers.

The results further reveal that sustainable agricultural production practices in the host country are a pull factor for FDI to Africa's agriculture, fishing and forestry sectors, possibly due to environmental re-orientation or stewardship or to the advantages of cleaner production technologies and knowledge that multinational firms already have thereby contradicting the view that multinational firms are more likely to extend their operations to locations with poor environmental regulations and performance (Cole et al., 2017). The effectiveness of regulatory frameworks and green investment policies could have influenced this outcome. Literature suggests that sustainable production in a host country will be an attraction factor for FDI when the FDI is export-oriented, which will impose some strict sustainable production compliance (Tang, 2015). Similar compliance behaviours involving export-oriented agriculture producers are observable in Ghana. As our results indicate and have been shown in the empirical literature (see, e.g., Bai & Zhang (2020)), improving output value without harming the environment is possible.

The Granger causality between domestic credit, output value, and sustainable agriculture production indicates possible training financial institutions offer to farmers to promote green financing and overall environmental sustainability. In general, the variables in each system have joint statistical significance (ALL) in each equation, which justifies the statistical significance of each of our models in the system. Table C.5.9 in the Appendix also shows that all the lags for each specific dependent variable in the system of equations are statistically significant. All these support our model's relevance and our methodology's justification.

Table 5.5: PVAR Granger Causality Wald Test

Equation\Excluded		chi2	df	Prob> chi2
LNOV				
	LNCREDIT	2.449	1	0.118
	FDI	0.098	1	0.755
	PRICE	7.171	1	0.007
	SNMI	2.206	1	0.138
	ALL	23.871	4	0.000
LNCREDIT				
	LNOV	13.341	1	0.000
	FDI	4.768	1	0.029
	PRICE	3.44	1	0.064
	SNMI	4.71	1	0.030
	ALL	31.343	4	0.000
FDI				
	LNOV	18.233	1	0.000
	LNCREDIT	15.191	1	0.000
	PRICE	0.484	1	0.487
	SNMI	3.161	1	0.075
	ALL	29.781	4	0.000
PRICE				
	LNOV	18.85	1	0.000
	LNCREDIT	15.946	1	0.000
	FDI	0.703	1	0.402
	SNMI	0.533	1	0.465
	ALL	29.357	4	0.000
SNMI				
	LNOV	12.104	1	0.001
	LNCREDIT	13.394	1	0.000
	FDI	3.184	1	0.074
	PRICE	23.278	1	0.000
	ALL	31.378	4	0.000

Notes: Estimations were based on GMM-PVAR estimator
Ho: Excluded variable does not Granger-cause equation variable
Ha: Excluded variable Granger-causes equation variable
Source: Author's estimation.

5.6.1 Post PVAR Estimation Diagnostics

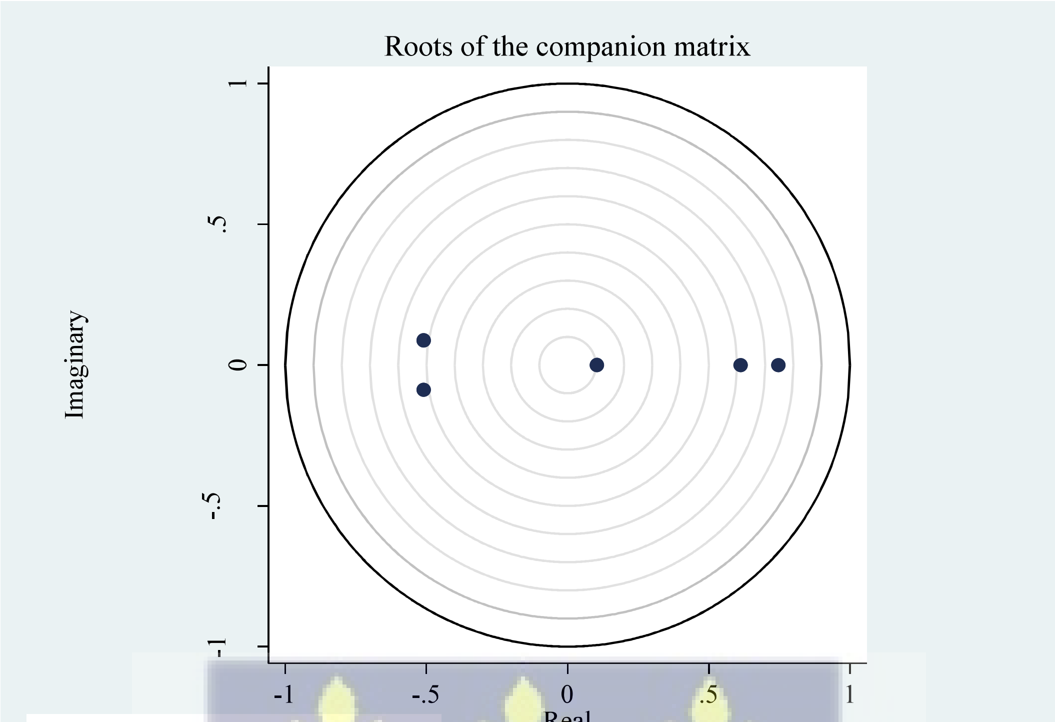
After estimating the PVAR model and the Granger causality tests, it is ideal to ascertain the stability of the PVAR model using the modulus of each eigenvalue of the fitted model (Abrigo & Love, 2016). The VAR(1) model is stable when all eigenvalues of the VAR(1) model have a modulus less than 1 (Lütkepohl, 2005). By this, the PVAR is invertible, has an infinite-order vector moving average representation, and offers meaningful interpretation to estimated impulse response functions and forecast error variance decompositions (Abrigo & Love, 2016). Table 5.6 shows the stability condition results of our analysis. It can be observed from the table that all five models have modulus values less than one. Figure 5.1 provides a pictorial representation. Therefore, our VAR(1) model is statistically stable.

Table 5.6: Eigenvalue Stability Condition

Eigenvalue		
Real	*Imaginary*	*Modulus*
0.7467679	*0*	*0.7467679*
0.613191	*0*	*0.613191*
-0.5099536	*0.0877482*	*0.517448*
-0.5099536	*0.0877482*	*0.517448*
0.1036977	*0*	*0.1036977*

Source: Author's estimation.

Figure 5.1: PVAR Stability Condition



Source: Author's empirical results

5.7 Impulse Responses

The IRF shows how one variable responds to a shock or innovations arising from another variable in the VAR model. When the effect of the shock fades away over the long term, the innovations are classified as transitory, but if, on the other hand, the response fails to abate, the shock is then considered permanent. We present selected IRFs under our objectives in Figure 5.2 below. From the top left corner of Figure 5.2, the graph shows that a shock from LNOV first drives FDI (net) downwards to negative at the end of year one before it begins to have an upward effect up to the second period. Similar but negligible downward and upward traces exist between years three and four. However, the effect of the LNOV innovations on FDI died out after the fifth year.

From the top right graph of Figure 5.2, we observe again that a shock from LNOV sharply sends LNCREDIT in a negative direction at the first phase. An upward trajectory is, however, experienced until a positive outcome at about the second period. After that, a marginal decline is witnessed compared to the initial period, followed by much smaller upward and downward trends between periods three and five. Eventually, the shocks fade away after the fifth year, highlighting a nonlinear relationship between LNOV and LNCREDIT.

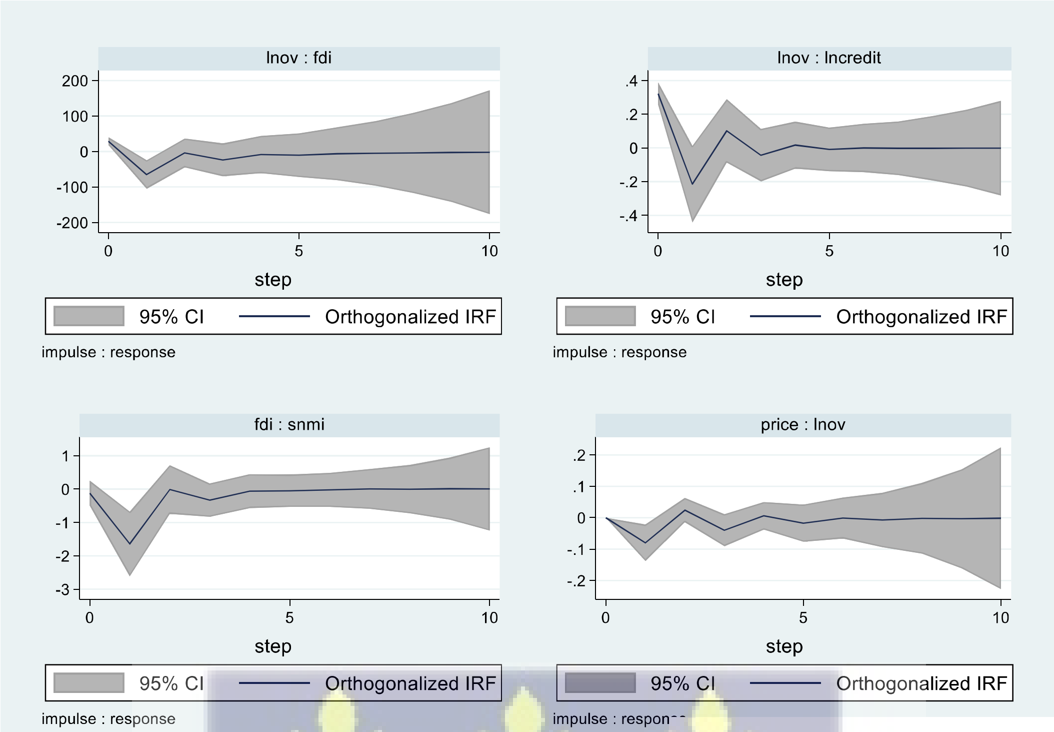
The bottom left graph of Figure 5.2 displays SNMI's response to a shock in FDI. The first year indicates a negative response. However, we observed an upward recovery up to the second year, and the long-term response remained negative. This adverse effect remained gradually into the fourth year before it died away.

The bottom right graph shows the effect of PRICE shock on LNOV. We find a nonlinear effect of a PRICE shock on LNOV in the short to medium term. Specifically, LNOV responded negatively within the first period of the shock and improved positively at the end of the second period. The reaction is a natural one from the farmers. They will reduce or completely shift away from the production of crops that have experienced negative price variations in the previous year and produce those with high positive price variation tendencies in the current year. The response, however, declined to an adverse effect again at the end of the third period. Lighter, unstable effects characterise the fourth and fifth periods after this. The effect remained transitory for the rest of the periods. The varied innovation over the period signifies the dynamic nature and response of the farmer to market information regarding price sensitivities.

From the IRFs, we note that the response of FDI to a shock in the value of agricultural output is not immediate. Instead, it takes a short to medium term to start experiencing some desired outcomes. The effects, however, fade away gradually in the long term. We also report a nonlinear effect of agriculture output value on domestic credit to agriculture, fishing and forestry in the medium to long term. Sustainable agriculture production responds positively to FDI shock in the long term. We also see a nonlinear effect of price shocks on agricultural output value.

Whereas high price variations will benefit net producers, they will negatively affect net consumers (Magrini et al., 2017). Low-income consumers will likely be significantly affected, with consequences for food security implications. We observe a lag-positive response in output following a price shock, consistent with Xie and Wang (2017). A possible explanation is that the rise in farmers' interest in cultivating a particular crop may be due to the price variation leading to an increase in product price. On the contrary, when the variation results in a downward price trend of a currently cultivated crop, the farmers will shift to the production of a different crop that has higher prices or plan to cultivate crops with higher value in future cropping cycles as captured in the Granger causality results between food price variation and output.

Figure 5.2: Impulse Response Functions



Source: Author's empirical results

5.8 Forecast Error Variance Decomposition (FEVD)

Another way of expressing the effect of the innovations in the impulse variables on the response variables is through the FEVD (Abrigo & Love, 2016). The FEVD is the percentage or fraction of the variance of the error made in forecasting a variable due to a specific shock or innovation in a variable within a time frame (Abrigo & Love, 2016; Stock & Watson, 2001). The results of the FEVD are in Table 5.7. If we look at the LNOV response variable, we can observe some level of interaction among the respective innovation variables. Notably, the LNCREDIT innovations significantly influence LNOV over the forecast horizon, with the highest being 22.8 percent in the 10th forecast horizon, which means that 22.8 percent of the error in the forecast of LNOV is attributable to LNCREDIT shocks. FDI also have as much as 12.4 per cent influence on the forecast error of LNOV at the third forecast horizon, underscoring the significant importance of foreign capital in agricultural production.

Regarding the highest contributing factor to the forecast error of LNCREDIT, FDI dominates, contributing approximately 40.2 per cent to the forecast error from the 4th to the 10th forecast horizon, followed by LNOV with a maximum 15 per cent contribution at the first forecast horizon. The highest forecast error in FDI is attributable to LNCREDIT at 34.9 per cent in the first forecast period, indicating the reverse signalling effect of LNCREDIT and FDI. PRICE, however, has low forecast error on LNCREDIT.

At the second forecast horizon, we observe that 55.3 per cent of the forecast error in PRICE is due to FDI. Throughout the forecasts, SNMI provides the lowest innovations to the response variables over the forecast period. In the same way, all the innovation variables contribute minimally to the forecast error of SNMI. The highest innovation variable contributing to the SNMI forecast is FDI at 6.8 per cent, indicating the possible significant sustainable production technologies that FDI brings to the domestic market and a closer drift towards the pollution halo hypothesis.

Table 5.7: Forecast-error Variance Decomposition

Response variable and forecast horizon	Impulse variable				
LNOV	LNOV	LNCREDIT	FDI	PRICE	SNMI
0	0	0	0	0	0
1	1	0	0	0	0
2	0.7268856	0.128862	0.101633	0.040176	0.002444
3	0.6585836	0.181866	0.124154	0.032663	0.002733
4	0.6414814	0.204491	0.11446	0.036998	0.002571
5	0.6329727	0.216468	0.11281	0.035256	0.002493
6	0.6292906	0.221948	0.110682	0.035642	0.002437
7	0.6273444	0.225303	0.109779	0.035168	0.002405
8	0.6263233	0.226891	0.109255	0.035137	0.002395
9	0.6257752	0.227867	0.108955	0.035016	0.002388
10	0.6254715	0.228355	0.108802	0.034985	0.002387
LNCREDIT					
0	0	0	0	0	0
1	0.1504761	0.849524	0	0	0
2	0.1225095	0.484807	0.373048	0.011211	0.008424
3	0.1205706	0.446579	0.398918	0.02307	0.010862
4	0.1200717	0.439659	0.402183	0.026525	0.01156
5	0.1195813	0.437159	0.402165	0.028995	0.0121
6	0.1195252	0.436766	0.401988	0.029531	0.01219
7	0.1194682	0.436558	0.401842	0.029851	0.01228
8	0.1194632	0.436531	0.40181	0.029901	0.012295
9	0.1194604	0.436509	0.401789	0.029933	0.012308
10	0.1194603	0.436508	0.401786	0.029936	0.01231
FDI					
0	0	0	0	0	0
1	0.0389266	0.349097	0.611976	0	0
2	0.1287265	0.219223	0.645836	0.001556	0.004658
3	0.1212695	0.213913	0.647916	0.011323	0.005579
4	0.1299017	0.21312	0.638721	0.012434	0.005823
5	0.1305816	0.213874	0.634541	0.01489	0.006113
6	0.1323224	0.21476	0.631759	0.015011	0.006147
7	0.132946	0.215138	0.630312	0.015398	0.006206
8	0.1333962	0.215474	0.62953	0.015386	0.006213
9	0.1336386	0.215613	0.629088	0.015437	0.006224
10	0.1337722	0.215718	0.628854	0.015431	0.006225

Table 5.7 Continued: Forecast-error Variance Decomposition

Response variable and forecast horizon	Impulse variable				
PRICE	LNOV	LNCREDIT	FDI	PRICE	SNMI
0	0	0	0	0	0
1	0.0268945	0.347526	0.49676	0.12882	0
2	0.1165199	0.226925	0.552603	0.103188	0.000764
3	0.1101651	0.218975	0.544874	0.12416	0.001827
4	0.1178107	0.219452	0.535594	0.125309	0.001834
5	0.1190238	0.219727	0.530738	0.128415	0.002097
6	0.1205974	0.220796	0.528286	0.128218	0.002103
7	0.1213557	0.221092	0.526966	0.128432	0.002155
8	0.121785	0.221452	0.526317	0.128287	0.002159
9	0.1220549	0.221577	0.525945	0.128254	0.002169
10	0.1221874	0.221684	0.525752	0.128206	0.00217
SNMI					
0	0	0	0	0	0
1	0.0043042	0.0317	0.000579	0.003937	0.95948
2	0.0052371	0.021638	0.068136	0.060653	0.844336
3	0.0066046	0.020514	0.062755	0.055999	0.854127
4	0.006844	0.019975	0.062563	0.06163	0.848989
5	0.0077472	0.020591	0.06185	0.06096	0.848852
6	0.0084134	0.020958	0.061479	0.061667	0.847484
7	0.008896	0.021396	0.061326	0.061565	0.846818
8	0.0092575	0.02166	0.061233	0.061639	0.84621
9	0.0094712	0.021859	0.06119	0.061619	0.845861
10	0.0096175	0.021978	0.061168	0.061621	0.845615

Source: Author's empirical estimation

5.9 Summary, Conclusion and Recommendations

The agriculture sector in Africa has yet to receive the optimal financial investments it deserves despite its substantial contribution to the economies of African countries. The source of the low levels of financing is traceable to the low orientations towards agriculture by the public sector and the shadow effect on private-sector financiers. This chapter investigates the intricate dynamic interconnections among agricultural output value, domestic credit to agriculture, FDI in agriculture, food price variation, and sustainable agriculture in Africa, utilising the GMM-panel vector autoregressive econometric approach. From the Granger causality test, the study reveals notable interdependence among these variables. Specifically, the findings indicate that the value of agricultural output drives domestic credit, FDI to the sector, enhances sustainable agriculture practices, and influences price anomalies. However, only price anomalies have a reverse effect on output value. Bi-directional causality exists also between FDI and domestic credit, and FDI and sustainable agriculture production, which highlights the sustainability effect of FDI and the strong causative effect between food price variations and agriculture output.

The IRFs indicate that the responses of FDI and domestic credit to a shock in agriculture output value are not direct and immediate. However, their drifting effects are short to medium-term in nature. The findings also show non-linear effects of food price variation shock on agriculture output value over a longer duration of up to five years, with implications for low-income consumers and food security. The research contributes to the empirical literature by providing a holistic understanding of the interdependencies in African agriculture, addressing specific SDG targets, and offering practical evidence of the impact of FDI and domestic credit on sustainable farming practices.

We observed from the FEVDs that a significant proportion of the variations in agriculture output are accountable to domestic credit and FDI but more to domestic credit. The study further notes that domestic credit to the agriculture sector and FDI to the sector both have high signalling effects on each other. The FEVDs also show that a significant proportion of the variations in food prices is accounted for by domestic credit and FDI. However, FDI contributes the most and highlights the critical influence private capital can have in stabilising food price anomalies on the African continent. Hence, there is a need to extend the needed credit to the sector. Variations in sustainable agriculture production, on the other hand, are, to a lesser extent, inspired by domestic credit, FDI and price variation, indicating a starting phase of environmental stewardship in agriculture production in Africa.

The following policy recommendations follow our findings. Policies for improving the quality and availability of institutional credit support for the agriculture sector must be strengthened, particularly measures to enhance actual credit for smallholder farmers and agribusinesses. The policy can be made possible through small-sized financial institutions such as microfinance institutions and cooperatives, since they operate closer to most rural farmers. African countries must also position themselves to attract agriculture FDI to contribute to the growth and sustainability of the sector. While doing this, regulatory agencies should be mindful of the possible environmental consequences of FDI.

Maintaining food price stability requires that national governments aid farmers in planning and organising their productions appropriately to mitigate both negative and positive price variation shocks. The stability plan is possible through well-informed localised extension services operated by people with technical production and market expertise.

Despite this chapter's significant contributions to the extant literature, it did not tackle the spatial spillover effect of neighbouring countries in influencing the empirical findings. Hence, future research can explore these interconnections in a geospatial manner.

CHAPTER SIX

AGRICULTURE VALUE ADDED IN AFRICA: HAVE R&D INVESTMENT AND GLOBALISATION BEEN INFLUENTIAL?

Abstract

Innovations arising from research and development (R&D) tremendously benefit agricultural value addition. Even so, little is known of the specific impact of agricultural R&D expenditure and the dynamics of globalisation on agriculture value-added in Africa. This chapter explored the dynamic impacts of R&D expenditure and globalisation on agriculture value-added in Africa. We used data from 48 African countries between 2000 and 2019 from varied sources, notably the World Bank's World Development Indicators and the KOF globalisation index. We applied the dynamic common corrected effects mean group and the local projections estimators, considering the inherent cross-sectional heterogeneities in the econometric estimation process. Our empirical evidence shows that R&D investments only positively influence agriculture value-added in the medium to long term. The findings also indicate that economic integration has yet to positively influence the value-added in agriculture in Africa. Nonetheless, significant positive outcomes are achievable through financial development synergies. The chapter provides a detailed, more robust, and long-term understanding of the dynamics of R&D investments in agriculture within the global marketplace.

6.1 Introduction

A multi-sectoral approach to development in Africa is indispensable, yet its success is largely contingent upon prioritising agricultural productivity growth (Otchia & Asongu, 2021). Much of the agricultural production in Africa is by smallholder farmers with little value-enhancing capacity for their outputs. Research has, however, consistently demonstrated that agriculture value addition has a profound and sustained impact on poverty reduction in Africa, surpassing the contributions of any other sector (Enongene, 2023; Otchia & Asongu, 2021). Moreover, it is pivotal in bolstering food security (Lee et al., 2017). Economically, agriculture value addition accounts for an average of 14.7% of African states' annual gross domestic product (GDP) and is the primary source of employment (FAO, 2017). Therefore, the sustainability and effective transformation of the value-enhancing capacity of the sector are crucial to all African economies and should be improved. One way to achieve this is through continuous and consistent financial investments in research and development (R&D), driving the required technological advancements for the sector's industrial transformation and the effective diffusion of these technologies to promote primary and secondary processing, particularly among Africa's many smallholder farmers. Such initiatives are essential for sustainable industrialisation and offer many far-reaching gains.

Farmers in Africa and developing countries generally earn the least for their agricultural produce (Akiwumi, 2022), mainly due to the raw state in which most agricultural produce is sold. Also, the report of the 2021 biennial review of the progress in the implementation of the 2014 Malabo Declaration indicates that out of the set target of 6% for the growth rate in agricultural value added in Africa, only 2.6% on average growth was achieved, obviously due to low financial commitment to agricultural value addition (African Union, 2022). Meanwhile, this was one of the poverty reduction strategies for participating African countries to halve poverty by

2025. Indeed, the enhanced value of agricultural produce delivers substantial economic gains to the vulnerable groups of producers through market competitiveness (Liebenberg et al., 2011; Jung & Park, 2014) through fair market prices.

Whereas numerous empirical studies have revealed various contributory factors influencing agriculture value added in the literature (see Enongene, 2023; Otchia & Asongu, 2021; Asongu & Odhiambo, 2022a), the influence of R&D investments in Africa remains underexplored. Although Qayyum et al. (2023), Liebenberg et al. (2011), and Jung and Park (2014) have contributed empirically to the discourse, they centred on technology innovation adoption in agriculture value-added but not investments in R&D. Thus, the impact of agriculture R&D investments on value transformation is unknown in the literature. We hence provide the first empirical evidence on this vital variable using two robust estimators: the dynamic common corrected effects mean group (DCCEMG) estimator of Chudik and Pesaran (2015) and the linear projections (LP) estimator of Jordá (2005).

Globalisation promotes competition and drives change. Therefore, it is expected to influence the decision to add value to agricultural output since economies are globally interconnected. This nexus has been studied in the literature (see Alagidede et al., 2020; Ibrahim & Vo, 2020). However, despite the contribution of these studies to the literature, the decoupled data used were limited to *de facto*(actual) measures and excluded *de jure* (legal) measures despite the numerous potential implications of country-specific trade and financial laws on global integration. More importantly, harmony of trade laws is essential for seamless economic integration among countries. These could affect the outcome of any research on this matter since trade and financial openness for instance are indeed governed by laws irrespective of how liberal the rules or laws are. Alagidede et al. (2020) argue that loose capital restrictions do not translate into extensive international transactions, and strict capital controls are ineffective when there is a capital flight.

Notwithstanding, it is worth noting that laws govern international trade and financial transactions, and their effectiveness depends on enforcement by participating countries. Therefore, laws that govern global economic integration cannot be overlooked. As such, excluding these legal aspects of globalisation could result in conflicting outcomes. *De jure* measures of globalisation also provide insightful commonalities and regulatory legal frameworks among countries, which are essential for effective cross-country trade and financial transactions. It is also for dispute resolution. To bridge this gap, our study includes the combined effect of *de facto* and *de jure* measures of trade and financial globalisation as a composite measure of global economic integration to offer a more holistic perspective of globalisation's effect on agriculture value added.

Also, despite several contributions to the literature in this study area, particularly in the African context, the effect of possible commonalities and heterogeneities of the samples in past studies was not considered. Meanwhile, unobserved commonalities and unaccounted heterogeneities across the samples can provide inconsistent and conflicting empirical results (Pesaran, 2006; Chudik & Pesaran, 2015). As a remedial measure, we employ the methodological approach of Chudik and Pesaran (2015) to model these unobserved commonalities and heterogeneities for the first time in this area.

Given all the above, the objectives of the chapter are: 1) to ascertain the impact of agriculture R&D investments on agriculture value-added in Africa; 2) to project the long-term effects of agriculture R&D investments on agriculture value-added in Africa; and 3) to examine the effects of global trade and financial integration on agriculture value added in Africa. In line with these objectives, our study differs from previous studies and significantly contributes to the existing literature in several ways. By employing methodologies that account for unobserved commonalities and slope heterogeneity among a sample of African countries, the study first shows both immediate and medium to long-term projected effects of agriculture R&D investments on agriculture value added. Secondly, our study adopts a holistic approach to measuring global trade and financial integration, aiming better to understand their impact on value addition in Africa. It reflects the broader realities facing the sector, contrary to existing evidence provided in the literature.

The rest of the chapter is structured as follows: In the next section, we review related and relevant theoretical and empirical literature. The econometric strategy follows this, followed by the empirical findings. The last section comprises the summary, conclusion, and policy recommendations.

6.2 Literature Review

6.2.1 Theoretical Review

The chapter is based on three theories: the endogenous growth models of Romer (1986; 1990) and Schumpeter (1942). It also considers the global value chains (GVCs) and global commodity chains (GCCs) models.

Romer's endogenous growth theory (1986, 1990) argues that factors of production like capital and labour do not exogenously determine economic growth but are endogenously generated through innovation and knowledge accumulation of human capital. By implication, investments in R&D to drive sectorial technological advancements and innovation are essential to economic growth. The Schumpeter (1942) endogenous growth model offers valuable insights into the significance of innovation in both production and overall economic growth. The model strongly emphasises the pivotal role of creative destruction and innovation in driving economic growth through enhanced production. The creative destruction arises from replacing old technologies with innovations (Aghion & Howitt, 1992; Aghion et al., 2014). We can apply the model to agriculture in several ways.

Innovations in agricultural practices, such as developing high-yield crop varieties, precision farming technologies, and sustainable farming techniques, drive agricultural productivity and growth. Farmers and agribusiness entrepreneurs who adopt and implement new technologies are crucial in enhancing agricultural efficiency and output.

New agricultural technologies can create temporary monopolies for innovators (e.g., proprietary seed varieties or patented farming equipment) until these innovations are widely adopted and further innovations emerge. The agricultural sector may experience rapid growth during technological breakthroughs, followed by adjustment periods as the industry adapts to new technologies and practices.

By incorporating these elements, the Schumpeterian growth model provides an avenue for understanding technological innovation and how entrepreneurial activities drive growth to pave the way for agricultural transformation, instilling optimism about its future.

The chapter also draws on theoretical concepts from Gereffi's (1995) global value chains (GVCs) and Whitley's (1996) global commodity chains (GCCs) to assess the impact of globalisation on the value of agricultural output. The GVCs theory focuses on how products are produced and processed across multiple countries or regions. It emphasises the global interconnectivity of production, distribution, and marketing activities. GVCs define the essence of globalisation, which is central to or forms the basis of the flow of materials, goods, information, knowledge, finance, and people. These collectively influence the participation of countries in GVCs. Those who position themselves well in the chain earn good profits at the detriment of those who fail to take advantage of the numerous opportunities it offers. The GVC framework suggests that countries should specialise in producing goods for which they have a comparative advantage and trade these products globally, which can lead to increased value addition.

A related concept to the GVC is the Global Commodity Chains (GCCs) framework. The GCC theory centres on the global production networks of specific commodities. It examines these chains' power dynamics and governance structures (Whitley, 1996). Gereffi (1996) indicates that one of the critical principles of the commodity chains perspective is its tendency to reduce the impact of national origins on business systems. How firms conduct their business in the international economy is determined by their position within global commodity chains rather than their national heritage. This behaviour means that the status or history of countries has low potential to influence their global performance in the global business arena, but rather for those who will strategically position themselves, irrespective of their origin. Therefore, a global commodity chain (GCC) encompasses all the procedures for creating a particular product or service, including manufacturing, consumption, design, retailing, marketing, advertising, and disposal.

Financial development plays a crucial role in fostering innovation and knowledge creation in all the above frameworks, which are essential drivers of economic growth. Financial institutions, such as banks and capital markets facilitate investments in research and development (R&D) plans of private firms and public agencies. This suggests that economies with well-developed financial systems are potentially more capable of sustaining high rates of innovation and, consequently, experiencing productivity growth in the long term. These theoretical views have policy implications. Therefore, policies that promote healthy competition and fair trade and protect intellectual property rights while supporting country-level entrepreneurship and financial investments are critical to the conditions for growth and development. Hence, underscoring our argument to include a broader measure of globalisation covering both *dejure* and *defacto* characteristics (see e.g. Aghazadeh et al., 2023).

6.2.2 Empirical Review

In recent years, the potential of technology and innovation for improving agricultural productivity and environmental sustainability has been recognised (Qayyum et al., 2023). To understand the significance of technology innovation in an eco-friendly manner, Qayyum et al. (2023) investigated 21 agriculture-dependent Asian countries using two machine-learning techniques. The study also touched on the determinants of technology adoption. The findings highlight the varying levels of technology adoption.

Some empirical studies have also emphasised the crucial role of technological adoption in enhancing agricultural productivity on a broader scale. For instance, Villano et al. (2015) demonstrated the significance of modern rice technologies on Philippine rice farmers' productivity, efficiency, and income. Similarly, Emerick et al. (2016) found that adopting new agricultural technologies increases productivity. While these studies have contributed significantly to the literature, the literature has yet to record the level of financial investments in agriculture innovation and its attendant impact on value added in the sector.

One barrier to technology adoption is the transfer of the knowledge to the end users and scalability (Hermans et al., 2023). Therefore, enhancing the effectiveness of sustainable agricultural innovation requires facilitating a more open and inclusive interaction space that fosters effective and ongoing co-creation of technologies, social learning, and the collaborative construction of shared knowledge that benefits the target audiences for efficient productivity (Hermans et al., 2023).

Following these steps, agriculture innovations that involve vertical integration with manufacturing, processing, and sales activities and horizontal integration with service activities with environmental considerations have yielded tremendous outcomes (Liu et al., 2021). Liu et al. (2021) reiterated that the source of agricultural value added from innovation offers different motivations to farmers: Farmers oriented towards processing and services-centred activities prioritise output quality over production volume.

Benfica (2022) assessed how to allocate R&D resources in Senegal's agriculture to maximise development outcomes like poverty reduction, economic growth, job creation, and dietary diversity. The paper identified the most effective agricultural value chains for R&D support, including traditional export crops, groundnuts, rice, poultry, sorghum/millet, and cattle. The need for financial investment in agricultural research in Africa, in light of its importance for socio-economic development, has also been extensively studied by AU-SAFGRAD (2022) and Stads et al. (2021). The studies also emphasised the importance of strategic, sustained investment in R&D for long-term agricultural development. From the literature thus far, we can hypothesise that:

H8: Agriculture R&D investments will have significant effects on agriculture value-added.

Asongu and Odhiambo (2022a) examined the impact of financial access on value added in three sectors of the economy in 25 Sub-Saharan African countries using over three decades of data. Using the generalised method of moment, they find that increasing financial access does not significantly enhance value added in the agricultural and manufacturing sectors. However, it does have a positive impact on value added in the service sector. On the contrary, Oloukoi's (2022) study of the response of agricultural value added to credit in the West African Economic and Monetary Union indicates that credit positively impacts agricultural value added in the medium and long term. Nonetheless, short-term credit had varied effects on value-added across different countries (Oloukoi, 2022). In a related paper, Asongu and Odhiambo (2022b) evaluated the impact of increasing remittances on economic sectors in Sub-Saharan Africa. The study found no significant effects of remittances on the agricultural sector.

The roles of financial development and economic integration to enhance sectorial value-added were explored by Ibrahim and Vinh Vo (2020), covering 28 Sub-Saharan African countries between 1985 and 2015. Their findings reveal that higher economic integration stimulates sectorial value-added, particularly in the industrial sector. Trade integration was found to have a consistently more substantial effect than financial integration. The study further indicated that improved financial development enhances the output in the industrial sector, with less impact on the agricultural and service sectors.

Earlier evidence also showed that enhanced financial integration spurs economic growth, ultimately aided by better financial development (Ekpo & Chuku, 2017). Ibrahim and Sare's (2018) study on the determinants of financial development in Africa also proved that human capital and trade openness are critical factors, with human capital having a more substantial impact on financial development and trade openness being more influential in private credit than domestic credit. Ibrahim and Sare (2018) showed further evidence indicating that the accumulation of human capital and the level of trade openness can be used interchangeably to affect the progress of finance in Africa. It is therefore hypothesised that:

H9: Financial development significantly and positively enhances the value added of agriculture.

The success and positive net effect of all global integrations mainly depend on endogenous enabling factors in the integrating country, such as crucial infrastructure development. As Jiya et al. (2020) noted, this forms the basis for meaningful integration and economic transformation of countries. For instance, energy, telecommunication, and transport infrastructure, including well-developed and interconnected road, rail and water transport systems, will facilitate seamless trade integration among participating countries, thereby deepening integration and economic transformation. Indeed, trade integration will only be deepened and may become counterproductive to the value added of agriculture if not accompanied by a well-functioning and financially integrated system (Alagidede et al., 2020). We can hence hypothesise that:

H10: Global integration will have a significant positive impact on the value added in agriculture in Africa.

The nexus between structural transformation through production value addition and poverty has also been explored by Enongene (2023). The findings show that agriculture, manufacturing, industry, and services reduce short- and long-term poverty. More importantly, the agriculture sector was more effective in reducing poverty than the other sectors analysed in the paper. Otchia and Asongu (2021) found that prioritising agricultural productivity growth in Africa leads to holistic and robust economic development. In this chapter, we contribute to the broad literature by presenting a holistic impact of agricultural innovation on agricultural value added using R&D investments. Fresh evidence is also adduced employing broader variable dimensions of the importance of globalisation from both trade and financing segments of global integration and how they have shaped agriculture value addition in Africa. Our study also contributes to the literature by illustrating how the combined effect of financial development and trade integration can significantly facilitate agriculture value addition. The DCCE-MG approach adopted by the study also offered a more robust understanding of the influences of agriculture value-added.

6.2.3 Gaps in the Existing Literature

In this review section, we present a brief analysis of the existing gaps in the literature focusing on agriculture R&D investments, globalisation, and their influences on agriculture value-added. We also discussed the limitations of the methodological approaches adopted in the literature.

The literature has explored the importance of technological adoption in agricultural production (Villano et al., 2015; Emerick et al., 2016). These studies demonstrated the significance of modern technology adoption on farmers' productivity, efficiency, and income. The papers, however, did not investigate the effects of financial investments in technology and innovation. Moreover, the outcome variable was not related to the agriculture value-added. This study, however, focuses on the R&D financial investments required to drive agriculture value addition. This is vital as driven by the theoretical underpinning of innovation in growth and development.

The importance of globalisation on agriculture has been studied in the literature by Jiya et al. (2020) and Alagidede et al. (2020). Nonetheless, the variable dimensions were limited to *defacto* measures. Also, the econometric approaches adopted in these empirical analyses fail to consider the potential cross-sectional dependence and heterogeneities inherent in cross-country studies. Therefore, we provide insightful evidence by employing broader variable dimensions (*defacto* and *dejure*) of globalisation from both trade and financing segments of global integration and how they shape agriculture value addition in Africa using a more robust econometric approach that accounts for cross-sectional heterogeneity.

In addition, our research addresses the lack of information in the literature regarding the combined impact of financial development and trade integration on agricultural value added. The DCCE-MG approach used in the study context is unique and provides a more reliable comprehension of the factors affecting agricultural value added.

6.3 Methodology and Data

In this section, we develop our methodological approach following the chapter's objectives, the characteristics of the data, and the literature. First, the econometric model is introduced to tackle cross-sectional heterogeneity and other possible misspecifications, followed by the local projections estimator to ascertain the long-term investment horizon of R&D expenditure on agriculture value added.

6.3.1 The Dynamic Common Corrected Effects Mean Group Estimator

The study applied the dynamic common corrected effects mean group (DCCEMG) estimator of Chudik and Pesaran (2015) to examine the factors influencing agricultural output value. The DCCEMG estimator was used because of the unique characteristics observed in the data, mainly slope heterogeneity and cross-sectional dependence (CSD). The DCCEMG estimator provides consistent, efficient and unbiased estimates for several reasons.

First, the estimator efficiently models the dynamism introduced by the lagged dependent variable while considering the heterogeneity and cross-sectional dependence in the data. Second, the endogeneity introduced by the dynamic and other variables is accurately modelled in the DCCEMG estimator. Third, the DCCEMG estimator is robust to multicollinearity. It checks the entire model across all cross-sectional units and levels to ascertain any existence of multicollinearity, which informs the matrix inversion method of the estimated model (Ditzen, 2018). Fourth, modelling the unobserved common corrected effects in the estimator also caters for omitted variable bias. Because, in essence, omitted variable bias arises from the correlation between observed explanatory variables and unobserved variables (Ditzen, 2018).

According to Schmolck (2000), the homogeneity test can be formulated as the hypothesis of an omitted variable. In this regard, the ability of the DCCEMG estimator to model the cross-sectional heterogeneity of panels makes it robust to omitted variable bias. The estimator also accounts for weak exogeneity of regressors (Chudik & Pesaran, 2015) thereby eliminating any serious problem of endogeneity.

Non-accounting for CSD is dominant in the literature. Also, not accounting for slope heterogeneity can lead to biased estimates (Chudik & Pesaran, 2015). The failure to address these issues can result in inconsistent estimates (Pesaran, 2006). A residual measure is the multifactor approach of the common corrected effects mean group (CCEMG) estimator (Chudik & Pesaran, 2015). The underlying assumption of the estimator is that the cross-sectional dependence arises from unobservable, time-varying, common factors that distinctly impact each unit (Pesaran, 2006). The underlying assumption differs from the time-fixed effects, which assume uniform cross-sectional dependence across panels.

In what ensues, we can write the classical DCCEMG model following Chudik and Pesaran (2015) with insights from Ditzen (2018) as:

$$Y_{it} = \alpha_i + \alpha_t^* + Y_{it-1}\lambda + X_{it}\beta + \mu_{it} \tag{6.1}$$

Decomposing μ_{it} into a multifactor error structure becomes,

$$\mu_{it} = \gamma_i' \vartheta_t + \varepsilon_{it} \tag{6.2}$$

where, Y_{it} is the dependent variable of country $i, i = 1, \ldots, N$ at time $t = 1, \ldots, T$. α_i is the specific country fixed effects, α_t^* is the time effect. Y_{it}, α_i and α_t^* are $n \times 1$ vectors. Y_{it-1} is the dynamic variable or lag of the dependent variable with dimension $n \times l$ and λ is its corresponding coefficient vector of dimension $l \times 1$. l is the lag order. X_{it} is a $n \times k$ matrix of regressors over the cross-sectional dimension, β is a $k \times 1$ corresponding vector of mean group coefficients to be estimated. k is the number of regressors and n is the number of observations. μ_{it} is the multifactor error structure made up of m unknown or unobserved vector of common factors. Following the literature (see Chudik & Pesaran (2015); Gaibulloev et al. (2014)) we can write ϑ_t as a $m \times 1$ vector of unobserved common factors, and γ_i as its corresponding heterogeneous factor loadings which is the transpose of the vector $m \times 1$. ε_{it} is the idiosyncratic error term of dimension $n \times 1$. Since $\gamma_i' \vartheta_t$ is a scalar after the matrix multiplication but dimensionality needs to be preserved, $\gamma_i' \vartheta_t$ becomes a broadcast scalar of dimension $n \times 1$ in conformity with ε_{it} and μ_{it}. A broadcast scalar is a single value that is conceptually expanded to match the shape of an array. However, since μ_{it} is cross-sectionally dependent, and $E(\lambda_i) = \lambda, Y_{it-1}$ is no longer strictly exogenous and has to be modelled (Ditzen, 2018, p.587). To achieve consistency, $\sqrt[3]{T}$ lags of the cross-sectional averages of the dependent and independent variables are added to (6.1) to keep an adequate number of degrees of freedom (Chudik & Pesaran, 2015; Ditzen, 2018). Equation (6.1) then becomes,

$$Y_{it} = \alpha_i + \alpha_t^* + Y_{it-1}\lambda + X_{it}\beta + \sum_{l=0}^{L_T} \delta_{il}' \bar{Z}_{it-l} + \varepsilon_{it} \tag{6.3}$$

where $\bar{Z}_{it-l}$ is the lag of the average cross-sectional dependent variables in the model with dimension $m \times 1$. δ is the associated coefficient, which is the transpose of the vector $m \times 1$. L_T is the upper limit of the number of lags. The scalar, $\delta_{il}' \bar{Z}_{it-l}$ also takes the broadcast form $n \times 1$: A broadcast scalar is a single value that is conceptually expanded to match the shape of an array.

Following from equation (6.3), the estimated empirical model is;

$$AVA_{it} = \alpha_i + \alpha_t^* + \lambda AVA_{it-1} + \beta_1 INN_{it} + \beta_2 FD_{it} + \beta_3 GI_{it} + \psi_i \theta_{it}$$

$$+\sum_{l=0}^{p_T} \delta_{il}' \bar{Z}_{it-l} + \varepsilon_{it} \quad (6.4)$$

where AVA_{it} is the agriculture value added of country i at time t, INN_{it} is innovation as a proxy for agriculture R&D expenditure, FD_{it} is financial development level of country i at time t, GI_{it} is the global integration level of country i at time t, θ_{it} is a vector of control variables comprising, GDP per capita growth (GDP_{pc}) and regulatory quality (REGQ) and ψ_i is the associated parameter vector estimates.

The selected interaction effects models based on the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), as shown in Table 6.5, were estimated with the following empirical models:

$$AVA_{it} = \zeta_i + \zeta_t^* + \phi AVA_{it-1} + \phi_1 INN_{it} + \phi_2 FD_{it} + \phi_3 GI_{it} + \phi_4 FDINN_{it}$$
$$+\sum_{l=0}^{p_T} \eta_{il}' \bar{\pi}_{it-l} + \upsilon_{it} \quad (6.5)$$

$$AVA_{it} = \tau_i + \tau_t^* + \Theta AVA_{it-1} + \Theta_1 INN_{it} + \Theta_2 FD_{it} + \Theta_3 TRGI_{it} + \Theta_4 FIGI_{it} + \Theta_5 FDTGR_{it}$$
$$+\sum_{l=0}^{p_T} \varphi_{il}' \bar{\Gamma}_{it-l} + \epsilon_{it} \quad (6.6)$$

where $FDINN_{it}$ is the interaction term between FD and INN, $TRGI_{it}$ is trade integration, $FIGI_{it}$ is financial integration, and $FDTGR_{it}$ is the interaction term between FD and TRGI of country i at time t. ζ_i, ζ_t^* and τ_i, τ_t^* are the specific country fixed effects and time effects for equations (6.5) and (6.6) respectively of $n \times 1$ dimensions. $\bar{\pi}_{it}$ and $\bar{\Gamma}_{it}$ are the $m \times 1$ averages of the cross-sectionally dependent variables in the respective models. η and φ are their respective $m \times 1$ vector of cross-sectional average coefficients. $\eta_{il}' \bar{\pi}_{it-l}$ and $\varphi_{il}' \bar{\Gamma}_{it-l}$ are $n \times 1$ broadcast scalars for equations (6.5) and (6.6) respectively. υ_{it} and ϵ_{it} are idiosyncratic error terms for equations (6.5) and (6.6), respectively. The key assumptions underlying the DCCEMG estimator of Chudik and Pesaran (2015) are: 1) Stationary heterogeneous panels, 2) weakly exogenous panels, 3) independent distribution of errors, 4) stationarity and independent distribution of individual specific errors in unobserved common factors, 5) the factor loadings are independently and identically distributed across panels and common factors with respective means and 6) the regressors and their cross-sectional averages have bounded moments and their matrices are invertible and well-conditioned.

6.4 Local Projections Estimator

To understand the long-term trajectory of the causal effect of agriculture R&D expenditure on output value added over time, we employed the local projections (LP) approach first introduced by Jordá (2005). The approach provides a convenient yet robust way to estimate impulse response functions (IRFs) directly from what is called local projections with robustness to dynamic misspecifications of the data-generating process without having to specify and estimate the unknown true multivariate dynamic system itself (Jordá, 2005, p.162). It can also accommodate non-linear estimations and can be used to estimate various econometric models (Jordá, 2005). The LPs are based on successive regressions of the dependent variable shifted several steps ahead and, therefore, in harmony with direct multi-step forecasting (Jordá, 2005, p. 162).

Jordá (2005) indicates that statistically, IRFs are to achieve the best mean-square multi-step predictions through a recursive iterative model such as the classical vector autoregressive model. Nonetheless, the paper argued that the optimality of the multi-step predictive process depends on accurately representing the data-generating process. Jordá (2005), therefore, argue that better multi-step predictions can be made with direct forecasting models that are re-estimated for each forecast horizon (Jordá (2005, pp. 163), such as the LP estimator.

Therefore, following Jordá (2005), we can implement the LPs estimator using the DCCEMG estimator. As a preliminary step, if we project Y_{t+s} (the forecast of the dependent variable, herein, agriculture output value) onto a linear space generated by $(Y_{t-1}, Y_{t-2}, \dots, Y_{t-p})'$, then the LP model following Jordá (2005) can be expressed as;

$$Y_{t+s} = \alpha^s + \mathrm{B}_1^{s+1} Y_{t-1} + \mathrm{B}_2^{s+1} Y_{t-2} + \cdots + \mathrm{B}_p^{s+1} Y_{t-p} + \mu_{t+s}^s \tag{6.7}$$

where $s = 0, 1, 2, \dots, h$ is the number of horizons; Y_{t+s} is of dimension $n \times 1$, α^s is a $n \times 1$ vector of constants, B_i^{s+1} are $(n \times m)$ matrices of coefficients for each lag i and horizons $s + 1$. $Y_{t-1}, \dots, Y_{t-p}$ are $m \times 1$ vectors. μ_{t+s}^s are $n \times 1$ vector of residuals which are a moving average of the forecast errors from time t to $t + s$. As such, the errors are uncorrelated with the regressors. A group of h regressions in (6.7) is what Jordá (2005) calls local projections.

With insights from Jordá (2005), we can summarise (6.7) as follows;

$$Y_{i,t+s} = \alpha_{i,s} + \alpha_{t,s}^* + \sum_{p=1}^{P} \mathrm{B}_{1,p,s,i} Y_{i,t-p} + \sum_{l=1}^{L} \mathrm{B}_{2,l,s,i} d_{i,t-l} + \mu_{i,t,s} \tag{6.8}$$

where $Y_{i,t+s}$ is the dependent variable for country $i = 1, \dots, N$ at time $t = 1, \dots, T$. $\alpha_{0i,s}$ is the country fixed effects, $\alpha_{t,s}^*$ is the common linear time trend with slope, $Y_{i,t-p}$ is the lagged dependent variable, and p is its number of lags. $d_{i,t-l}$ is the shock (impulse) variable, and L is its lag length. $\mu_{i,t,s}$ is the idiosyncratic error term.

According to Jordá (2005), the IRF can be estimated from the differences between two forecast periods in (6.8). Therefore, the estimated IRFs from the LP in (6.8) can be written as;

$$\widehat{IR}(t, s, d_i) = \widehat{\mathrm{B}}_i^s d_i \tag{6.9}$$

where $\widehat{\mathrm{B}}_i^s$ is the IRF coefficient and d_i is the experimental shock to the i^{th} element in Y_t. In this study, the shock variable (d_i) is agriculture R&D expenditure as a measure of agriculture innovation.

Though (6.8) can be estimated as a stand-alone model, several econometric methods are incorporated depending on the study's objective (Jordá, 2005). In this chapter, we estimated (6.8) and subsequently (6.9) by incorporating the DCCEMG method of Chudik and Pesaran (2015) as implemented by Ditzen (2018), following econometric insights from Bakas and Mendieta-Muñoz (2020). The choice of estimating the LP model with the DCCEMG estimator resulted from our data's cross-sectional dependence and slope heterogeneity.

Data for the chapter was sourced from various databases. The objectives informed the choice of the data in the chapter and are theoretically founded on literature. The estimation of the econometric models in this chapter was done based on complete case analysis of data as a way of handling missing data in some of the series. Table 6.1 provides descriptions of each of the variables used in this chapter and their respective sources.

Table 6.1: Variable list and data sources

Variable	Prefix	Description	Source
Agriculture value added	AVA	Agriculture value added (% of GDP)	WDI
Financial development	FD	Financial development index. Measure for domestic financial depth, access and efficiency. Scale 0-1.	IMF
Innovation	INN	Agriculture R&D spending (% share of GDP)	ASTI
Global integration	GI	Globalisation of socio-economic systems. Scale, 1-100.	KOFGI
Trade integration	TRGI	Global trade integration. *De facto* and *de jure*. Scale, 1-100	KOFGI
Financial integration	FIGI	Global financial integration. *De facto* and *de jure*. Scale, 1-100	KOFGI
Regulatory quality	REGQ	Formulating and implementing sound economic policies and regulations that permit and promote private sector development. Regulatory quality estimate. Index $\in [-2.5, 2.5]$	WGI
GDP per capita growth	GDP_{pc}	GDP per capita growth (annual %)	WDI

Source: Author's compilation

Notes: FAOSTAT is the Food and Agriculture Organisation Statistics; IMF stands for the International Monetary Fund; WDI is the World Development Indicators; WGI is the World Governance Indicators; and KOFGI stands for the KOF Globalisation Index of Gygli et al. (2019), following the original index of Dreher (2006). ASTI is an Agricultural Science and Technology Indicator.

6.5 Empirical Results

6.5.1 Descriptive Statistics

The summary statistics of the data used in this chapter are presented in Table 6.2. It can be observed from the table that, on average, agriculture value addition constitutes 20.05% of the GDP of African countries. We observe from the data that Sierra Leon has the highest level of value addition, and Djibouti recorded the lowest percentage of agriculture value addition to GDP. On a scale of 0-1, the data indicates that the average level of financial development in Africa is 0.15, which appears to be very low. However, according to the data, South Africa had the highest level of financial development, while the Republic of Congo recorded the lowest on average over the study period. The data further show that, on average, only 0.91% of GDP is spent on R&D expenditure (INN), with Botswana spending the highest (5%) of GDP. The global integration level of African countries stands at 47.95 on a scale of 1-100. The most highly globally integrated country in Africa over the study period is Mauritius, and the least is Burundi. Decoupling the data, we record global trade and financial integration levels of 42.48 and 46.05, respectively. The most trade and finance-integrated country in Africa again is Mauritius. The study observes an average regulatory quality of -0.55 and an annual GDP per capita growth of 1.87%.

Table 6.2: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
AVA	926	20.0459	13.1503	0.9956	60.6111
FD	940	0.1468	0.1081	0.0264	0.5925
INN	956	0.9061	0.7941	0.0000	5.0000
GI	960	47.9531	9.5619	24.0000	72.0000
TRGI	960	42.4802	12.7476	16.0000	84.0000
FIGI	960	46.0500	11.8067	21.0000	87.0000
REGQ	802	-0.5512	0.8509	-2.6450	2.0980
GDP_{PC}	938	1.8703	4.6298	-50.7342	28.6760

Source: Author's estimation

6.5.2 Pre-estimation Data Characteristics

As a preliminary step in the empirical estimation process, the study assessed the data for the presence of cross-sectional dependence, unit roots, slope heterogeneity, and heteroscedasticity. The Pesaran (2015) cross-sectional dependence test (CD) was applied to test for cross-sectional dependence. The results are in Table 6.3 with their associated p-values. The null hypothesis is that errors are weakly cross-sectionally dependent. From the results, we conclude that the errors of all the variables exhibit cross-sectional dependence at the 0.01 significance level. The study further provides the alpha values of the estimated exponent of cross-sectional dependence. Bailey et al. (2019) indicate that for the estimated exponent of cross-sectional dependence to be weakly cross-sectional dependent, the residuals should be close to 0.5. Table 6.3 shows that all the variables' estimated alpha values are above 0.5, which confirms a strong case of cross-sectional dependence in our data.

Empirical estimates are inefficient when model slopes are heterogeneous yet unaccounted for in the estimation process (Chudik et al., 2017). To account for the presence or otherwise of the homogeneity of the panels, we implemented the Pesaran and Yamagata (2008) test for slope heterogeneity. The null hypothesis for the test is homogeneous slopes. From Table 6.3, the adjusted Delta values of 22.342 and 13.628 for the base and extended models are statistically significant at a 0.01 significance level. Hence, the presence of slope heterogeneity. There is also the presence of heteroscedasticity for the fitted values of AVA per the results of the Breusch-Pagan test.

Table 6.3: Tests for weak cross-sectional dependence, slope heterogeneity and heteroscedasticity

Variables/Stat.	AVA	FD	INN	GI	TRGI	FIGI	REGQ	GDP_{PC}
CD	127.25	43.558	56.596	127.963	13.143	5.254	5	18.419
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Alpha	0.8225	0.9785	0.7026	1.0066	0.7715	0.7840	0.6256	0.6965
Std. Err.	0.0964	0.0277	0.0422	0.0563	0.2140	0.2226	0.1527	0.0841
Slope Het. (Delta adj.)		22.342***						
		13.628***						
Breusch-Pagan (Chi-square)		69.41***						

Source: Author's estimation

Notes: CD is the Pesaran (2015) cross-sectional dependent statistic. An alpha above 0.5 implies strong cross-sectional dependence. Standard errors are associated with the estimated alpha values only. *** is significance at 0.01 significance level. Slope Het. is the adjusted delta statistic of the Pesaran and Yamagata (2008) testing for slope heterogeneity. Breusch-Pagan is the Breusch-Pagan / Cook-Weisberg test for heteroscedasticity test for fitted values of AVA.

6.5.3 Second Generation Panel Unit Root Test

Since the errors in our data series are cross-sectional dependent, and the slopes are heterogeneous, it is advised to perform second-generation unit root tests to ascertain the stationarity or otherwise of the series. We relied on the second-generation Pesaran (2003) cross-section averages unit root test, which is ideal for testing the stationarity of series in the presence of cross-sectional dependence and heterogeneous panels. The null hypothesis is that all series are non-stationary. We implemented the test at level (lag zero). Per the results as presented in Table 6.4, we reject the null hypothesis and conclude that all the variables are stationary at the level of 0.05 significance. This means that the panels in the data exhibit stationary heterogeneity.

Table 6.4: Second Generation panel unit root tests

Variables/Stat.	AVA	FD	INN	GI	TRGI	FIGI	REGQ	GDP_{PC}
$\hat{t}_c$	-	-2.594	-	-2.637	-2.306	-2.386	-	-
$\hat{t}_m$	-2.109	-5.806	-5.629	-6.163	-3.910	-4.539	-4.013	-12.152
P-value	0.017	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: Author's estimation

Notes: # of lags (0).

$\hat{t}_c$ is calculated for variables with only complete observations.

$\hat{t}_m$ statistic is calculated for all variables, including those with missing observations.

6.5.4 Empirical Findings

Table 6.5 presents the empirical results of the DCCEMG estimator. The estimates reveal that the lag of the dependent variable (AVA_1) positively and significantly influences the current values of AVA at the 0.01 significance level. The level of significance, as well as the direction of the effect, remains the same across all three different models estimated. This means that short-term past performances of agriculture value addition have a significant and positive influence on current production value added. This also justifies the dynamism of the model.

The study reveals a significant negative correlation between agricultural innovation expenditure and the value added to agricultural output across all estimated models, contradicting our hypothesis H8, which posits that agricultural R&D investments will have a significant positive impact on agricultural value-added.

. This seemingly counterintuitive result suggests either a delayed diffusion effect of technological innovations or a potential misallocation of funding for R&D purposes. According to Romer's (1986; 1990) endogenous growth model, economic growth hinges on factors within the economic system, including technological progress from R&D investments. Increased R&D spending in agriculture leads to advancements like improved crop varieties, farming practices, machinery, and enhanced value-added techniques. These innovations aim to enhance quality, reduce post-harvest losses, and create high-value markets, aligning with GVCs and GCCs in the context of globalisation. The Schumpeterian growth model provides an alternative perspective.

R&D investment requirements are enormous, with an estimated cumulative global R&D spending under balanced growth at $2.276 trillion (2015 PPP dollars) (Beckman et al., 2024). While increased R&D expenditures lead to higher TFP growth, R&D also boosts productivity and is regarded as an essential element for sustaining agricultural productivity worldwide (Beckman et al., 2024). As indicated by Beckman et al. (2024), without additional R&D investment beyond 2016 levels, TFP growth will be insufficient to meet the projected global food demand for corn, rice, soybeans, and wheat by 2050.

This may disrupt existing practices and markets by offsetting climate-induced yield declines and rising consumption needs. New product innovations can reduce demand for products that fail to evolve and remain in their raw forms, impacting the agricultural sector's structure. The increasing rate of urbanisation, coupled with changing product demands by urban dwellers, could influence demand and supply response. The broader literature also suggests that there is a time lag for innovations emanating from R&D investments to manifest in increased agricultural output productivity (see e.g. Beckman et al., 2024; Rawat, 2020). This corroborates the temporary negative impact in our study and hence a rejection of H8 before the long-term projection as shown in the outcome of the local projections (see Table 6.6).

The above outcome is crucial in understanding the long-term horizons in R&D investments, which have been shown to evolve from the long-term nature of technology innovations coupled with volatility and uncertainty effects (Beckman et al., 2024; Cai et al., 2017). Therefore, to achieve the desired long-term results of R&D investments, there is a need for consistency and stability of investment expenditure (Rawat, 2020). This is evident from global R&D investment trends in agriculture from China, United States of America, Europe, India and Brazil (Nelson & Fuglie, 2022). It has been shown by Beckman et al. (2024) that TFP growth depends on R&D source and region. In particular, public R&D in developed countries is shown to have a longer lag (up to 50 years) but higher productivity impact while private R&D investments have shorter lags (peaking at 10 years) and are more adaptive, especially in developing regions. The responsiveness also varies by region. Developed countries show higher responsiveness, while Sub-Saharan Africa shows lower responsiveness (Beckman et al., 2024).

Our empirical findings also indicate a negative relationship between financial development and agricultural output value added in model 1, though this is statistically insignificant. However, when the control variables were included (model 2) and global integration (GI) was decoupled (model 3), we observed a positive but statistically insignificant association between financial development and agriculture value-added, similar to the findings of Asongu and Odhiambo (2022a) hence a rejection of H9 that financial development significantly and positively enhances the value added of agriculture in Africa.

The negative outcomes of financial development in models 1, 4, and 5 of Table 6.5 can be explained within the endogenous growth framework. An emphasis on financial development may have redirected resources away from the agricultural sector to other sectors of the economy, thus diminishing agricultural output. It is also a sign of poor financial depth, as it directly affects the sector. The positive but statistically insignificant outcomes in models 2 and 3 of Table 6.5 suggest that, despite resource allocation in the financial sector, it may need to translate more effectively into increased agricultural productivity. The sector may be under-financed or is not attracting the right financing. Inefficient fund allocation and a lack of financial inclusion may have also contributed to this outcome. Even with the significant contribution of agriculture to the real sector of African economies, the agriculture sector should have received a relative measure of reciprocal investment from the financial system.

The study also reveals a positive but statistically insignificant connection between globalisation and output value added in empirical models 1, 2 and 4 of Table 6.5, suggesting that while Africa has become more interconnected with the global economy, agriculture value added has yet to benefit significantly from this increased globalisation. Enhanced competition in the global market may explain this lack of substantial impact on agriculture value added. It underscores Africa's position in terms of global socio-economic competitiveness in the agricultural sector. This empirical finding thus fail to confirm the hypothesis H10 that globalisation will have a significant positive impact on agriculture value added in Africa.

To capture a more detailed impact of globalisation on agriculture value-added, we disaggregated the global integration data into two important components: global trade and global financial integration. Our findings show a negative and statistically insignificant impact of global trade and financial integration on agriculture value added. This suggests that despite access to global markets and financial integration, Africa's agriculture sector has yet to benefit positively from these developments. The findings fit into the GVCs' proposition that countries well-positioned in the global value chain will earn good profits to the detriment of poorly positioned countries. The latter is the case in Africa, per the empirical findings. Both trade and financial globalisation have been detrimental to the value addition in agriculture.

As a result, low-income countries often remain stuck at the lower ends of GVCs, exporting raw commodities while missing out on higher returns. This imbalance is intensified by the dominance of multinational agribusinesses and the increasing emphasis on quality, safety, and environmental standards, which create barriers for smallholder farmers lacking resources and technical support (Greenville et al., 2019), further confirming the rejection of H10.

Juxtaposing the current findings with the GCC concept, African governments lack the dynamism to position the agriculture sector to benefit from the opportunities associated with value addition in the agriculture sector on the global stage. There appears to be a significant competitive disadvantage in Africa's value-added products, hindering their ability to compete effectively with products from other countries in the global market space. As posited by the

GCC concept, the competitiveness of products in the global value chain relies more on the merit of the output and not just the stature of the country of origin. This is in Africa's interest, particularly in terms of agriculture value-added products that can compete effectively on pricing, design, and quality within the value chain. Even so, some weak international investment and regulatory policies in Africa might have altered the power dynamics and given undue advantage to global competitors to exploit in the global interconnected market.

Competitiveness in the global market depends on other domestic factors, such as the cost of production, development of physical infrastructure, and economic and political commitments, for effective transformation (FAO, n.d.). Globalisation has reshaped agricultural production by speeding up the spread of technology and expanding markets, but its benefits critically rely on investments in agricultural research and development (R&D). Cost reduction, the main driver of competitiveness, increasingly comes from technological innovation, making strong national research systems and connections to global science vital. Low-income countries that underinvest in R&D face falling incomes as global prices decline due to innovations elsewhere, a trend especially evident in Africa’s experience with crops like oil palm, cocoa, and coffee (FAO n. d). Conversely, countries that enhance research capacity and promote public–private collaboration are better suited to diversify into high-value commodities (value-added goods), lower production costs, and foster rural development. Therefore, globalisation amplifies the returns to R&D. While innovators gain through productivity improvements and trade opportunities, non-innovators risk becoming trapped in subsistence farming and facing increased food insecurity (FAO, n.d.). It is therefore apparent from both the perspectives of GVCs and GCCs theories that our empirical outcome reflects the ineffective strategic positioning of African agriculture in the fiercely and rapidly integrating global markets, and potentially, underinvestment in agricultural R&D.

From the perspective of financial integration, it is apparent that the global integration of African financial markets has yet to yield positive gains for the agricultural sector. The results indicate that financial development in African countries has not significantly affected agriculture production. The sector will need better positioning to attract financial support from within the countries. It could also be due to the sector's perceived risk of several external and environmental shocks. As indicated by Jiya et al. (2020), the ability of countries to reap the positive benefits of integration relies significantly on endogenous factors in the integrating country. These could range from physical infrastructure to other supportive or enabling factors.

Concerning the control variables, we found no statistical significance in the relationships between GDP per capita growth, regulatory quality, and agriculture value added. Real GDP per capita growth showed a positive relationship, while regulatory quality exhibited a negative one. Indeed, policies concerning agriculture in Africa have little impact, though statistically insignificant. Economic significance-wise, they may have a lasting negative impact. These findings contribute to understanding the complex relationships within this multifaceted context.

To provide a vivid perspective of the effects of innovation and financial development, we estimated the interactive effects between financial development and agriculture innovation on one hand and then financial development and trade integration on the other in a series of regression analysis. These can be observed from models 4 and 5 in Table 6.5 and Table D.6.7 in Appendix. These interaction outcomes were compared to select the best model based on the AIC and BIC calculated by hand using the mathematical formulae by Pardoe (2020) shown by A1.6.10 and A2.6.11 respectively in the Appendix. From the AIC and BIC statistics, models 4 and 5, represented in Table 6.5, were the best suited for the data in the interactive regression analysis since they produced the least AIC and BIC under the two categories of estimations (see Table D.6.7 in the Appendix for other models). Hence, for our interactive empirical analysis, we focused only on models 4 and 5 shown in Table 6.5. It can be observed from model 4 that the combined effect of financial development and agriculture innovation (FDINN) has no significant statistical influence on agriculture value added though positive relationship pertains. The following reasons could account for this outcome: lack of access to capital for innovation, poor technological adoption, high risk perception and the inadequacy of de-risked innovative agriculture projects fit for private financing. Notwithstanding, these and other opportunities such as value chain integration of innovative practices from production processing, and distribution remain for more efficient and sustainable outcomes for farmers and all actors in the value chain.

Interestingly, the interaction effects between financial development and trade integration (FDTGR), as shown in empirical model 5 of Table 6.5, reveal a significant positive influence on agriculture value added at the 5 per cent alpha level. Clearly, this can create synergies that enhance the productivity, competitiveness, and sustainability of agricultural trade, leading to broader economic benefits for producers (farmers), entrepreneurs (traders), and final consumers. These are possible through improved and enhanced access to trade finance, allowing producers and exporters to obtain the necessary funds for international trade. It could also facilitate investment in export infrastructure, such as storage facilities and transportation, to boost agriculture trade and deepen economic integration.

As a risk mitigation tool, enhanced financial development can manage risks associated with currency exchange rate volatilities and uncertainties, encouraging agriculture value chain actors to actively do business in the global market. Other possible synergies include supply chain financing and investment in export-oriented technologies to enhance the quality, safety and competitiveness of processed and raw agricultural products in the international market.

Another important aspect of synergy is trade insurance, which is in the form of trade credit guarantees. If harnessed well, it will have significant positive implications for the agriculture sector in Africa.

The estimated DCCEMG models, as shown in models 1 to 5 of Table 6.5, are statistically fit judging from the F-statistic. The mean group R-squares are also relatively high across all the models. The Pesaran (2015) cross-sectional dependent test statistic's post-estimation test shows no presence of CSD in the empirical estimations. Also, the heteroscedasticity is robustly modelled by the DCCEMG estimator because the variance/covariance estimator depends on the difference between the individual and the mean group estimates.

Table 6.5: DCCE-MG Empirical Results

				Interaction Effects	
Mean Group	1	2	3	4	5
AVA_1	0.2049***	0.2678***	0.1927***	0.1038*	0.1296**
	(0.0577)	(0.0808)	(0.0514)	(0.0629)	(0.0625)
INN	-2.6705**	-1.6687*	-2.8404***	-17.3122*	-2.1269***
	(1.0703)	(0.9022)	(0.8975)	(9.2134)	(0.7456)
FD	-5.2669	14.5346	32.7016	-87.55787	-23.4332**
	(15.7011)	(15.6533)	(21.8032)	(71.4540)	(12.9898)
GI	0.0621	0.131		0.0383	
	(0.0826)	(0.1287)		(0.0911)	
FDINN				164.1232	
				(106.661)	
TRGI			-0.0534		-0.6834**
			(0.0330)		(0.3290)
FIGI			-0.0151		-0.0500
			(0.0689)		(0.0897)
FDTGR					7.2921**
					(3.4574)
REGQ		-0.1681	-2.9394		
		(1.5529)	(2.0510)		
GDP_{pc}		0.0613	0.0565		
		(0.0605)	(0.0725)		
Con	-19.7516	-21.6360	-2.2646	-2.9394	-31.5430
	(20.2284)	(22.5433)	(19.2516)	(22.5137)	(32.0970)
F-statistic	1.22	1.55	1.55	1.2	1.22
Prob > F	0.020	0.000	0.000	0.05	0.02
R-squared	0.47	0.20	0.11	0.39	0.29
R-squared (MG)	0.74	0.83	0.87	0.76	0.8
CD Statistic	1.07	-0.86	-1.24	0.76	0.4
Prob > CD	0.2846	0.3904	0.2052	0.4473	0.6915
AIC	-	-	-	97.158	-302.971
BIC	-	-	-	125.494	-269.912
No. Obs.	841	662	647	831	831

Source: Author's estimation.
Notes: The dependent variable is AVA. Values in brackets are standard errors. ***, **, and * are significant at 0.01, 0.05, and 0.0 significance levels, respectively. MG is mean group. The CD statistic is the Pesaran (2015) cross-sectional dependent test statistic. Both AIC and BIC were manually calculated following Pardoe (2020), as shown in Appendix 2. The DCCEMG model was estimated using the STATA command xtdcce2 by Ditzen (2018).

6.5.5 Local Projections

To further understand the long-term relationship trajectory between agricultural R&D expenditure and output value-added, we employed Jorda's (2005) local projections approach. This approach projects the long-term impact of the impulse variable, here referred to as R&D investments, on the response variable represented by agriculture output value-added, which is shown in Table 6.6 and illustrated graphically in Figure C.6.1 in the Appendix. The IRF from the LP reveals an adverse effect within the first two years of the shock, followed by a positive effect, with the most substantial positive effect occurring in the fourth year after the impulse. The findings here are also robust to cross-sectional dependence since the DCCEMG estimator was applied to estimate the local projections. The empirical outcome of the local projections emphasises the central role and long-term impact of investments in innovation as a catalyst for driving economic growth, as posited by the endogenous growth models of Romer (1986, 1990) and Schumpeter (1942). The declining effect observed after the fourth year is likely due to diminishing returns from continued R&D investments.

Notwithstanding, impacts vary by region. For instance, while developed regions (e.g., North America, Europe) leverage high funding and infrastructure to drive yearly productivity growth, focusing on precision agriculture and high-value crops, developing regions (e.g., Sub-Saharan Africa) invest little of their agricultural GDP, limiting value-added growth despite agriculture's large GDP share, hindered by weak extension and infrastructure (www.ers.usda.gov). Emerging economies (e.g., China, Brazil) see substantial annual gains from growing R&D, but face uneven benefits and environmental challenges. China, however, is the largest global investor in agricultural R&D (spending over $10 billion annually), followed by the European Union, the United States, India and Brazil (Nelson & Fuglie, 2022).

Regional differences stem from funding, adoption rates, R&D focus, and local conditions like infrastructure and policy.

Table 6.6: Five-year horizon of Impulse Responses

Years after impulse	IRF	Std. Err.	IRF LOW	IRF UP
0	-2.6907	0.8084	-2.6907	-2.6907
1	-1.7320	0.9774	-1.7320	-1.7320
2	0.3330	0.6722	0.3330	0.3330
3	1.2459	0.9602	1.2459	1.2459
4	1.9052	1.1795	1.9052	1.9052
5	1.5622	1.4754	1.5622	1.5622

Source: Author’s estimation.
The method used in the LP model is the DCCEMG estimator.

6.6 Summary, Conclusion and Recommendations

The chapter examined the impact of agriculture R&D investments, globalisation, and domestic financial developments on agriculture value added in Africa across 48 countries over twenty years. Our findings reveal that while R&D investments affect agriculture value added negatively in the immediate term, positive and enduring effects emerge after two years, peaking in the fourth year. The empirical results further indicate that global integration has a positive but insignificant influence on agriculture value added. However, disaggregating the global integration data into trade and financial integration components, we again find a negative and insignificant impact on agriculture value added. These empirical insights underscore the necessity for sustained investments in agriculture R&D to drive technological advancements, particularly in value addition, given agriculture's substantial contribution to African economies. Long-term benefits also require patient capital and unwavering financial commitment to the sector, which is pivotal to the economies of African countries. In this regard, agricultural innovations across the entire value chain will improve the sector.

The empirical evidence of agricultural value-added and global trade/financial integration signals Africa's inability to leverage positive synergies, resulting in the underutilisation of available endowments. This points to the potential deepening of global inequality as less competitive products struggle amid stiff competition. The empirical evidence further indicates that domestic financial development alone has been unfavourable to agricultural value added in Africa, possibly due to perceived risks, market volatility, and other contributing factors. Notwithstanding, the combined effect of financial development and trade integration offers significant positive outcomes for more robust and deeper agriculture trade financing and integration among African countries. Intentional and progressive funding of this crucial real sector of African economies must be considered. Whereas R&D investments in the agriculture sector provide significant long-term benefits, globalisation has yet to influence the sector significantly.

In response, African countries must cautiously deepen global integration by implementing internal strategies that provide advantages to local agriculture production and value addition to secure a competitive advantage. Addressing the financial sector challenges also requires risk mitigation for farmers, investments in rural infrastructure, improved market access, and incentivising financial institutions to extend the needed credit to the sector. These measures will go a long way to bolster the sustainability and growth of the agriculture sector in Africa, aligning with the imperatives highlighted in this current research.

CHAPTER SEVEN

SUMMARY, CONCLUSION AND RECOMMENDATIONS

7.1 Summary and Conclusion

The socio-economic prosperity of the African continent largely rests on agriculture's contributions to employment creation, poverty alleviation, and overall GDP contribution. Notwithstanding, the sector faces numerous challenges, the key being underinvestment amidst a growing environmental uncertainty. In this thesis, we relied on a broad array of rich data to explore the contribution of traditional and alternative finance and investments in driving sustainable agricultural production in Africa in four empirical chapters.

The first empirical chapter examined the green efficiency of African agriculture using the slacks-based measure data envelopment analysis with undesirable outputs. The results indicate that agricultural productivity in Africa is green inefficient at an average rate of 66%. The inefficiencies are driven primarily by resource misallocation, resulting in unsustainable input intensification involving land, labour, fertiliser, irrigation water and pesticides and secondarily by high pollution levels from unfriendly environmental production practices. These have specific financial consequences on farmers and economies in general. The precise optimal rates of inputs, output, and agricultural emissions levels required to achieve agricultural green efficiency were estimated to guide practice and policy.

The second empirical chapter of the thesis studied the influencing factors of agricultural green efficiency in Africa using a two-staged econometrics approach. The empirical results reveal that effective investments in agricultural innovation, prudent government budget allocation to agriculture, agricultural aid, sustainable fiscal policies, and environmental management practices significantly and positively influence agricultural green efficiency. Conversely, urbanisation poses a significant threat to sustainable agriculture productivity.

In our third empirical chapter, we studied the complex dynamics of agriculture output value, domestic credit, foreign direct investment in agriculture, food price anomalies, and sustainable agriculture practices in Africa by employing the panel vector autoregressive model. Significant interdependencies were found among these variables. In particular, agriculture output value has a one-way transmission effect on domestic credit, FDI, and sustainable farming practices. On the contrary, bi-directional causality was found between food price variation and output value, FDI and domestic credit, as well as FDI and sustainable farming. The latter signifies the environmental sustainability effect of FDI on agriculture production in Africa, supporting the pollution halo hypothesis. Our empirical evidence also shows the causal effect between food price anomalies and agricultural output, with associated implications on poverty and hunger. Strikingly, we observe a two-way signalling effect between domestic credit and FDI on agriculture production in Africa, indicating a mirroring effect of both financial investment sources on each other. However, the pull factor of domestic credit is larger. Thus, to attract foreign capital to the agriculture sector in Africa, the domestic credit market must lead the way.

In our final empirical chapter of the thesis, we examined the multivariate effects of agriculture R&D investment, globalisation, and financial development on agriculture value added in Africa. The evidence indicates that although the short-term effects of agriculture R&D investments on agriculture value added are negative, there are significant positive impacts in the long term. The research findings further indicate that despite the widespread adoption of globalisation, the value added to agriculture has not seen any significant boost. This highlights the need for a more targeted approach that can align the benefits of globalisation with the specific requirements of agricultural practices. We must take proactive measures to enhance the positive impact of globalisation on agriculture and to generate sustainable growth and development in this crucial sector.

7.2 Policy Recommendations

Based on the thesis's empirical outcomes, we offer the following recommendations to guide agricultural policy and practice.

Public sector agriculture interventions must be carefully done with prior insights into their resource allocation efficiency and sustainable environmental consequences to curb resource wastage and promote green productivity. Efficient resource allocation leads to higher productivity. Properly managed land, water, and labour result in larger crop yields and increased productivity, ensuring food availability and reducing hunger. Optimal resource use directly impacts food security. Africa's population growth demands more food production, which can be met through the efficient allocation of production resources to enable an adequate food supply. From an economic perspective, improved productivity directly translates to higher farmer welfare. This is manifested in the form of improved incomes, reduced poverty, and empowerment of smallholders and rural communities. Environmentally efficient resource use minimises waste and environmental pollution and improves biodiversity for future generations. It thus aids farmers to adapt to climate change through practices like agroecology to enhance resilience. The implementation of this recommendation has financing implications. Therefore, it could mean that governments would have to trade off other expenses to allocate more resources to the agriculture sector as a way of prioritising it. Since African countries are essentially and highly budget-constrained, it could also mean that governments might have to resort to debt as a means of closing the financing gap. This can result in exacerbating the already existing debt burden faced by African countries.

Financial investments in agriculture must be a priority of African governments through effective fiscal policies to drive sustainable urban agriculture, mechanisation, and technological transformation through innovation. These are essential to driving food security, creating jobs, improving climate adaptation, and managing resources. Investments in the sector will also enhance local production, reducing import dependence. This will reduce the pressure on foreign exchange demand and promote a healthy exchange rate system within African countries. Per the Malabo Declaration, African countries pledged to allocate and invest at least 10% of their national expenditure budgets to agriculture production and transformation to alleviate poverty and hunger on the African continent. However, as it stands, the pledge has been honoured only in parts. Indeed, such strategic investments are more crucial now than ever to meet the growing demand for food on the continent and globally to curtail global hunger and prevent starvation. This requires high dedication to financing the sector, which could lead to fiscal policy and budgetary allocation trade-offs.

The domestic private credit market must lead in agriculture financing to attract foreign capital and augment the capital requirement of the sector. To augment public funding, private sector funds are vital to drive efficiency in applying funds and successful implementation of agricultural projects. Our findings indicate that domestic private sector financial support is critical in augmenting governmental interventions. More especially, domestic private capital financing provides a strong signal for attracting foreign capital to the sector. Therefore, the necessary policy guidelines and environment must be created to position the agriculture sector well enough to attract the required domestic private financing. A possible challenge to implementing this recommendation is the existing risk perception of the sector, which is reflected in the low credit disbursement to the sector. Until the existing agriculture financing frameworks in Africa, such as GIRSAL, are fully scaled up to cover a high proportion of farmers, private-sector financing of the sector will remain a significant challenge.

African governments must implement measures to safeguard the price exposure of farmer outputs to grow and sustain agricultural production. Some of these measures could include food buffer systems to buy agricultural produce during bumper seasons and subsequent availability of storage facilities to keep the produce in safe and wholesome condition. Processing and value-added chains should also be enhanced and encouraged to prevent glut, which frustrates existing farmers and discourages potential ones. Developing well-functioning value chains will also help reduce waste and enhance value within the supply chain. Risk management practices, such as insurance, must be encouraged among producers, aggregators, processors, and all actors in the food value chain to build resilience and reduce uncertainty. These will stabilise prices and improve market efficiency to the benefit of consumers. It will also guarantee stable producer prices for farmers to better plan and forecast. However, one major possible hindrance to these is the high market volatility in Africa due to poor infrastructure (e.g., inadequate storage, weak value chains) and external shocks (e.g., climate variability, global price fluctuations).

African countries must cautiously deepen global integration by implementing internal strategies that align with their respective competitive advantages in agriculture production and value addition. Cautious integration is necessary to maximise the benefits while minimising potential risks and negative impacts. This will enable Africa to maintain economic stability, environmental protection, and regulatory readiness. Additionally, it will offer opportunities for learning, adaptation, and building strong international relationships. By integrating cautiously, African countries can navigate the complexities of globalisation in a way that promotes sustainable and inclusive development.

While all policy recommendations are vital for the growth and transformation of Africa's agriculture sector, urgent steps are first needed to align public sector investments with agriculture's potential and to encourage private sector-led investments. These align closely with the renewed goal of the CAADP of the African Union, which aims for a holistic transformation of agriculture in Africa by 2036.

7.3 Direction for Further Research

Given the outcomes of the thesis, we propose the following to guide future research.

Other agricultural input factors and practices specific to small-holder farmers in Africa could be explored in addition to the ones used in this thesis to estimate the agricultural green efficiency in Africa. This will offer an extended understanding of sustainable agricultural systems for resilient and productive agriculture that benefits both the environment and society.

Future studies can also consider the geospatial dynamics of African countries' finance and investment decisions regarding sustainable agriculture production. Geospatial econometrics play a crucial role in comprehending the intricate spatial dynamics of agricultural systems, maximising resource efficiency, evaluating environmental effects, and facilitating the establishment of harmonised, sustainable and just agricultural practices and policies.

A comprehensive analysis of the agriculture value proposition and its influence on bridging agriculture financing will significantly contribute to the existing literature. A comprehensive research analysis of the agriculture value proposition is essential to identify opportunities for efficiency, sustainability, and profitability, ensuring informed decision-making, optimising resource use, enhancing market competitiveness, addressing environmental impacts, and promoting equitable economic growth within the agricultural sector in Africa.

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APPENDICES

Table A.3.6: Green Agricultural Efficiency Scores

Country	Years																				Ave.	SD	#Eff
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019			
Algeria	0.65	0.70	0.76	1.00	0.78	0.96	0.88	0.87	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00	0.97	0.98	1.00	0.93	0.11	10
Angola	1.00	1.00	0.82	0.78	0.59	0.66	0.59	0.61	0.54	0.55	0.60	0.58	0.61	0.63	0.52	0.49	0.44	0.48	0.40	0.39	0.61	0.17	2
Benin	0.69	0.70	0.65	0.83	1.00	0.83	1.00	1.00	1.00	0.71	0.63	0.82	0.61	0.75	0.82	0.86	0.65	1.00	0.54	0.57	0.78	0.16	5
Botswana	0.37	0.33	0.31	0.35	0.35	0.34	0.33	0.33	0.33	0.32	0.31	0.34	0.33	0.32	0.31	0.31	0.30	0.28	0.31	0.30	0.32	0.02	0
Burk. Faso	0.35	0.49	0.50	0.38	0.42	0.36	0.37	0.37	0.41	0.40	0.41	0.41	0.42	0.44	0.46	0.43	0.43	0.45	0.48	0.49	0.42	0.04	0
Burundi	0.80	0.84	1.00	1.00	1.00	1.00	1.00	0.86	0.79	0.81	0.64	0.62	0.61	0.63	0.61	0.67	0.64	0.69	0.56	0.54	0.77	0.17	5
C. Verdi	1.00	1.00	1.00	1.00	0.98	1.00	0.96	1.00	0.95	0.96	0.96	1.00	0.99	1.00	1.00	0.99	0.97	1.00	1.00	1.00	0.99	0.02	12
Cameroon	0.37	0.37	0.37	0.39	0.38	0.40	0.41	0.46	0.54	0.54	0.55	0.55	0.57	0.60	0.63	0.55	0.57	0.57	0.62	0.63	0.50	0.10	0
C. Africa Rep.	0.80	0.81	1.00	1.00	0.83	0.82	0.81	1.00	1.00	1.00	1.00	0.91	1.00	1.00	1.00	0.87	0.88	0.93	1.00	1.00	0.93	0.08	11
Chad	1.00	1.00	0.88	0.83	0.79	0.78	0.77	0.50	0.70	0.72	1.00	0.78	1.00	0.94	0.97	0.55	0.68	0.65	0.70	0.70	0.80	0.15	4
Comoros	1.00	0.96	0.95	0.96	0.95	0.96	0.95	1.00	0.98	1.00	0.97	0.99	0.99	0.98	1.00	1.00	0.99	1.00	1.00	1.00	0.98	0.02	8
Congo	1.00	0.82	0.74	0.59	0.74	1.00	1.00	1.00	0.85	0.77	1.00	1.00	0.91	1.00	1.00	1.00	1.00	0.98	0.99	1.00	0.92	0.12	11
Cote d'Ivoire	0.39	0.39	0.39	0.41	0.40	0.41	0.41	0.43	0.50	0.52	0.58	0.61	0.58	0.59	0.61	0.60	0.61	0.64	0.67	0.69	0.52	0.11	0
D. Rep. Congo	1.00	0.91	0.89	0.89	0.90	1.00	0.87	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.91	0.92	0.95	0.93	1.00	1.00	0.96	0.05	10
Djibouti	1.00	0.98	1.00	1.00	1.00	1.00	1.00	0.99	0.99	1.00	0.98	1.00	0.98	1.00	0.98	0.99	0.98	0.97	0.99	1.00	0.99	0.01	9
Egypt	0.71	0.67	0.67	0.62	0.64	0.68	0.71	0.77	0.84	0.84	0.89	0.93	1.00	1.00	0.95	1.00	0.86	0.77	0.78	1.00	0.82	0.13	4
Eritrea	0.37	0.41	0.44	0.58	1.00	0.58	1.00	0.58	0.58	0.60	1.00	0.77	0.73	0.68	0.67	0.62	0.63	0.63	0.54	0.54	0.65	0.18	3
Eswatini	0.59	0.60	0.60	0.59	0.59	0.61	0.62	0.62	0.65	0.65	0.62	0.62	0.63	0.63	0.63	0.64	0.63	0.63	0.63	0.63	0.62	0.02	0
Ethiopia	0.33	0.32	0.32	0.35	0.34	0.38	0.39	0.45	0.49	0.48	0.45	0.46	0.49	0.51	0.51	0.50	0.50	0.50	0.48	0.49	0.44	0.07	0
Gabon	1.00	1.00	0.56	0.65	0.55	0.50	0.50	0.49	0.48	0.48	0.67	0.53	0.48	0.47	0.46	0.43	0.43	0.42	0.43	0.42	0.55	0.17	2
Gambia	0.73	0.76	0.78	0.49	0.50	0.49	0.46	0.48	0.61	0.53	0.52	0.46	0.74	1.00	0.97	1.00	0.96	1.00	0.50	0.50	0.67	0.21	3
Ghana	0.44	0.41	0.45	0.44	0.46	0.54	0.50	0.54	0.58	0.56	0.58	0.63	0.60	0.61	0.63	0.60	0.67	0.62	0.66	0.64	0.56	0.08	0
Guinea	0.44	0.44	0.46	0.49	0.46	0.45	0.45	0.44	0.44	0.50	0.45	0.39	0.40	0.40	0.45	0.46	0.40	0.35	0.39	0.39	0.43	0.04	0
G. Bissau	0.37	0.35	0.36	0.35	0.36	0.38	0.38	0.41	0.44	0.42	0.43	0.44	0.44	0.43	0.40	0.40	0.39	0.40	0.41	0.41	0.40	0.03	0

Source: Author's estimation.

Notes: SD is standard deviation; #EFF means number of efficient times; Ave. is average. Optimum efficiency score is 1.00

Table A.3.6 Continued: Green Agricultural Efficiency Scores

Country	Years 2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Ave.	SD	#Eff
Kenya	0.50	0.37	0.37	0.37	0.38	0.42	0.43	0.45	0.48	0.48	0.49	0.49	0.54	0.53	0.55	0.56	1.00	0.83	0.86	1.00	0.55	0.20	2
Lesotho	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.91	0.84	0.83	0.91	0.90	0.94	1.00	0.87	0.87	1.00	0.95	0.06	11
Libya	1.00	1.00	1.00	1.00	0.93	0.90	0.89	1.00	0.96	0.85	0.89	1.00	0.92	0.88	0.93	1.00	0.96	0.93	1.00	1.00	0.95	0.05	9
Madagascar	0.36	0.37	0.38	0.37	0.37	0.35	0.38	0.41	0.40	0.47	0.43	0.41	0.38	0.39	0.37	0.36	0.37	0.35	0.35	0.35	0.38	0.03	0
Malawi	0.39	0.42	0.38	0.38	0.39	0.38	0.41	0.45	0.50	0.64	0.60	0.62	0.61	0.63	0.86	0.67	0.62	0.68	0.74	1.00	0.57	0.17	1
Mali	0.42	0.39	0.39	0.41	0.39	0.41	0.40	0.40	0.48	0.56	0.52	1.00	1.00	0.87	0.76	0.72	0.88	0.94	1.00	0.96	0.64	0.25	3
Mauritania	0.60	0.60	0.86	0.86	0.54	1.00	0.92	0.70	0.66	0.84	0.60	0.67	0.63	0.63	0.63	0.62	0.63	0.61	0.62	0.62	0.69	0.13	1
Mauritius	0.67	0.72	0.67	0.73	1.00	0.89	0.85	0.83	1.00	0.88	1.00	1.00	0.96	1.00	0.94	0.94	0.90	1.00	0.99	1.00	0.90	0.12	7
Morocco	0.45	0.46	0.46	0.49	0.50	0.48	0.50	0.49	0.52	0.53	0.52	0.53	0.52	0.53	0.52	0.51	0.51	0.51	0.52	0.51	0.50	0.02	0
Mozambique	0.42	0.39	0.39	0.46	0.42	0.51	0.42	0.44	0.43	0.43	0.37	0.41	0.45	0.38	0.35	0.38	0.36	0.36	0.47	0.43	0.41	0.04	0
Namibia	0.76	0.76	0.46	0.59	0.49	0.55	0.50	0.53	1.00	0.60	0.45	0.41	0.34	0.34	0.40	0.33	0.32	0.34	0.34	0.33	0.49	0.18	1
Niger	0.50	0.68	0.62	0.68	0.69	0.72	0.73	0.76	1.00	1.00	0.91	0.89	0.81	0.83	0.84	0.84	0.87	0.90	1.00	1.00	0.81	0.14	4
Nigeria	0.79	0.80	0.91	0.82	0.88	0.87	1.00	1.00	1.00	0.77	0.80	0.86	0.86	0.88	1.00	0.94	0.83	0.77	0.77	0.78	0.87	0.08	4
Rwanda	0.95	1.00	0.65	0.64	0.68	0.66	0.70	0.70	0.72	1.00	1.00	1.00	1.00	1.00	0.72	0.69	0.72	0.80	0.70	0.71	0.80	0.15	6
Senegal	0.34	0.35	0.33	0.36	0.35	0.38	0.47	0.48	0.48	0.44	0.42	0.42	0.40	0.39	0.41	0.41	0.39	0.43	0.47	0.47	0.41	0.05	0
Seychelles	0.62	0.66	0.66	0.71	0.95	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.88	1.00	0.89	0.92	0.92	0.91	0.13	11
S. Leon	1.00	1.00	0.88	0.71	0.64	0.69	0.53	0.61	0.61	0.58	0.56	0.48	0.54	0.72	1.00	0.66	0.47	0.46	0.43	0.40	0.65	0.19	3
S. Africa	0.62	0.62	0.63	0.70	0.74	0.80	0.81	0.86	0.91	0.93	1.00	1.00	1.00	0.97	1.00	0.90	0.89	0.96	1.00	0.98	0.87	0.14	5
Tanzania	0.36	0.41	0.35	0.35	0.35	0.35	0.36	0.35	0.38	0.36	0.36	0.35	0.50	0.53	0.56	0.55	0.52	0.54	0.75	1.00	0.46	0.17	1
Togo	0.42	0.44	0.48	0.45	0.54	0.79	1.00	1.00	1.00	0.64	0.52	0.59	0.64	0.58	0.80	0.64	0.53	0.63	0.65	0.64	0.65	0.18	3
Tunisia	0.51	0.51	0.52	0.55	0.54	0.55	0.56	0.56	0.58	0.57	0.56	0.59	0.59	0.61	0.61	0.62	0.59	0.60	0.62	0.61	0.57	0.03	0
Uganda	0.55	0.58	0.54	0.51	0.52	0.57	0.53	0.53	0.42	0.45	0.47	0.47	0.45	0.43	0.46	0.47	0.45	0.44	0.40	0.40	0.48	0.05	0
Zambia	0.33	0.32	0.31	0.31	0.31	0.24	0.26	0.24	0.26	0.27	0.31	0.32	0.33	0.33	0.34	0.33	0.34	0.35	0.35	0.35	0.31	0.04	0
Zimbabwe	0.31	0.31	0.31	0.31	0.32	0.32	0.30	0.30	0.31	0.30	0.26	0.27	0.30	0.27	0.30	0.35	0.35	0.35	0.31	0.31	0.31	0.02	0

Source: Author's estimation.

Notes: SD is standard deviation; #EFF means number of efficient times; Ave. is average. Optimum efficiency score is 1.00

Figure A.5.3: Quantile Plots

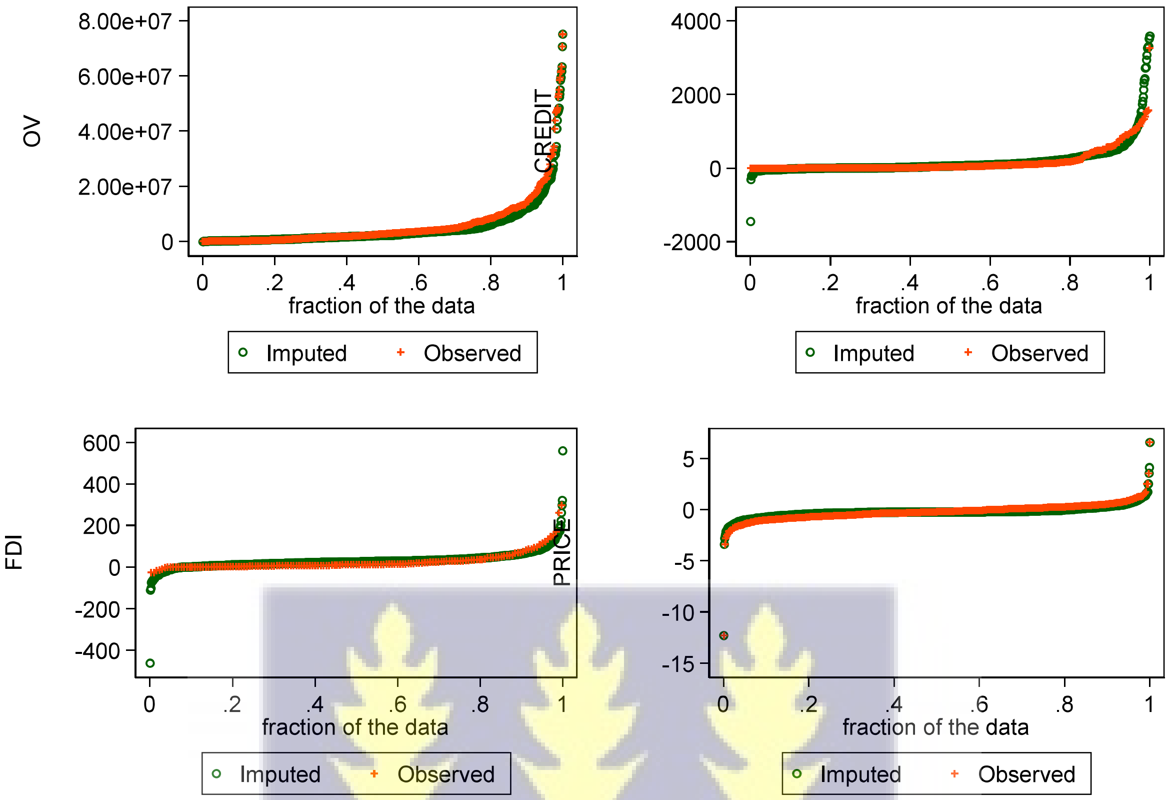


Figure B.5.4: Kernel Densities

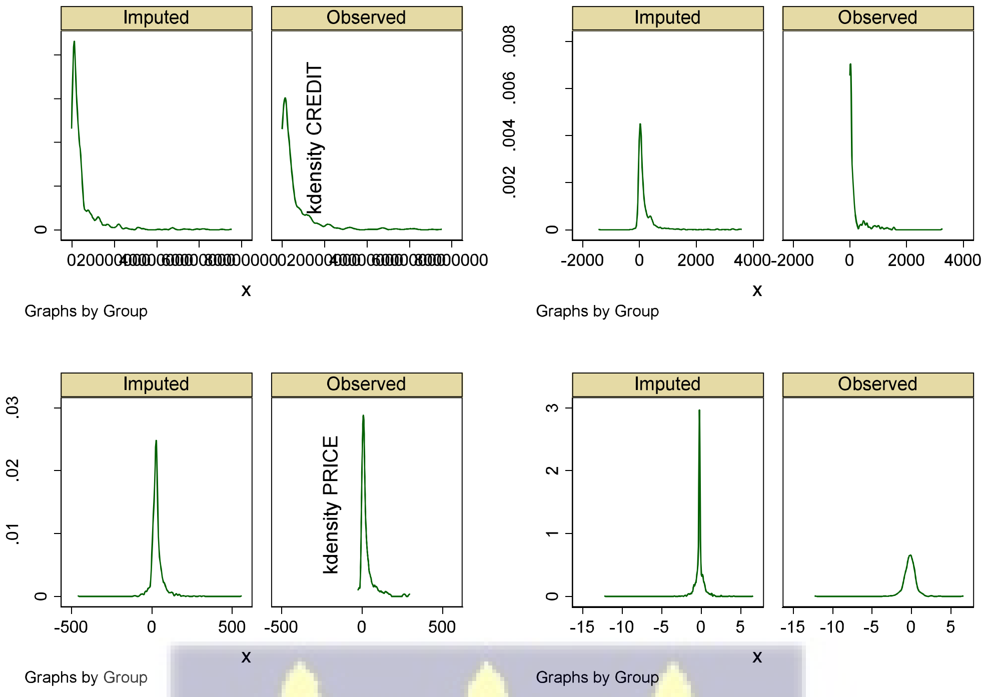


Table B.5.8: Variance Information to Multiple Imputation

	Imputation variance			RVI	FMI	RE
	Within	Between	Total			
OV	0.0026	0.0042	0.0068	1.6015	0.6172	0.9967
CREDIT	0.0001	0.0008	0.0009	7.1179	0.8778	0.9954
FDI	0.0001	0.0011	0.0012	11.3198	0.9196	0.9951
PRICE	0.0002	0.0008	0.0010	3.9445	0.7991	0.9958

Source: Author's estimations.
Notes: RVI is relative variance increase, FMI stands for fraction of missing information as a result of imputation, RE means relative efficiency.

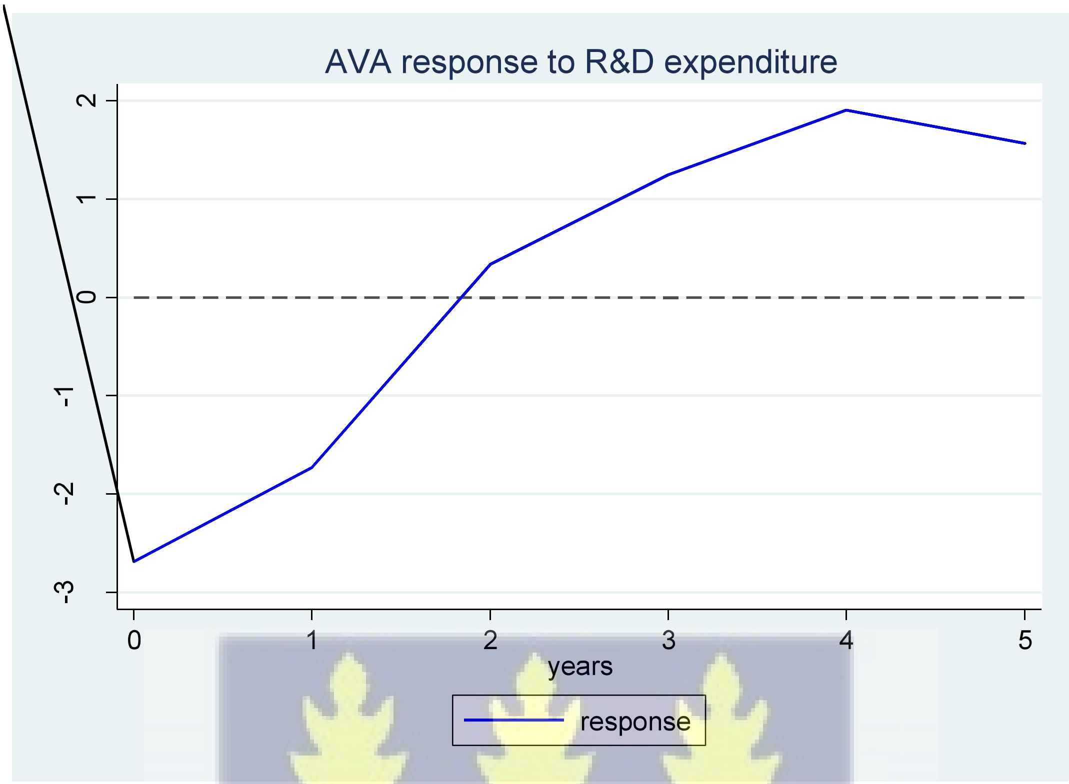
Table C.5.9: PVAR GMM Estimates

	Coefficient	Std. err.	z	P>z
LNOV				
$LNOV_{t-1}$	.5323051	.1205246	4.42	0.000
$LNCREDIT_{t-1}$	-.0396615	.0253454	-1.56	0.118
FDI_{t-1}	.0002804	.0008974	0.31	0.755
$PRICE_{t-1}$	-.1475069	.0550845	-2.68	0.007
$SNMI_{t-1}$	-.0040052	.0026969	-1.49	0.138
LNCREDIT				
$LNOV_{t-1}$	-.9863485	.2700419	-3.65	0.000
$LNCREDIT_{t-1}$	.8403916	.2556215	3.29	0.001
FDI_{t-1}	-.0038248	.0017517	-2.18	0.029
$PRICE_{t-1}$	-.2239974	.1207745	-1.85	0.064
$SNMI_{t-1}$	-.0205744	.0094801	-2.17	0.030
FDI				
$LNOV_{t-1}$	-277.5304	64.99501	-4.27	0.000
$LNCREDIT_{t-1}$	160.594	41.20423	3.90	0.000
FDI_{t-1}	-.8302665	.3679552	-2.26	0.024
$PRICE_{t-1}$	-15.72028	22.59493	-0.70	0.487
$SNMI_{t-1}$	-2.738724	1.54052	-1.78	0.075
PRICE				
$LNOV_{t-1}$	-3.077883	.7089212	-4.34	0.000
$LNCREDIT_{t-1}$	1.789036	.4480196	3.99	0.000
FDI_{t-1}	-.003121	.0037213	-0.84	0.402
$PRICE_{t-1}$	-.7209073	.2372578	-3.04	0.002
$SNMI_{t-1}$	-.0118264	.0161953	-0.73	0.465
SNMI				
$LNOV_{t-1}$	-2.002537	.5755868	-3.48	0.001
$LNCREDIT_{t-1}$	1.422233	.3886062	3.66	0.000
FDI_{t-1}	.009119	.0051105	1.78	0.074
$PRICE_{t-1}$	-2.407415	.4989738	-4.82	0.000
$SNMI_{t-1}$	.6222265	.0778426	7.99	0.000

Notes: Instruments: *L(1/4), (LNOV LNCREDIT FDI PRICE SNMI)*
N = 654
Standard errors are White heteroskedasticity consistent

Source: Author's estimations.

Figure C.6.1: Impulse Response of AVA from a Shock in R&D Investment



Mathematical Formulae for Model Selection Criterion

The AIC and BIC were calculated using the following formulae (Pardoe, 2020):

$$AIC_K = Nln(SSE) - Nln(N) + 2(K+1) \quad \text{A1.6.10}$$

$$BIC_K = Nln(SSE) - Nln(N) + (K+1)\, ln(N) \quad \text{A2.6.11}$$

where N is number of observations, SSE represent sum of squared errors, and K is the number of parameters in the model.

Table D.6.7: DCCEMG Empirical Results from Interaction Effects

	FD & Innovation		FD & Trade Integration	
Mean Group	1	2	3	4
AVA_1	0.1803***	0.2366***	0.1330**	0.2255***
	(0.0542)	(0.0533)	(0.0532)	(0.0542)
INN	-7.2212*		-2.4880***	
	(4.1600)		(0.8582)	
FD		5.7293		-17.1546
		(21.2582)		(12.0974)
GI	0.0439	0.0440		
	(0.0925)	(0.0827)		
FDINN	78.3138	-23.0125*		
	(-71.3318)	(13.9429)		
TRGI			-0.065	-0.5373*
			(0.0500)	(0.3117)
FIGI			-0.0290	-0.0618
			(0.0931)	(0.1038)
FDTR			0.1787	5.8870*
			(0.3346)	(3.2896)
Con	-17.3193	-20.2248	16.8794*	-35.9242
	(17.2395)	(19.8062)	(9.1588)	(31.8456)
F-statistic	1.16	1.62	1.17	1.25
Prob > F	0.06	0	0.05	0.01
R-squared	0.52	0.4	0.38	0.37
R-squared (MG)	0.72	0.73	0.79	0.79
CD Statistic	1.64	1.54	1.74	-0.32
Prob > CD	0.1019	0.124	0.0821	0.7507
AIC	398.9245	372.3352	-17.0583	-7.66467
BIC	422.5975	396.0081	11.27753	20.69273
No. Obs.	841	841	831	834