CARBON EMISSIONS, CLIMATE RISK, PRICE DYNAMICS, AND AGRICULTURAL PERFORMANCE IN SOUTH AFRICA: ECONOMETRIC ANALYSIS OF SHORT- AND LONG-RUN IMPACTS

By:

Femi Emmanuel Oni

Submitted in fulfilment of the academic requirements of the degree
Doctor of Philosophy in Agricultural Economics



School of Agriculture and Sciences

College of Agriculture, Engineering, and Science

University of KwaZulu-Natal

Pietermaritzburg

Supervisor: Professor Lloyd Baiyegunhi

MAY 2026

DECLARATION 1: PLAGIARISM

I, Femi Emmanuel Oni, declare that;

i. The research reported in this thesis is my original research work;

ii. This thesis has never been submitted for any degree or examination at any other university or institution of higher learning;

iii. This thesis does not contain other authors' data, pictures, tables, graphs or other information, unless specifically acknowledged as being sourced from those authors. Where other written sources were quoted:

a. Their words have been rephrased and duly referenced;

b. General information attributed to them was duly referenced; and

iv. This thesis does not contain text, graphics, or tables copied from the Internet without having been specifically acknowledged and the source details mentioned in the reference section.

Signed: [redacted] Date: 21/04/2026

Femi Emmanuel Oni

(Student)

Signed: [redacted] Date: 21/04/2026

Professor Lloyd Baiyegunhi

(Supervisor)

DECLARATION 2: PUBLICATIONS

The following publications form part of the research presented in this study.

Publication 1 – Chapter three of this thesis.

Oni, F.E and Baiyegunhi, LJS. **(Accepted).** The Influence of Carbon Dioxide Emissions on Food Consumption Patterns and Farm Produce Prices in South Africa. *Food and Energy Security.*

Publication 2 – Chapter four of this thesis.

Oni, F.E and Baiyegunhi, LJS. **(Under review)**. Decoupling Agricultural Growth from Carbon Emissions in South Africa: An Empirical Analysis of the Sustainability Nexus. *Climate Policy.*

Publication 3 – Chapter five of this thesis.

Oni, F.E and Baiyegunhi, LJS. **(Under review).** Climate variability, price risk, and agricultural output in South Africa: An econometric assessment. *Environmental Development.*

Publication 4 – Chapter six of this thesis.

Oni, F.E and Baiyegunhi, LJS. **(Under review).** Carbon Emission Risks and Price Volatility: Implications for Agricultural Productivity in South Africa. *Sustainable Agriculture and Environment.*

The data analyses and discussion of empirical results for all the above-listed publications were conducted in their entirety by Femi Emmanuel Oni with technical advice from Prof. Lloyd J.S. Baiyegunhi. All Figures and Tables were produced by the same, unless otherwise referenced in the respective publications.

ABSTRACT

Agriculture is one of the cornerstone sectors of the South African economy, providing a significant contribution to gross domestic product (GDP), employment, rural livelihoods, and food security. However, it is an industry exposed to increasing risks of carbon emissions, climate variations, and price fluctuations, combining all these together puts productivity, market stability, and longevity at risk. South Africa is the continent's highest emitter of CO_2, yet its agriculture is also among the most vulnerable to climate change. However, robust data on the combined influence of emissions, climate risks, and price dynamics on agricultural performance in the short and long term have been elusive. To bridge this knowledge gap, this dissertation examines the relationships between carbon emissions, climate variability, price risk, and agricultural productivity through an empirical analysis of these variables in South Africa for the period 1992–2021.

This work consists of four empirical parts, each addressing a different element of the emissions–climate–price–agriculture nexus. The first investigates the effects of CO_2 on food consumption patterns and prices of important farm goods. Employing the Vector Error Correction Model (VECM) methodology, along with Johansen cointegration techniques, unit-root tests, impulse response analysis, and variance decomposition, the study proposes long-run equilibria between emissions, consumer price inflation, purchasing power, and consumption trends. Results show that CO_2 emissions lead to increased food prices in the long run through production variability, which in turn affects consumption among the poorest consumers. In the short term, the effects of shocks related to emissions spread through price inflation channels, which decrease dietary diversity and increase the vulnerability of food-insecure households.

Secondly, the research explores the couplings between agricultural growth and carbon emissions in South Africa, and whether the agricultural sector in South Africa has undergone a decoupling process. Using the Autoregressive Distributed Lag (ARDL) modeling, Fully Modified Ordinary Least Squares (FMOLS), and Dynamic OLS (DOLS), the results reveal that CO_2 emissions have a strong long-run relationship with agricultural value-added, trade openness, and renewable energy. Results provide evidence for partial but insufficient decoupling: productivity gains from technological efficiency improvements have been offset by increasing emissions resulting from high demand for mechanization, fertilizer use, and land-use changes to sustain agricultural growth. It concludes that renewable energy adoption has not

yet transpired at the level needed to counterbalance the emissions burdens, indicating an imperative for policy to facilitate energy diversification and support low-carbon farming innovations.

The third part studies the combined effects of climate variability and price risk for agricultural production. The study also includes external trade Variables, domestic price volatility indicators, temperature, and rainfall anomalies using ARDL, cointegration analysis, and Granger causality. Results show that rainfall variability has a highly significant long-run impact on agricultural production, not surprising given South Africa's dependence on rain-fed agricultural systems. The short-term effects of temperature increases, especially heatwaves, are detrimental to productivity, while sustained exposure results in long-term soil deterioration and a reduction in output. Driven by climate-related shocks to agricultural production, international market dynamics, and exchange rate volatility, this is compounded by the volatility in production, which constrains farm investment decisions and leads to lower output in the long run. The bidirectional causality between climate variables and prices indicates that climate disturbances not only affect markets but also reinforce these disturbances through the structures of markets and trade conditions.

In the final empirical section, the joint impacts of CO_2 emission risk and price volatility on agricultural output are examined within a risk-adjusted Vector Error Correction (VEC) framework. The study reveals robust long-run linkages; i.e., emission risks significantly hinder agricultural productivity by exacerbating environmental degradation, reducing input-use efficiency, and increasing yield variability. These losses are compounded by price risk, which raises costs for inputs and disincentivizes longer-term investments in technology and adaptation. Emission risk and price volatility have a joint negative effect that is more detrimental than the sum of the negative effects of emission risk and price volatility taken independently, which signals the need for integrated risk management.

The econometric evidence is consistent across all components, revealing that the South African agricultural sector is substantially vulnerable to environmental and market shocks, with significant short- and long-term effects on productivity, prices, and food security. The results highlight the critical importance of enhancing climate-smart agriculture, expanding renewable energy options, increasing capacity to stabilize markets, and providing targeted investment in adaptation strategies for both commercial and smallholder farmers. To this end, policies such as carbon credit systems, strategic grain reserves, enhanced access to advanced early-warning

climate information, and subsidies for low-carbon technologies emerge as essential points of intervention.

This dissertation makes several contributions. Conceptually, it advances a unified framework of emissions, climate, price, and agricultural production, which is theoretically presented as separate parcels in South African literature. Methodologically, complementary econometric methods can identify both short-run dynamics and long-run equilibrium relationships, providing a more detailed insight into the sector's fragilities. In practical terms, the results provide concrete guidelines for policymakers, agribusinesses, and rural development actors seeking to design sustainable and resilient agricultural pathways.

More broadly, results confirm that sustainable agricultural development pathways in South Africa will only be achieved through integrated interventions that address the environmental, economic, and technological components of emissions mitigation, market stabilization, and adaptive capacity simultaneously. By quantifying the soil, climate variability, and price risk impacts on crop production, the research enables an empirical basis for integrated policies compatible with national productivity growth, food security, and sustainable climate change adaptation over the long term.

Graphical Abstract for the thesis

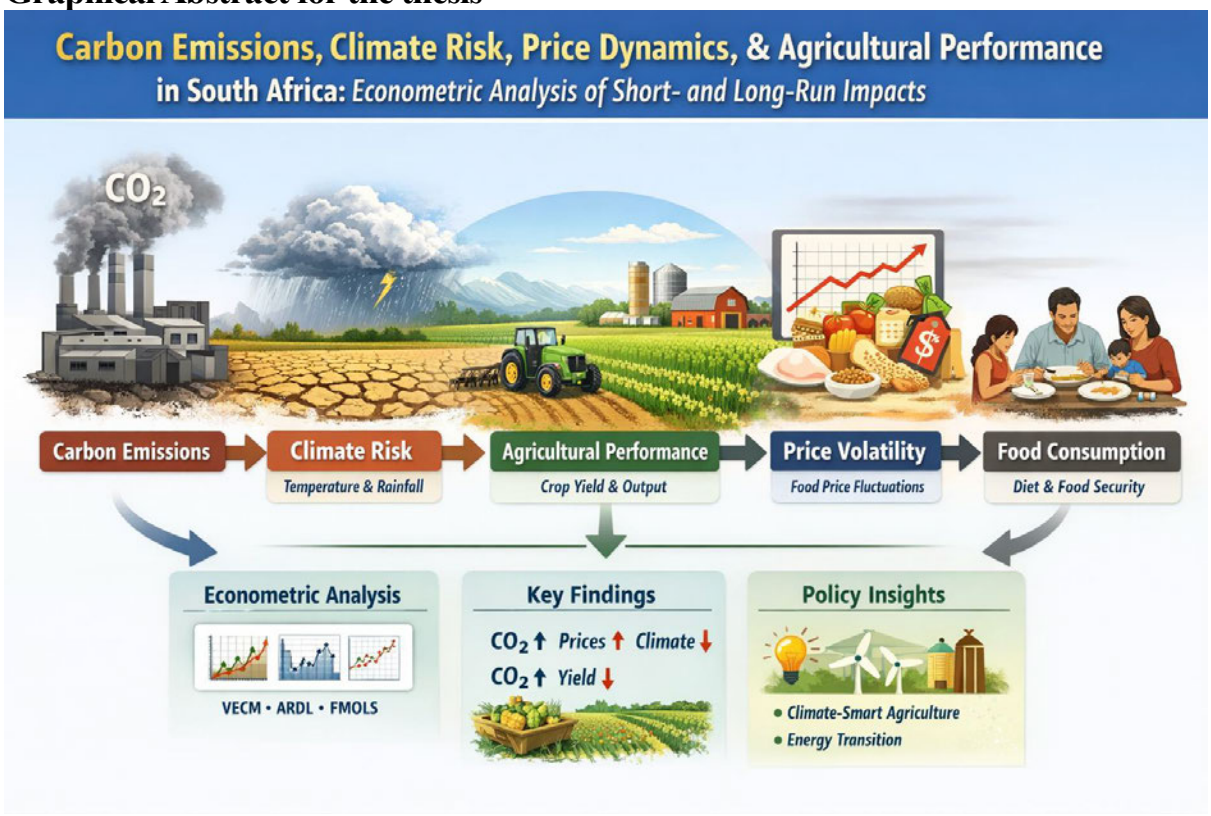


TABLE OF CONTENTS

DECLARATION 1: PLAGIARISM i
DECLARATION 2: PUBLICATIONS ii
ABSTRACT iii
TABLE OF CONTENTS vi
LIST OF TABLES xii
LIST OF FIGURES xiv
DEDICATION xv
ACKNOWLEDGEMENT xvi
LIST OF ACRONYMS xvii
Chapter 1: Introduction 1
1.1. Background to the Study 1
1.2. Statement of Research Problem 2
1.3. Research Questions 3
1.4. Research Objectives 4
1.5. Research Hypothesis 4
1.6. Conceptual Framework 5
1.7. Justification for the study 5
1.8. Significance of the Study 9
1.9. Scope and Limitations of the Study 10
1.10. Suggestions for Future Research 12
1.11. Overview of the study 13
Chapter 2: Literature Review 15
2.1. Introduction 15
2.2. South Africa in Global and Regional Context 15
2.3. Climate Factors, Price Risk, and Agricultural Productivity in South Africa 19
2.3.1. Overview of South Africa's Agricultural Sector and Economy 19
2.3.2. Climate Change, CO_2 Emissions, and Agricultural Productivity 19
2.3.3. Price Risk and Market Uncertainties in Agriculture 20
2.3.4. Consumption Pattern and Price of Farm Produce in South Africa 21
(i). Household Food Demand Elasticities and Expenditure Response in South Africa 22
(ii). Sector-Specific Consumption and Production Trends in South Africa 23
(iii). Shifts in Consumption Due to Environmental and Economic Factors 23
(iv). Consumption Patterns and their Environmental Footprint 24
2.4. Theoretical Frameworks Underpinning Econometric Analysis 25

2.4.1. Agricultural Production and Climate-Economy Models 26
2.4.2. Environmental Kuznets Curve (EKC) and Its Extensions 27
2.4.3. Econometric Approaches: ARDL and Cointegration Techniques 27
2.5. Indicators and Variables of Interest 28
2.5.1. CO_2 Emissions and Environmental Degradation Metrics 28
2.5.2. Climate Variability Indicators: Temperature, Rainfall, and Weather Extremes 29
2.5.3. Price Risk and Market Dynamics Variables 29
2.6. Empirical Methodologies 30
2.6.1. Short-Run Impact Analysis 30
i. Causality Tests and Direction of Influence 31
ii. Robustness Checks: FMOLS, DOLS, and CCR Estimations 32
2.6.2. Long-Run Impact Analysis 32
2.6.3. Instrumental Variable Regression and Ricardian Models 33
2.6.4. Data Envelopment Analysis and Malmquist Index 33
2.6.5. Time Series and Auto-Regressive Distributed Lag (ARDL) Models 34
2.6.6. Methodological Gap Addressed by This Study 34
2.7. Empirical Evidence from Literature 35
2.7.1. Impacts of CO_2 Emissions on Agricultural Output 36
2.7.2. Climate Variability Impacts on Agricultural Economic Growth 37
i. Temperature Effects on Productivity and Output 37
ii. Precipitation Variability and Extreme Weather Events 37
iii. Crop Yield Responses and Food Security Implications 37
iv. Livestock Production under Climatic Stress 38
v. Fisheries and Aquaculture Impacts 38
2.7.3. Price Risk and Its Link to Climate Variability in South Africa 39
i. Inflation and Food Price Volatility in South Africa 39
ii. Farmers' Perceptions and Risk Management Strategies 39
iii. Market Structures and Price Signals for Adaptation 40
iv. Price Risk and Market Volatility Effects 40
2.7.4. Integrating Econometric Results into Economic Systems 40
2.7.5. Price Elasticity and Price Transmission in Agricultural Markets 41
2.7.6. Impact of Macroeconomic Variables and Inflation on Agricultural Prices 42
2.7.7. Trade Competitiveness and Export Market Pressures 42
2.8. Agricultural Productivity and Climate Resilience 43

2.8.1. Climate-Smart Agriculture Adoption 43
2.8.2. Technological and Innovation Factors....43
2.8.3. Diversification and Livelihood Strategies 44
2.9. Institutional and Policy Frameworks for Agriculture in South Africa 44
2.9.1 Government Expenditure and Agricultural Support....44
2.9.2. Agricultural Extension Services 45
2.9.3. Climate Services and Information Dissemination 45
2.9.4. Policy Implications on Emission Management....45
2.9.5. Economic Trade-Offs and Policy Trade-offs....46
2.10. Adaptation Strategies and Barriers to Agricultural Productivity in South Africa . 46
2.10.1. Adoption Constraints for Climate-Smart Practices....46
2.10.2. Risk Management Through Insurance and Financial Instruments 46
2.10.3. Market-Based and Community Adaptation Approaches 47
2.11. Synthesis of Climate, Price Risk, and Productivity Interactions.... 47
2.11.1. Complex Interplay Between Climate Factors and Market Dynamics 47
2.11.2. Impact of Technological and Policy Interventions on Mitigating Risks 48
2.11.3. Impact of Renewable Energy and Technological Innovations 48
2.12. Research Gaps and Future Opportunities.... 49
2.12.1. Methodological Limitations and Data Gaps 49
2.12.2. Directions for Future Research 49
2.12.3. Conclusion 50
Chapter 3: The Influence of Carbon Dioxide Emissions on Food Consumption Patterns and Farm Produce Prices in South Africa.....51
3.1. Introduction 51
3.2. Analytical Framework.... 53
3.2.1. Specification of VEC model 54
3.2.2. Error Correction Term (ECT) 55
3.2.3. Model diagnostic tests....56
3.3. Study area and data source 57
3.4. Results and Discussion.... 60
3.4.1. Descriptive and trend analysis for key variables (CPI, CE, ICP, PLR-PPP, and TE) used in this study....60
3.4.2. Test for stationarity result: Augmented Dickey-Fuller and Phillips-Perron....64
3.4.3. Optimal lag length criteria 65
3.4.4. Result of the Johansen co-integration test 65

3.4.5. Result of the normalised co-integrating coefficient. 67
3.4.6. Estimation of the VEC model 67
3.4.7. VEC Granger causality/block exogeneity Wald tests 70
3.4.8. Pairwise Granger causality test 70
3.4.9. Residual Diagnostic Tests 71
3.4.10. Inverse root of autocorrelation 71
3.4.11. Impulse response function of the VEC model 72
3.4.12. Variance decomposition of the VEC model 72
3.4.13. Historical decompositions for nonlinear Vector Error Correction models 73
3.5. Conclusion and Recommendation 74
Chapter 4: Decoupling Agricultural Growth from Carbon Emissions in South Africa: An Empirical Analysis of the Sustainability Nexus 77
4.1. Introduction 77
4.2. Analytical Techniques 79
4.2.1. Data Sources and Definition of Variables 79
4.2.2. Testing for Unit Roots 80
4.2.4. Cointegration Testing 81
4.3. Estimation Methods 81
4.4. Model Specification 82
4.5. Results and Discussions 82
4.5.1. Descriptive Statistics of Explanatory Variables 82
4.5.2. Result of Unit Root Test 84
4.5.3. Johansen Co-integration Test Result 84
4.5.4. Estimation of Models (ARDL, FMOLS, and DOLS) 85
4.6. Discussion 89
4.7. Conclusion and Policy Recommendations 91
Chapter 5: Climate variability, price risk and agricultural output in South Africa: An econometric assessment. 94
5.1. Introduction 94
5.2. Research Methods 96
5.2.1. Data Sources 97
5.3. Analytical Framework 97
5.3.1. Model Specification 97
5.3.2. ARDL and Co-integration 98
5.4. Findings and Discussion 99

5.4.1 Presentation of Result 99
5.4.1 Discussion of Results 104
5.5. Implications for South African Agricultural Landscape 107
5.6. Conclusion and Policy Recommendations 108
Chapter 6: Carbon Emission Risks and Price Volatility: Implications for Agricultural Output in South Africa. 110
6.1. Introduction 110
6.2. Conceptual Framework 112
6.3. Methodology 112
6.3.1. Study Design 112
6.3.2. Data Sources and Variables 113
6.3.3. Econometric Specification 113
6.3.4. Model Justification 114
6.3.5. Limitations and Assumptions 114
6.3.6. Analytical Framework 115
6.5. Results and Discussion 115
6.5.1. Descriptive Statistics 115
6.4.2. Stationarity and Cointegration Tests 116
6.4.3. Vector Error Correction Model (VECM) Results 117
6.4.4. Impulse Response Functions (IRFs) 119
6.4.5. Variance Decomposition 120
6.5. Discussion 121
6.6. Conclusion and Policy Implications 122
6.6.1. Conclusion 122
6.6.2. Policy Implications 122
Chapter 7: Summary, Conclusion, and Policy Recommendation. 124
7.1. Summary 124
7.2. Conclusion 126
7.3. Recommendations for Policy Implications 128
7.3.1 Short-Term Policy Priorities (0–3 Years) 128
7.3.2 Medium-Term Policy Priorities (3–7 Years) 130
7.3.3 Long-Term Policy Priorities (7+ Years) 131
7.3.4 Integrated Policy Insight 132
7.4. Limitations of the Study and Suggestions for Further Research 132
REFERENCES 134

APPENDIX **158**

LIST OF TABLES

Table No	Title	Page
2.1	Summary of South Africa's Agricultural CO_2 Emissions Context	17
2.2	Summary of Key Empirical Studies and Research Gaps	35
3.1	Summary of variables used in the empirical analysis	59
3.2	Descriptive statistics for trend analysis	61
3.3	Stationarity unit root test	65
3.4	Johansen Co-integration test	66
3.5	VEC model estimation	69
4.1	Descriptive Statistics of explanatory variables	84
4.2	Unit Root Test Results	84
4.3	Johansen Co-integration Test (Trace Statistic)	85
4.4	Johansen Co-integration Test (Maximum Eigenvalue)	85
4.5	ARDL F-Bounds Test and Critical Value	86
4.6	ARDL Error Correction Model	87
4.7	FMOLS and DOLS Long-Run Estimation Results	88
4.8	Priori expectations of the variables	91
5.1	Descriptive Statistics	99
5.2	Results of Unit Root Test	100
5.3	Johansen Unrestricted Co-integration rank test between the variables TACGDP, CE, EXP, IMP and TAE (Trace)	100
5.4	Johansen Unrestricted Co-integration rank test between the variables TACGDP, CE, EXP, IMP and TAE (Maximum Eigenvalue)	101
5.5	Result of Granger Causality Test	102
5.6	ARDL Bounds Test	102
5.7	ARDL Error Correction Model Result	103
5.8	ARDL Long-run results	104
6.1	Descriptive Statistics (1992–2021)	115
6.2	Stationarity unit root test	116
6.3	Lag Length Selection	117
6.4	The result of the Johansen co-integration test	117

6.5 Long-Run Coefficients (VECM) 118
6.6 Short-Run Dynamics (Error Correction Term) 118
6.7 Variance Decomposition of TACGdp 120
7.1 Summary of Thesis Chapters 125

LIST OF FIGURES

Figure No	Title	Page
1.1	Conceptual Framework Diagram	5
2.1	CO_2 emissions in mega tonnes from the agricultural sector over the period 2015-2021	18
3.1	Agricultural regions of South Africa with provincial breakdowns of farm produce and other land uses	58
3.2	Trend analysis patterns of the key variables (CPI, CE, ICP, PLR-PPP, and TE) used in this study	63
3.3	VEC model Inverse roots of AR characteristics polynomial	71
3.4	Impulse Response of CPI to One Standard Deviation Innovations	72
3.5	Variance decomposition of CPI using Cholesky factors	73
3.6	Decomposition of variable CPI	74
6.1	Impulse Response of TACGdp to CO_2 Emissions Shock	119
6.2	Impulse Response of TACGdp to CPI Shock	120

DEDICATION

This thesis is dedicated to the Most-High God—El-Sali. (“**The Lord is my strength”**) for His unwavering strength throughout this challenging journey.

ACKNOWLEDGEMENT

I extend my sincere appreciation to my diligent and amiable mentor, Professor Lloyd Baiyegunhi, for his unwavering guidance, continuous support (both financial and moral), and insightful feedback. His profound knowledge, constructive criticism, and recommendations greatly contributed to the accomplishment of this study. I am privileged to have benefited from the mentorship of such an exceptional individual and to have tapped into his wealth of knowledge. May divine blessings be bestowed upon him. Furthermore, I would like to express my gratitude to the faculty members of the Agricultural Economics Discipline at the University of KwaZulu-Natal, Pietermaritzburg campus.

Secondly, to my colleagues and friends, not to mention names, in South Africa, Nigeria, and other parts of the world, thank you for your support, encouragement, insightful discussions, and companionship throughout this academic journey. Your contributions, whether through collaboration, motivation, or simply believing in me, helped make this achievement possible.

I also express my profound appreciation to my parents for their lifelong guidance, prayers, and steadfast belief in my aspirations and capabilities. Their foundation of love, discipline, and support has been instrumental in shaping the person I am today. To my siblings and in-laws, your prayers and support are greatly appreciated and instrumental to the success of this program.

To my soulmate, I extend my deepest gratitude to my beloved wife, Joy Oluwafunsho Oni, whose unwavering support, love, and encouragement sustained me throughout the challenging journey of my PhD programme. Your faith in me, your sacrifices, and your constant reassurance gave me the strength to keep moving forward, even in the most demanding moments. I am eternally grateful.

To my son, Joshua Oluwaferanmi Oni, thank you for being a source of joy, inspiration, and renewed motivation. Your smiles and innocent disturbance reminded me of what truly matters and gave me the courage to persevere.

This achievement is not mine alone, it is ours. Thank you for walking this path with me.

LIST OF ACRONYMS

ADF	Augmented Dickey-Fuller
AFOLU	Agriculture, Forestry, and Other Land Use
AIC	Akaike Information Criterion
AR	Autoregressive
ARDL	Auto-Regressive Distributed Lag
BRICS	Brazil, Russia, India, China, and South Africa
CA	Coherence Analysis
CCR	Canonical Cointegrating Regression
CH_4	Methane
CO_2	Carbon Dioxide
CPI	Consumer Price Index
CSA	Climate-smart agriculture
DF-GLS	Dickey-Fuller Generalized Least Squares
DOLS	Dynamic Ordinary Least Squares
ECM	Error Correction Model
ECT	Error Correction Term
ECT	Error Correction Term
EKC	Environmental Kuznets Curve
EXP	Exports
FAO	Food and Agriculture Organization
FAOSTAT	Food and Agriculture Organization Statistical Database
FEVD	Forecast Error Variance Decomposition
FMOLS	Fully Modified Ordinary Least Squares
GHG	Greenhouse Gas
ICP	Inflation of Consumer Price
ICT	Information and Communication Technology
IMP	Imports
IPCC	Intergovernmental Panel on Climate Change

N_2O	Nitrous Oxide
NAMC	National Agricultural Marketing Council
PLR-PPP	Price Level Ratio for Purchasing Power Parity
PP	Phillips-Perron
PPP	Purchasing Power Parity
R&D	Research and Development
SBC	Schwarz Bayesian Criterion
SD	Standard Deviation
SDG	Sustainable Development Goal
SSA	Sub-Saharan Africa
TACGdp	Total Agricultural Contribution to GDP
TAE	Total Agricultural Employment
TE	Total Employment
VAR	Vector Autoregressive
VEC	Vector Error Correction
VECM	Vector Error Correction Model
WDI	World Development Indicators

Chapter 1: Introduction

1.1. Background to the Study

Agriculture remains one of the most important sectors of the South African economy, contributing significantly to gross domestic product (GDP), employment creation, rural livelihoods, and national food security. The sector supports agro-processing industries, generates export revenue, and plays a central role in rural development. However, the sustainability of agricultural production is increasingly threatened by a combination of environmental and economic risks, particularly rising carbon emissions, climate variability, and agricultural price volatility. These risks interact in complex ways and have the potential to undermine agricultural productivity, destabilize markets, and weaken food security systems in the long term.

One of the most pressing environmental challenges affecting agriculture globally is the rise in greenhouse gas emissions, particularly carbon dioxide (CO_2). Agricultural activities contribute to greenhouse gas emissions through fertilizer application, livestock production, land-use change, and energy consumption. At the same time, agriculture is highly vulnerable to the impacts of climate change resulting from these emissions. Rising temperatures, changing rainfall patterns, and the increased frequency of extreme weather events such as droughts and floods directly influence crop yields, soil fertility, and water availability (Malhi et al., 2021; Thornton et al., 2014).

In South Africa, greenhouse gas emissions originate primarily from the energy sector, particularly coal-based electricity generation, although agricultural activities also contribute through livestock production, fertilizer use, and soil management practices (Moeletsi & Tongwane, 2015; Muzangwa et al., 2021). Despite contributing a relatively smaller share of national emissions, the agricultural sector remains highly vulnerable to climate change due to its strong dependence on natural resources and climatic conditions. This vulnerability is particularly pronounced in semi-arid regions where rainfall variability significantly affects agricultural productivity.

Beyond environmental pressures, agricultural productivity is also influenced by economic factors such as agricultural price volatility. Price fluctuations may arise from seasonal supply variations, global market dynamics, exchange-rate movements, and trade policy changes. In developing economies such as South Africa, where farmers often operate under limited

financial resources and weak risk-management mechanisms, price instability can significantly affect farm profitability and investment decisions. Climate-induced production shocks frequently exacerbate price volatility by reducing agricultural supply and increasing market uncertainty (Raihan et al., 2022; Van Meijl et al., 2024).

Technological innovation and institutional support mechanisms play a crucial role in mitigating these environmental and economic risks. Climate-smart agricultural practices such as improved irrigation systems, conservation agriculture, crop diversification, and climate-resilient crop varieties can enhance productivity while reducing vulnerability to climate shocks (Shiferaw et al., 2014; Thornton et al., 2014). However, the successful implementation of these practices depends on supportive policy frameworks, institutional capacity, and adequate investment in agricultural research and development (Santra, 2017; Thabane et al., 2024).

Despite the growing body of literature on climate change and agricultural productivity, most studies examine environmental and economic risks independently rather than within an integrated framework. Many studies focus on the effects of climate variability on agricultural yields, while others investigate the relationship between carbon emissions and economic growth or the determinants of food price volatility. Consequently, relatively few studies analyse the combined effects of carbon emissions, climate variability, and agricultural price dynamics on agricultural productivity, particularly within the South African context.

1.2. Statement of Research Problem

Agricultural production systems across the world are increasingly confronted with complex environmental and economic challenges that threaten their sustainability. Among these challenges, carbon emissions, climate variability, and agricultural price volatility have emerged as critical factors influencing agricultural performance. Although these issues have attracted considerable scholarly attention, their combined effects on agricultural productivity remain insufficiently understood, particularly in developing economies such as South Africa.

Rising carbon emissions have become one of the most significant contributors to global climate change. Increased greenhouse gas concentrations in the atmosphere contribute to rising global temperatures, shifts in rainfall patterns, and a greater frequency of extreme weather events. These climatic changes directly influence agricultural production by affecting crop growth cycles, soil moisture levels, and water availability (Malhi et al., 2021; Thornton et al., 2014).

Consequently, climate-related shocks pose substantial risks to agricultural productivity and food security.

In South Africa, climate variability has become increasingly pronounced over the past several decades. The country has experienced more frequent droughts, heat waves, and irregular rainfall patterns, all of which have significant implications for agricultural production systems. Given that a substantial portion of South African agriculture depends on rainfall, these climatic fluctuations can lead to considerable yield variability and income instability for farmers.

In addition to environmental pressures, agricultural markets are increasingly characterised by price volatility. Fluctuations in agricultural prices are influenced by a variety of factors, including supply shocks, global commodity market dynamics, exchange-rate movements, and policy interventions. Climate-induced production shocks frequently exacerbate price volatility by reducing supply and increasing market uncertainty. These price fluctuations create significant challenges for farmers, particularly small-scale producers who often lack adequate financial buffers and risk-management tools.

Despite the growing literature on climate change and agricultural productivity, many existing studies examine the relationships among carbon emissions, climate variability, and agricultural productivity in isolation rather than as part of an interconnected system. Similarly, studies on agricultural price volatility often overlook the role of environmental and climatic factors in shaping price dynamics. As a result, there remains a significant knowledge gap regarding the integrated impacts of carbon emissions, climate risk, and price dynamics on agricultural performance.

1.3. Research Questions

Based on the problems stated above, it was crucial to ascertain how carbon emissions and climate change impact agriculture and prices, both in the short term and over time, in South Africa. It was, therefore, essential to ask pertinent questions that served as a guide in proffering solutions to the research problem. The study is guided by four central research questions:

i. How do carbon dioxide emissions impact food consumption patterns and the prices of farm produce in South Africa?

ii. Can agricultural production be decoupled from carbon emissions within the South African context?

iii. How does climate variability influence agricultural productivity in South Africa?

iv. What role do carbon emissions and climate risks play in shaping agricultural price dynamics?

1.4. Research Objectives

The primary objective of this research is to investigate the impact of carbon emissions and climate change on agriculture and prices in South Africa, both in the short term and over time. To achieve this broad objective, the specific goals for the study are to:

i. Evaluate the impacts of carbon dioxide emissions on food consumption patterns and farm produce prices in South Africa.

ii. Analyse the decoupling relationship between agricultural production and carbon emissions in order to assess whether agricultural growth can occur without corresponding increases in environmental degradation.

iii. Investigate the impact of climate variability on agricultural productivity and assess how climatic factors influence agricultural output over time.

iv. Evaluate the relationship between carbon emissions, climate-related risks, and agricultural price volatility in South Africa.

1.5. Research Hypothesis

The hypotheses put forward to investigate the extent to which carbon emissions and climate change impact agriculture and prices, both in the short term and over time, in South Africa, are:

H1: CO_2 emissions significantly affect food prices and consumption patterns.
H2: Agricultural production and carbon emissions exhibit a measurable decoupling relationship.

H3: Climate variability significantly affects agricultural productivity in South Africa.

H4: Carbon emissions and climate-related risks contribute to agricultural price volatility.

1.6. Conceptual Framework

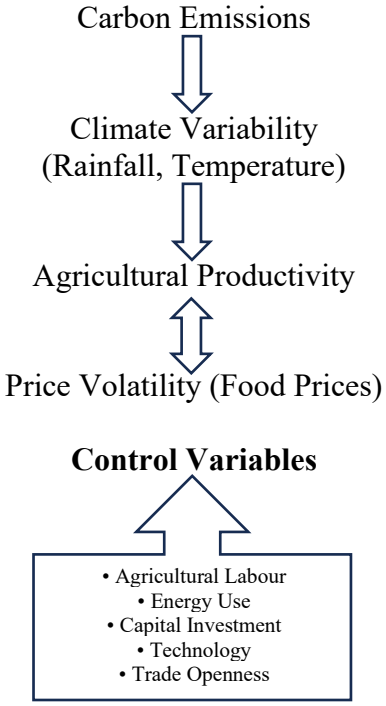


Figure 1.1. Conceptual Framework Diagram. *(Source: Author's computation)*

Figure 1.1. This study adopts an integrated conceptual framework that examines the interaction between environmental and market factors influencing agricultural productivity. Carbon emissions contribute to climate variability through changes in temperature and rainfall patterns. Climate variability directly affects agricultural production by altering crop growth conditions, water availability, and soil fertility. Agricultural productivity is also influenced by agricultural price volatility, which affects farmers' investment decisions and input utilization. In addition, several control variables, including labour availability, energy consumption, technological development, and trade openness, are incorporated to capture broader structural influences on agricultural performance. This framework therefore provides a comprehensive approach for analysing the dynamic relationships between environmental change, market risks, and agricultural productivity.

1.7. Justification for the study

The agricultural sector plays a vital role in South Africa's economy, contributing significantly to gross domestic product (GDP), rural employment, and national food security. However, the sustainability of the sector is increasingly threatened by the combined pressures of carbon emissions, climate variability, and agricultural price volatility. These environmental and

economic risks have become central concerns for policymakers and researchers because of their potential to undermine agricultural productivity, destabilize food markets, and weaken rural livelihoods. In the absence of effective mitigation and adaptation strategies, projections indicate that the agricultural sector's contribution to national output may decline due to reduced crop yields, rising input costs, and increased variability in production associated with climate change.

Growing levels of carbon dioxide (CO_2) emissions represent one of the major drivers of climate change and environmental degradation, with significant implications for agricultural systems. Agricultural production both contributes to and is affected by greenhouse gas emissions through land-use changes, fertilizer application, and energy consumption in farming operations. As emissions increase, climatic conditions become more unpredictable, resulting in higher temperatures, altered precipitation patterns, and increased frequency of extreme weather events. These changes have direct consequences for agricultural productivity, affecting crop growth cycles, soil fertility, water availability, and livestock production systems. Consequently, addressing emission-related environmental risks is essential for ensuring the long-term sustainability of agricultural production in South Africa.

At the same time, agricultural markets are exposed to significant volatility arising from climate shocks, global commodity price fluctuations, and macroeconomic instability. Price volatility affects farmers' production decisions, investment behaviour, and income stability, thereby influencing overall agricultural performance. When agricultural prices fluctuate unpredictably, farmers may delay investments in new technologies, reduce input use, or shift production patterns, which can ultimately reduce productivity and increase vulnerability among farming households. Such instability also threatens food security, particularly for low-income households that are highly sensitive to changes in food prices. Therefore, understanding the drivers and implications of agricultural price volatility is critical for designing effective market stabilization policies.

Addressing the challenges of climate change and market instability requires coordinated policy interventions that simultaneously promote emissions reduction and agricultural productivity. Empirical evidence suggests that the integration of emission-reduction strategies with productivity-enhancing measures can support long-term economic growth while maintaining environmental sustainability. Policies that stimulate investment in research and development (R&D), provide vocational training for farmers, and implement green incentive schemes for

agricultural producers can foster the adoption of environmentally friendly production practices without compromising agricultural output (Aluwani, 2023; Feyen et al., 2020; Gyimah et al., 2023). These initiatives enhance the adaptive capacity of farmers and strengthen the resilience of agricultural systems to climate-related shocks over the long run.

Government intervention also plays a crucial role in mitigating the adverse effects of agricultural price volatility and climate shocks. Policy instruments such as strategic grain reserves, targeted subsidies, and regulatory oversight of agricultural markets can help stabilize food prices during periods of supply disruptions. In addition, carbon credit systems and other market-based environmental policies offer opportunities to incentivize climate-smart agricultural practices that reduce emissions while maintaining productivity levels (Hayo and Hasegawa, 2024; Gyimah et al., 2023). Such mechanisms encourage farmers to adopt sustainable land management practices, improve resource efficiency, and invest in technologies that reduce greenhouse gas emissions.

Another important aspect of sustainable agricultural development is the promotion of climate-smart agricultural technologies and practices. Investments in improved irrigation systems, soil fertility management, efficient fertilizer application, and livestock management techniques can significantly reduce emissions while increasing production efficiency. In addition, improving rural market access, strengthening agricultural extension services, and expanding financial support systems for farmers can enhance the sector's resilience to both environmental and market risks. These policy measures collectively contribute to the development of a more sustainable and adaptive agricultural system capable of withstanding the impacts of climate change and economic uncertainty.

Despite the growing recognition of these challenges, the relationship between carbon emissions, climate variability, and agricultural productivity remains complex. Empirical evidence from South Africa indicates that carbon emissions often exhibit a negative relationship with agricultural productivity in the short run. However, the magnitude of this effect may decline over time as farmers adapt to changing environmental conditions through technological innovation and improved management practices (Aluwani, 2023; Aye and Edoja, 2017; Smith et al., 2008). Climate variability, particularly fluctuations in rainfall and temperature, also plays a significant role in shaping agricultural outcomes, influencing crop yields, soil quality, and water availability. These environmental factors interact with economic

variables such as agricultural prices and market demand, creating complex feedback mechanisms that affect agricultural performance.

Furthermore, agricultural price volatility remains a persistent challenge for farmers and policymakers. Price fluctuations may arise from seasonal supply variations, global market dynamics, exchange rate movements, and trade policy changes. In developing economies such as South Africa, where many farmers operate under resource constraints and limited access to risk-management instruments, price volatility can have severe consequences for farm profitability and food security. Climate-induced production shocks often exacerbate these price fluctuations by reducing agricultural supply and increasing the sensitivity of food markets to external disturbances. Consequently, stabilizing agricultural markets and reducing exposure to price risk is essential for maintaining long-term agricultural productivity.

Although numerous studies have examined the impacts of climate change, carbon emissions, and price volatility on agricultural systems, most of these studies analyze these factors separately rather than within an integrated framework. This fragmented approach limits the ability of researchers and policymakers to understand how environmental and economic risks jointly influence agricultural productivity. In the South African context, limited empirical research has investigated the combined effects of carbon emissions, climate variability, and agricultural price dynamics on agricultural performance. This gap in the literature is particularly important because these factors interact through complex feedback mechanisms that influence production decisions, market stability, and rural livelihoods.

Understanding these interactions is essential for developing effective policies that promote sustainable agricultural development while mitigating environmental risks. An integrated analysis of emissions, climate variability, and price volatility can provide valuable insights into the mechanisms through which environmental and market shocks affect agricultural productivity. Such knowledge is crucial for designing policies that enhance resilience, stabilize agricultural markets, and promote climate-smart agricultural practices.

This study is therefore justified by the need to generate empirical evidence on the dynamic relationships between carbon emissions, climate variability, agricultural price volatility, and agricultural productivity in South Africa. By examining these relationships within a unified analytical framework, the research seeks to address the limitations of previous studies that have treated environmental and market risks independently. The findings are expected to contribute to a better understanding of how environmental and economic factors interact to influence

agricultural outcomes and to provide evidence-based recommendations for policymakers seeking to promote sustainable and resilient agricultural systems.

Ultimately, the sustainability of South Africa's agricultural sector depends on the ability to balance environmental sustainability, economic stability, and agricultural productivity. Integrated policy approaches that combine emissions reduction strategies, climate-smart agricultural technologies, and market stabilization mechanisms are essential for achieving this balance. By providing empirical evidence on the interactions between emissions, climate variability, and price dynamics, this study contributes to the development of policies and strategies that support sustainable agricultural growth, strengthen rural livelihoods, and enhance national food security

1.8. Significance of the Study

This study is significant because it contributes to the growing body of knowledge on the interactions between environmental sustainability, climate variability, and agricultural market dynamics. The agricultural sector plays a critical role in economic development, food security, and rural livelihoods in many developing economies, including South Africa. However, increasing carbon emissions, climate variability, and agricultural price volatility present significant challenges to the sustainability and stability of agricultural production systems. By examining the dynamic relationships among these factors, this study provides new insights into how environmental and economic risks jointly influence agricultural productivity.

From a theoretical perspective, the study contributes to the literature by integrating environmental and economic determinants of agricultural productivity within a unified analytical framework. While previous studies have often examined the impacts of climate change, carbon emissions, or agricultural price volatility separately, this research simultaneously investigates these factors and their interactions. In doing so, the study advances understanding of the complex linkages between environmental degradation, climate variability, and agricultural market instability. The study therefore provides a broader perspective on the determinants of agricultural productivity, contributing to sustainability and environmental economics literature, particularly in relation to the Environmental Kuznets Curve and climate–agriculture interaction frameworks.

From an empirical perspective, the study provides evidence specific to South Africa, where research examining the combined effects of carbon emissions, climate variability, and

agricultural price volatility remains limited. By employing an integrated empirical approach, the study generates country-specific insights into the environmental and economic factors influencing agricultural productivity. These findings contribute to the existing literature by expanding empirical evidence on the relationship between climate change and agricultural performance in developing economies. The results are expected to provide a deeper understanding of how environmental and market dynamics influence agricultural productivity in a climate-vulnerable economy.

The study also has important policy implications. Policymakers require reliable empirical evidence to design effective strategies that promote sustainable agricultural development while addressing environmental challenges. By identifying the relationships between emissions, climate variability, price volatility, and agricultural productivity, this study provides valuable information for developing policies that strengthen agricultural resilience to environmental and market shocks. The findings can inform the design of policies related to climate adaptation strategies, emission reduction initiatives, agricultural market stabilization, and the adoption of climate-smart agricultural technologies.

Furthermore, the study contributes to broader global sustainability discussions by providing insights relevant to international development goals related to food security, environmental sustainability, and climate change mitigation. The findings may assist policymakers and development agencies in designing strategies that support sustainable agricultural systems while improving food security and rural livelihoods.

Overall, the significance of this study lies in its ability to provide an integrated understanding of the environmental and economic determinants of agricultural productivity. By examining the interaction between carbon emissions, climate variability, and agricultural price volatility, the research contributes to both academic literature and policy development aimed at promoting sustainable agricultural growth and long-term food security in South Africa.

1.9. Scope and Limitations of the Study

This study examines the interrelated effects of carbon emissions, climate risk, price dynamics, and agricultural performance in South Africa from 1992 to 2021, utilizing advanced econometric time series methods. Focusing on South Africa provides country-specific insights while offering potential relevance to other Sub-Saharan African countries confronting analogous climatic and economic challenges (Cullis et al., 2015). The chosen period is

particularly significant as it encompasses notable shifts in climatic variability, agricultural policy reforms, economic globalization, and social adjustment mechanisms, which collectively influence the dynamics between emissions, climate factors, agricultural productivity, and price fluctuations (Emediegwu et al., 2022).

The study considers key economic and environmental variables, including carbon emissions as a proxy for environmental impact, climate risk indicators such as temperature and rainfall variability, commodity price dynamics, and agricultural performance metrics, including yield, productivity, and total production (Ngcamu and Chari, 2020). To disentangle short- and long-term relationships among these variables, a range of advanced econometric techniques were employed, including the Autoregressive Distributed Lag (ARDL) model, Vector Error Correction (VEC), Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and Coherence Analysis (CA) (Ali et al., 2021). These methodologies provide a robust framework for quantifying the impacts of carbon emissions and climate variability on agricultural output and prices, offering insights critical for climate change adaptation strategies and sustainable agricultural development.

Despite its methodological rigor, the study faces several limitations. Data quality and granularity are primary constraints. Although datasets for time series analysis of emissions, climate indicators, and agricultural economic variables in South Africa are generally available, accuracy and temporal resolution vary, potentially affecting the reliability and consistency of econometric estimates (Cullis et al., 2015). Moreover, available datasets often cover only selected sectors, while disaggregated data for specific agricultural sub-sectors or regional variations remain limited (Ngcamu and Chari, 2020). Structural breaks, including policy reforms, exogenous shocks such as extreme weather events, and economic transitions, combined with temporal lags in climate responses, further complicate the modelling of long-term relationships (Ali et al., 2021).

The external validity of the findings represents an additional limitation. While results provide relevant insights for the South African context, their direct applicability to other Sub-Saharan countries is constrained by differences in institutional, climatic, and economic structures (Hertel and Rosch, 2010). Furthermore, evolving policy, technological, and market contexts mean that historical data may not fully capture future dynamics or innovations in agricultural practices ("Climate-Smart Agriculture Indicators," 2016).

Methodologically, potential omitted variable bias and endogeneity issues may arise. Important determinants of net emissions, such as government subsidies, technological innovations, or international policy shocks, may not be fully captured, which could bias parameter estimates (Sansika et al., 2023). Additionally, two-way causality between agricultural performance and emission or adaptation policies introduces endogeneity risks, complicating causal inference (Ali et al., 2021).

These limitations reflect broader challenges in empirical research on agriculture–climate–economy linkages in Sub-Saharan Africa. Climatic variability affects regional growing systems, crop production, household resilience, and food security in complex ways (Ngcamu and Chari, 2020; Emediegwu et al., 2022). The interactions among farming practices, greenhouse gas emissions, and adaptive strategies remain central to debates on sustainability and resilience. While econometric approaches provide essential insights to guide policy, they remain constrained by data availability, methodological complexity, and the inherent challenges of capturing dynamic environmental and economic interactions in the African context (Emediegwu et al., 2022; Sansika et al., 2023; Hertel and Rosch, 2010).

1.10. Suggestions for Future Research

Building on the limitations of this study, several avenues for future research are recommended. First, the collection and analysis of high-resolution, disaggregated data at the farm and regional levels would allow for a more precise understanding of the heterogeneity in agricultural responses to emissions and climate shocks.

Second, comparative studies across Sub-Saharan African countries could assess the generalizability of the findings and identify context-specific policy interventions. Third, future research should incorporate dynamic shocks and structural changes, including policy reforms, extreme weather events, and technological innovations, to better model long-term responses in agriculture and the market.

Fourth, employing advanced causal inference techniques, such as instrumental variables or structural modelling, could address potential endogeneity and omitted variable biases. Finally, examining the impacts of renewable energy adoption, climate-smart agriculture, and carbon credit schemes could provide valuable insights into strategies that simultaneously enhance productivity, reduce emissions, and strengthen sector resilience.

1.11. Overview of the study

The remaining chapters of this study will be organized into six sections, including this introductory chapter. Chapter 2 will provide the literature review of the study. Some key concepts and terminologies will be defined. It will also provide the theoretical and empirical evidence in an integrated discussion of variables, indicators, and econometric methods, forming the basis for subsequent model estimation in this dissertation. The next four chapters would consist of four studies, each of which intends to answer specific objectives in relation to carbon emissions and climate change impacts on agriculture and prices, both in the short term and over time. The final chapter will present the conclusions and policy implications of the research findings, along with associated recommendations for future research. The following enumerates the integral aspects of the study.

CHAPTER THREE: ***The Influence of Carbon Dioxide Emissions on Food Consumption Patterns and Farm Produce Prices in South Africa*****.**

This study investigates the effects of CO_2 emissions on food consumption patterns and the prices of major agricultural commodities. The analysis employs the Vector Error Correction Model (VECM) framework combined with the Johansen cointegration technique to examine both the long-run equilibrium relationships and short-run dynamics among the variables. Prior to estimation, unit root tests are conducted to determine the stationarity properties of the time-series data. The empirical analysis further incorporates impulse response functions and forecast error variance decomposition to assess the dynamic responses of food consumption patterns and agricultural prices to shocks in CO_2 emissions, consumer price inflation, and purchasing power. The results provide evidence of long-run equilibrium relationships among emissions, consumer price inflation, purchasing power, and food consumption trends.

CHAPTER FOUR: ***Decoupling Agricultural Growth from Carbon Emissions in South Africa: An Empirical Analysis of the Sustainability Nexus***

The study explores the couplings between agricultural growth and carbon emissions in South Africa and whether the agricultural sector in South Africa has undergone a decoupling process. Using the Autoregressive Distributed Lag (ARDL) modeling, Fully Modified Ordinary Least Squares (FMOLS) and Dynamic OLS (DOLS), the results reveal that CO_2 emissions have a strong long-run relationship with agricultural value-added, trade openness, and renewable energy.

CHAPTER FIVE: ***Climate variability, price risk, and agricultural output in South Africa: An econometric assessment.***

The studies looked at the combined effects of climate variability and price risk for agricultural production. The study also includes external trade Variables, domestic price volatility indicators, temperature, and rainfall anomalies using ARDL, cointegration analysis, and Granger causality.

CHAPTER SIX: ***Carbon Emission Risks and Price Volatility: Implications for Agricultural Productivity in South Africa.***

The study explore the impacts of CO_2 emission risk and price volatility on agricultural output are examined jointly within a risk-augmented Vector Error Correction (VEC) framework. The study shows robust long-run linkages; i.e., emission risks considerably hamper agricultural productivity by enhancing environmental degradation, reducing input-use efficiency, and heightening yield variability.

CHAPTER SEVEN: Conclusions and Recommendations. Finally, the study presents its overall conclusions and policy implications.

Chapter 2: Literature Review

2.1. Introduction

The agricultural sector in South Africa is closely linked to the country's economic performance, environmental sustainability, and climate dynamics. In recent decades, increasing carbon dioxide (CO_2) emissions, climate variability, and agricultural price volatility have emerged as major factors influencing agricultural productivity and long-term food security. Understanding the complex interactions among these environmental and economic forces is therefore essential for designing policies that promote sustainable agricultural development while mitigating the adverse effects of climate change.

This chapter reviews the existing theoretical and empirical literature related to the interconnections between carbon emissions, climate variability, agricultural price dynamics, and agricultural productivity. Emphasis is placed on econometric studies that investigate both short-run and long-run relationships among these variables.

The chapter synthesizes global, regional, and national evidence relating to four key areas:

1. The influence of CO_2 emissions on agricultural productivity and environmental sustainability.
2. The role of climate variability and climate change in shaping agricultural outcomes.
3. The effects of agricultural price volatility and market risks on farm production and food security.
4. The econometric and analytical frameworks used to examine these relationships.

The chapter concludes by identifying key variables, indicators, and methodological approaches that inform the empirical modelling strategy adopted in the subsequent chapters of this dissertation.

2.2. South Africa in Global and Regional Context

Globally, agriculture, forestry, and other land use (AFOLU) contribute roughly a quarter of net anthropogenic greenhouse gas (GHG) emissions, including a mix of CO_2, methane (CH_4), and nitrous oxide (N_2O) generated by livestock, cropland management, fertilizer use, and land-use changes such as deforestation and fire. However, CO_2 is not always the majority of agricultural

emissions globally; non-CO_2 gases (notably methane and nitrous oxide) often represent a larger share in the agricultural context. For South Africa, methane and nitrous oxide emissions from agriculture, especially from manure management and livestock, are particularly significant, but CO_2 emissions, while important, form a smaller proportion of the sector's total GHG emissions (Moeletsi and Tongwane, 2015; Mashiyi et al., 2024; Roman-Cuesta et al., 2016).

Among the BRICS countries (Brazil, Russia, India, China, and South Africa), South Africa has a relatively smaller agricultural footprint compared to countries such as Brazil, India, and China. This group, as a whole, is responsible for approximately 42% of global carbon emissions (not just agriculture), with South Africa being one of the smaller contributors in this category (Erkılıç et al., 2025). When looking specifically at South Africa's emissions, most recent studies and country-level inventories (including those following Intergovernmental Panel on Climate Change (IPCC) guidelines) show that the agriculture sector is a net emitter of GHGs, though agricultural CO_2 is a modest contributor compared to emissions from energy (notably coal combustion) and land-use change (Ncipha and Sivakumar, 2022; Ngarava et al., 2019). The direct CO_2 emissions from South African agricultural activities primarily arise from fuel use in farm machinery, on-farm energy use, lime application, urea fertilization, and, to some extent, soil carbon losses under conventional tillage systems (Muzangwa et al., 2021; Moeletsi and Tongwane, 2015).

One analysis focusing on agricultural growth, renewable energy, and CO_2 emissions in South Africa from 1990 to 2021 showed that while agricultural expansion and international trade can stimulate economic growth, the sector's emissions have contributed to environmental deterioration, with renewable energy currently insufficient to offset CO_2 increases (Aluwani, 2023). Conservation agriculture and intercropping systems can mitigate certain emissions, such as increasing soil carbon storage or reducing fossil fuel use; however, adoption rates remain limited (Mogale et al., 2023; Muzangwa et al., 2021).

Although agriculture is not the leading source of South Africa's national CO_2 emissions, which are predominantly from coal-fired power production, the sector does contribute directly to the country's CO_2 profile, especially through mechanization, fertilizer use, and some land-use practices (Kaya, 2025; Aluwani, 2023). South Africa's contribution to global agricultural CO_2 emissions is accordingly small, likely well under 1% of the world total, but regionally significant within Africa.

Notably, within the BRICS group, the expansion of agricultural land in South Africa has shown little long-term impact on total CO_2 emissions; instead, mechanization and fertilizer use are more significant drivers of emissions (Kaya, 2025). The implementation of carbon credits has expanded renewable energy use, and climate-smart agriculture policies are recommended to mitigate emissions and enhance sustainability (Hayo and Hasegawa, 2024). In summary, livestock manure and fertilizer management are leading sources of agricultural GHG in South Africa (Moeletsi, 2015; Mashiyi, et al., 2024) with mechanization and fertilizer use principal drivers of sectoral CO_2 emissions (Kaya, 2025). Expanding agricultural land in South Africa does not substantially contribute to national CO_2 emissions, but the adoption of renewable energy lags (Aluwani, 2023; Kaya, 2025).

Table 2.1: Summary of South Africa's Agricultural CO_2 Emissions Context

Region	**Agricultural CO_2 Emission Drivers**	**Relative Share**	**Key Notes**
Global	Fossil energy, land-use change, machinery.	100%	AFOLU ≈ 25% of all GHGs.
BRICS	Mechanization, fertilizer, trade, expansion.	42% (all CO_2, not agriculture-specific)	South Africa: smallest contributor in BRICS.
South Africa	Fossil fuels, lime, fertilizer, tillage.	<<1% of global agriculture CO_2	Most GHG from outside agriculture; livestock/methane are larger GHG sources in agriculture.

(Source: Author's computation)

The cropland fires contributed the most CO_2 emissions within the country`s agricultural sector (Climate Trace, 2023). In 2021, CO_2 emissions from cropland fires reached a level of about 3.6 million tonnes, constituting 2% of the global cropland CO_2 fire emissions. The windy, dry, and hot summer weather of the Western Cape Province is the major factor contributing to the cropland fires in South Africa (Climate Trace, 2023). The Western Cape Province lost 81.4 kilos of cropland due to fires over the period from 2001 to 2021 (Climate Trace, 2023). Better planning for land-use and fire awareness promotional campaigns against human-induced

wildfires can help reduce the frequency of cropland fires, thereby decreasing CO_2 emissions (Tagwi, 2022).

South African CO_2 emissions, which contribute to environmental and climate degradation on the African continent, are well-documented. South Africa has been identified as the top CO_2 emitter on the African continent, accounting for approximately half of the continent's CO_2 emissions (OWID, 2022). On the other hand, of all the South African economic sectors, the agricultural sector is the most vulnerable to climate change. According to the World Bank's predictions, the production of high-value-added agricultural exports, such as cereal crops and livestock, is inevitably negatively affected by CO_2 emissions, contributing to climate change in South Africa (World Bank, 2021). Nevertheless, on the contrary, tropical crops such as sugarcane productivity are projected to increase due to potential climate change resulting from CO_2 emissions. These benefits, however, can be encountered by increases in the distribution of diverse pests. Future projections of CO_2 emissions and potential climate impacts have significant implications for the economy, particularly regarding potential foreign direct investments in South Africa (Tagwi, 2022). As a result, changes in climate due to CO_2 emissions and resilience are critical to the growth of the South African economy and are normally used as a yardstick or barometer for future investments (World Bank, 2021; Tagwi, 2022).

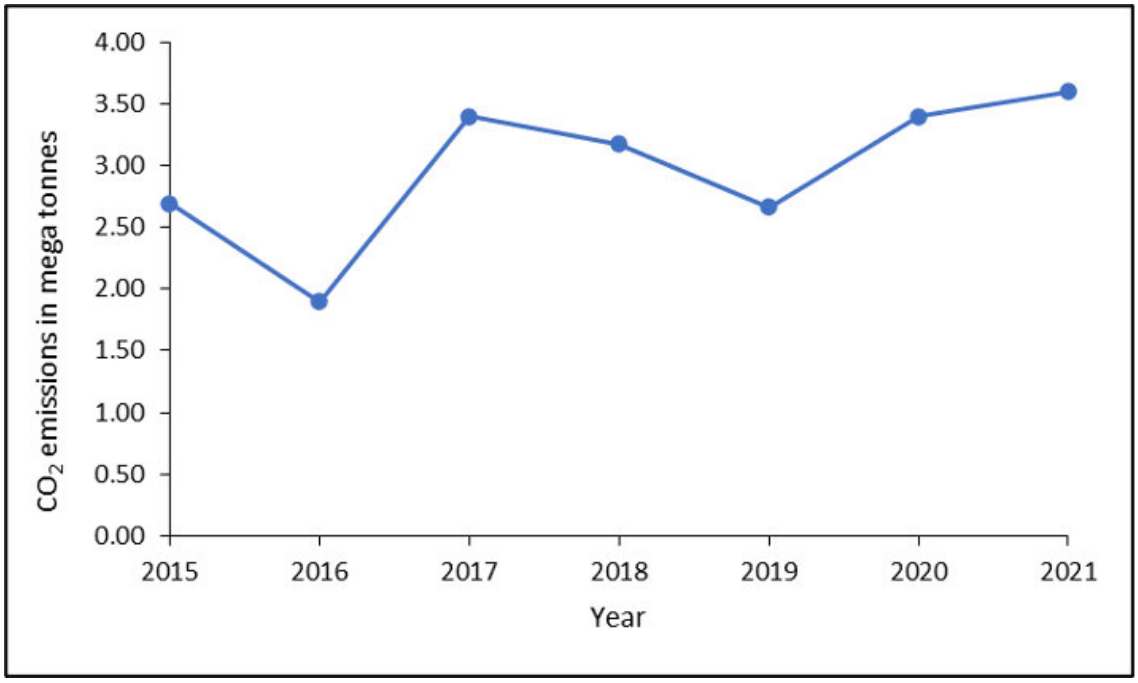


Figure 2.1: CO_2 emissions in mega tonnes from the agricultural sector over the period 2015-2021. (*Source: Climate Trace, 2023)*

2.3. Climate Factors, Price Risk, and Agricultural Productivity in South Africa

2.3.1. Overview of South Africa's Agricultural Sector and Economy

South Africa's agricultural sector holds a pivotal role in underpinning the country's economic structure and export performance. Agriculture not only contributes substantially to the gross domestic product (GDP) but also serves as an essential source of employment and livelihood, particularly in rural areas. The sector's integration with international markets has further sharpened its significance, with increasing agricultural exports, broadening trade opportunities, and fostering economic growth. South Africa's agricultural landscape reflects vibrant potential; however, it is also concurrently exposed to pronounced vulnerabilities stemming from environmental shifts and climate change. The intensification of climate change impacts has been linked to variability in temperature and rainfall patterns, both of which are critical determinants of crop yields and livestock productivity. These environmental disturbances propagate through the agricultural supply chain, manifesting as fluctuations in economic output and underpinning a tight linkage between agricultural performance and the broader economy (Aluwani, 2023).

The relationship between the agricultural sector and the overall economic performance is complex and multifaceted. As agricultural output fluctuates due to climatic and environmental stressors, the corresponding economic ripple effects can influence food security, rural incomes, and trade balances. Therefore, understanding these dynamics within South Africa's context is critical for developing adaptable and sustainable economic strategies. The nexus between agriculture, the environment, and the economy has increasingly been the target of econometric investigations employing advanced time series approaches that are adept at capturing both immediate and persistent effects on the agricultural economy (Tagwi, 2022). Furthermore, the broad spectrum of economic factors influencing agriculture, including trade, financial services, and policy interventions, creates layers of interdependency that necessitate comprehensive analytical frameworks to delineate causal pathways and policy levers effectively (Ruben and Burger, 2007).

2.3.2. Climate Change, CO_2 Emissions, and Agricultural Productivity

Carbon dioxide (CO_2) emissions are a principal driver of climate variability, exerting a considerable influence on temperature regimes and precipitation cycles globally, as well as within South Africa. The increase in atmospheric CO_2 is closely linked to the process of

anthropogenic global warming, which leads to shifts in climatic parameters crucial to agricultural productivity. Temperature escalation has a detrimental impact on key physiological processes in crops and livestock, often resulting in reduced yields, shortened growing seasons, and increased evapotranspiration demand. Similarly, changes in precipitation patterns, both spatially and temporally, influence water availability, impacting soil moisture, irrigation practices, and crop resilience. Consequently, these climatic factors modify the levels of agricultural output and the economic returns associated with the sector (Etienne et al., 2025).

Theoretically, agricultural economic models link these climate variables with output through several pathways, including the direct physiological effects on crops, shifts in pest and disease dynamics, and alterations in land-use suitability. This interconnectedness emphasizes that climate change impacts extend beyond environmental concerns—they are also economic and social, influencing farmers' decisions and national food security. Globally, similar studies underscore the detrimental effect of rising temperatures and erratic rainfall on staple food production, particularly in vulnerable developing regions such as Sub-Saharan Africa, where adaptive capacity may be limited (Sultan, 2012). Innovative econometric models, including dynamic ARDL simulations, have been employed to examine the complex relationships between CO_2 emissions, climate variables, and agricultural performance, offering quantifiable insights for policy formulation aimed at mitigating adverse impacts while harnessing potential benefits, such as CO_2 fertilization under specific conditions (Udeagha and Breitenbach, 2023).

2.3.3. Price Risk and Market Uncertainties in Agriculture

Price risk represents a significant dimension of uncertainty within the agricultural sector, particularly in contexts such as South Africa, where global market integration exposes producers to volatile commodity prices. Such price volatility influences farmers' investment decisions in inputs and technology adoption, alters production choices, and impacts income stability and market participation. The risk associated with fluctuating prices necessitates the incorporation of price risk into agricultural economic models to capture its immediate effects and dynamic feedback on production behaviour and economic growth (Ruben and Burger, 2007).

Econometric analyses often incorporate risk considerations through variables that capture price indices, volatility measures, and financial market indicators. These instruments highlight how price uncertainties, combined with climate-induced risks, exacerbate pressures on agricultural

output and rural livelihoods. Moreover, linkages between financial markets and agriculture emphasize that access to credit, insurance mechanisms, and financial inclusion play crucial roles in mediating the impacts of market uncertainties on production and investment patterns. In this respect, policy frameworks fostering market stabilization and financial risk mitigation become indispensable for reinforcing agricultural resilience and economic stability (Komarek et al., 2019). Empirical studies in South Africa and other emerging economies highlight the importance of integrating financial indicators, foreign direct investment, and market openness metrics in capturing the complexities of agricultural economic outcomes amid price risk (Soni and Manogna, 2024).

2.3.4. Consumption Pattern and Price of Farm Produce in South Africa

Research on food demand patterns in South Africa reveals that aggregate household consumption is a multifaceted phenomenon, encompassing a variety of food categories with different elasticities to price and income changes. For instance, studies using national household survey data from the early 1990s employed Linear Approximate Almost Ideal Demand System (LA/AIDS) modelling to investigate these patterns, demonstrating a general price elasticity for categories such as meat, fish, grains, dairy, fruits, and vegetables (Agbola, 2003). Price sensitivity and expenditure elasticities vary across these food groups, indicating that some items, such as fish and grains, behave like luxuries, while others serve as necessities in the diet. These consumption behaviours are influenced by socioeconomic factors, including urbanization, race, family size, and demographic characteristics, which collectively shape the demand structure.

The agricultural sector's significance extends beyond consumption, contributing substantially to South Africa's national economy and holding a vibrant position in global markets. The country's engagement in international trade highlights the intricacies of supply-demand dynamics, price volatility, and the pressures of competitiveness, especially in commodities such as maize, soybeans, and red meats that form the backbone of production and export activities (Aluwani, 2023; Geyser et al., 2024). These economic activities are closely linked to environmental considerations, particularly CO_2 emissions that arise from various agricultural processes, including the use of fertilizers, livestock management, and soil cultivation. CO_2 emissions from agriculture represent a crucial dimension of sustainability discourse in South Africa, given the sector's significant contribution to greenhouse gases and the country's obligations under international environmental frameworks.

Price effects on agricultural production and consumption further complicate this landscape. The interplay between inflation, input costs, market access, and price transmission mechanisms must be evaluated to understand how these factors influence farmers' incentives, consumer behaviour, and overall sector efficiency (Sibanda and Ndlela, 2020; Inglesi-Lotz and Blignaut, 2011). Hence, a thorough analysis of consumption patterns, CO_2 emissions, and pricing dynamics in farm produce is vital for policy formulation aimed at achieving sustainable economic growth, environmental stewardship, and food security goals in South Africa.

(i). Household Food Demand Elasticities and Expenditure Response in South Africa

The elasticity of demand for food products within South African households reveals notable variability contingent on the type of commodity and income levels. Empirical investigations using linear demand systems reveal that meat, fish, grains, dairy products, fruits, and vegetables generally exhibit price elasticities, indicating that the quantity demanded reacts sensitively to price changes. Specifically, grains and fish tend to be classified as luxury items, whereas other food groups, such as dairy products and vegetables, are more likely to be considered necessities (Agbola, 2003). Expenditure elasticities further underscore this division, with luxury goods experiencing greater proportional increases in consumption as household income rises, while necessities show comparatively inelastic behaviour.

Socioeconomic attributes have a pronounced influence on consumption patterns. Variables such as urbanization, the race and gender of the household head, and family size serve as determinants that shape the dietary preferences and purchasing power of consumers in South Africa. Urbanized households often exhibit higher consumption levels across diverse food groups due to better market access and income opportunities, whereas rural households may have more constrained options, which can influence demand elasticity (Agbola, 2003). These demographic influences underscore the heterogeneity in consumption, necessitating that models of food demand integrate these factors to accurately reflect real-world complexities.

Changes in consumption also respond markedly to shifts in income levels, with the elasticity of various food items reflecting their categorization as either luxuries or necessities. As household income increases, demand for higher-quality and more diverse foods, such as meat and fish, tends to rise, whereas demand for staple grains and basic food items displays relatively less sensitivity. This differentiation has implications for nutritional security and economic policy, indicating potential shifts in diet composition as economic conditions evolve.

(ii). Sector-Specific Consumption and Production Trends in South Africa

Consumption trends across specific food sectors in South Africa reveal varied dynamics. Meat and dairy products generally maintain significant positions in dietary intake, supported by both domestic consumption and export markets. Grains, especially maize, remain a staple, with production and consumption closely linked to both smallholder and commercial agrarian systems (Bowmaker and Nieuwoudt, 1990). Fruits and vegetables complement these staples, though their demand tends to be more elastic due to substitution possibilities and seasonal availability.

Importantly, export and import substitution effects influence South Africa's agricultural commodity markets. The elasticity estimates for various products highlight that grain markets tend to be more responsive to foreign competition compared to fruit and meat sectors, where domestic production is less substitutable by imports (Ntombela et al., 2018). Armington elasticities suggest imperfect substitution between imported and domestically produced agricultural products, influencing policy modelling related to trade and market access (Ogundeji et al., 2010). These dynamics affect the balance between promoting local production and managing exposure to global price fluctuations and trade policies.

The informal and smallholder sectors play a crucial role in shaping agricultural consumption behaviours. The deregulation of the meat industry in the early 1990s, for example, led to increased market participation from informal producers, who leveraged the freer marketing environment to sell directly to consumers, thereby bypassing some formal market requirements (van Tilburg and van Schalkwyk, 2012). Challenges such as limited access to slaughter facilities, market information, and concerns regarding carcass inspection continue to influence consumption patterns within these sectors (Sojl et al., 1970). The overlap between informal activity and formal markets contributes to a dualistic agricultural economy where consumption and production patterns in each domain respond to differing economic and regulatory incentives.

(iii). Shifts in Consumption Due to Environmental and Economic Factors

Economic factors such as inflation and price changes exert a substantial influence on agricultural consumption. South Africa experienced prolonged periods of double-digit inflation beginning in the 1970s, accompanied by slower increases in agricultural producer prices relative to input costs, which resulted in diminished profitability and increased financial risk

for farmers (van Zyl, 1986). These conditions created cash flow challenges that constrained input use and operational decisions, ultimately impacting production volumes and consumption availability.

More recently, studies examining short-run responses to fluctuating prices have indicated asymmetric price transmission in markets such as pasteurized milk, where retailers tend to respond more rapidly to price increases than to decreases, thereby affecting consumer welfare and market equilibrium (Ramoshaba et al., 2019). Relatedly, price volatility driven by global factors, including biofuel demand and currency fluctuations, manifests in food price spikes that disproportionately burden poor and vulnerable populations (Mitchel, 2008).

Agricultural consumption patterns are also adapting in response to environmental challenges and changing farmer behaviours, including climate variability and the adoption of crop insurance mechanisms as risk mitigation tools. Empirical analyses using probit models reveal that insurance adoption has a positive influence on crop revenue amid climatic uncertainty, incentivizing more resilient production practices (Elum et al., 2018). However, behavioural factors such as farmer experience and access to irrigation underscore the complexity of adoption patterns and the subsequent effects on consumption stability.

Consumer preferences are increasingly recognizing the importance of sustainability and food security considerations, influenced by the impacts of climate change and policy narratives advocating for equitable access and resilient food systems (Ojogiwa and Mubangizi, 2023). This shift is reflected in the demand for climate-smart agricultural products and integrated approaches that promote sustainable consumption. The influence of socioeconomic inequalities and rural-urban divides further complicates consumption trends, underscoring the need for contextually nuanced policies that address systemic disparities while promoting environmental stewardship.

(iv). Consumption Patterns and their Environmental Footprint

- **Household Consumption Impact on CO_2 Emissions from Food**

Household dietary choices have a significant impact on CO_2 emissions associated with food consumption. High consumption of meat and animal-based protein is associated with increased carbon footprints, primarily due to methane emissions and energy-intensive production processes (Ivanova et al., 2015). Comparative studies highlight that plant-based diets generally

exhibit lower emissions profiles, with rice and other staples presenting variable impacts depending on production methods and consumption volumes (Afrouzi et al., 2023).

Socioeconomic drivers influence consumption patterns and resulting emissions, with wealthier populations typically exhibiting higher per capita footprints, often associated with diversified diets and increased meat consumption (Ivanova et al., 2016). These findings advocate for policy interventions that address consumption behaviours as a lever for emission reduction

- **Regional and Sectoral Variations in Consumption and Emissions**

Agricultural practices and associated emissions reveal spatial heterogeneity within South Africa. Studies assessing agroecological regions have noted that intercropping systems, tillage practices, and crop density substantially influence CO_2 emission rates, validating localized management as a strategy to optimize carbon storage and reduce atmospheric losses (Mogale et al., 2023). Smallholder consumption and production behaviour further reflect diverse environmental footprints influenced by access to resources, technology, and markets (Elum et al., 2018).

- **Consumption Trends Related to Food Security and Climate Change**

Agriculture is pivotal in addressing Sustainable Development Goals related to food security and climate action, particularly in sub-Saharan Africa. Integrated assessment frameworks reveal that diversification toward micronutrient-rich crops and adoption of climate-smart practices are necessary to meet the adequacy of nutrient supply amidst population growth and climate risks (Ngarava et al., 2019). These strategies, however, may entail trade-offs, such as increased greenhouse gas emissions, if they rely on intensified production without emission controls (Jennings et al., 2024).

Elevated food prices disproportionately affect vulnerable populations, creating tensions between emission mitigation and access to affordable nutrition (Mitchel, 2008). Adaptation and mitigation strategies that alter dietary patterns and production systems hold promise for reconciling these challenges, requiring coordinated efforts across policy, research, and community engagement sectors (Asfew et al., 2023).

2.4. Theoretical Frameworks Underpinning Econometric Analysis

Econometric analysis forms the backbone of quantitative economic research, integrating theoretical constructs with statistical methods to examine relationships among economic

variables, test hypotheses, and inform policy decisions. The theoretical frameworks underpinning econometric analysis play a vital role in guiding model specification, ensuring methodological rigor, and interpreting empirical findings. A nuanced understanding of these frameworks enhances the fidelity and applicability of econometric results across diverse fields, from macroeconomic policy to microeconomic behaviour and institutional analysis. This comprehensive overview explores foundational theories, methodological advances, policy-oriented applications, behavioural and institutional perspectives, as well as recent innovations and critiques in econometrics.

2.4.1. Agricultural Production and Climate-Economy Models

Classical and contemporary economic theories provide a foundational understanding of the relationship between climatic conditions and agricultural productivity. Ricardian approaches, for instance, model the economic impact of climate change by associating land values with climate variables, thereby indirectly implying adjustments to production potential and farmer welfare in response to climatic shifts. Biophysical crop models complement this by simulating physiological responses of crops to temperature, precipitation, and CO_2 levels, enabling the integration of environmental change into economic projections. This dual modelling framework enables a nuanced analysis of both yield impacts and economic outcomes, reflecting real-world complexities (Bouteska et al., 2024).

Environmental externalities, particularly those resulting from CO_2 emissions and other pollutants, also have profound effects on agriculture. Economic theories of externalities elucidate situations where agricultural practices both impact and are impacted by environmental degradation, necessitating corrective policies or technological adaptations to internalize such costs. These concepts are increasingly embedded in models that project agricultural growth trajectories under varying climate scenarios, often incorporating market-based instruments and policy constraints to capture realistic decision-making landscapes (Sultan, 2012). Moreover, dynamic climate-economy integration acknowledges feedback mechanisms in which agricultural productivity affects emissions through land use, input applications, and energy consumption, and conversely, where climate shifts impact production and income (Dell et al., 2014).

2.4.2. Environmental Kuznets Curve (EKC) and Its Extensions

The Environmental Kuznets Curve (EKC) hypothesis posits an inverted-U relationship between income growth and environmental degradation, suggesting that initial economic expansion exacerbates emissions, followed by improvements as income reaches higher thresholds due to the adoption of cleaner technologies and the implementation of regulatory frameworks. In the South African context, the EKC model has been applied to explore the evolution of CO_2 emissions in relation to agricultural development and broader economic indicators (Udeagha and Breitenbach, 2023).

Extensions to the EKC incorporate financial development and trade openness as moderating factors influencing environmental outcomes. Financial development can promote investment in green technologies and renewable energy sources, potentially attenuating the adverse environmental impacts associated with economic growth. Similarly, trade openness influences environmental sustainability by altering production structures, technology diffusion, and resource allocation. Empirical investigations applying these enhanced EKC frameworks in South Africa reveal nuanced interactions where financial and trade dynamics modulate the trajectory of emissions in relation to economic growth, emphasizing the role of institutional and policy environments in shaping sustainable agriculture (Soni and Manogna, 2024). Furthermore, studies on BRICS S-T nations show that integrating renewable energy and eco-innovation components into EKC assessments enhances the understanding of agricultural sector environmental impacts, providing a more precise measure of policy effectiveness (Padhan et al., 2023).

2.4.3. Econometric Approaches: ARDL and Cointegration Techniques

The Autoregressive Distributed Lag (ARDL) model has gained prominence for its flexibility in estimating both short-run dynamics and long-run equilibrium relationships within a unified framework. It is particularly suitable for datasets with variables integrated of order zero, I(0), or one, I(1), making it advantageous in environmental-economic studies where variable stationarity may vary. ARDL's capacity to model lag structures enables the capture of the delayed effects of CO_2 emissions, climate variability, and price risk on agricultural outputs, allowing for inference on adjustment speeds towards long-run equilibria (Tagwi, 2022).

Cointegration techniques underpin the identification of stable long-run relationships among variables. The concept of cointegration articulates the idea that, despite short-term fluctuations,

economic and environmental variables exhibit a harmonious trajectory over extended periods, reflecting underlying equilibrium forces. Complementing ARDL, cointegration methods are crucial for ensuring model validity and guiding policy insights. Alongside, Granger causality testing is commonly applied to discern the directionality of influences among variables, clarifying whether, for instance, changes in CO_2 emissions predict shifts in agricultural growth or vice versa. Panel data methodologies further enrich such analyses by exploiting both cross-sectional and temporal dimensions, thereby enhancing the robustness of inference for policy applications (Aluwani, 2023). Similar modelling frameworks have been leveraged in analyses focusing on South Africa, linking renewable energy supply, CO_2 emissions, and agricultural performance (Olawuyi and Mushunje, 2025).

2.5. Indicators and Variables of Interest

2.5.1. CO_2 Emissions and Environmental Degradation Metrics

In empirical research assessing environmental impacts on agriculture, CO_2 emissions serve as a central indicator reflecting anthropogenic contributions to climate change. Precise measurement encompasses sector-specific emissions, including those arising from agricultural activities, energy consumption, land-use changes, and related industrial processes. Expanding beyond CO_2, some studies incorporate equivalent greenhouse gases and particulate emissions, offering a comprehensive depiction of environmental pressures (Jiaduo et al., 2023).

Furthermore, variables such as natural resource rents, which represent economic returns from resource exploitation, and renewable energy consumption are crucial in assessing environmental sustainability. These indicators help contextualize the scale of resource use and capture the dynamics of the transition towards cleaner energy sources. In South Africa, accounting for the interaction of these variables with agricultural productivity informs the degree to which alternative energy consumption mitigates environmental degradation, while resource rents reflect economic dependence on natural capital and potential environmental stress (Nesirov et al., 2022). Additional analyses of urbanization and industrialization impact on emission profiles provide complementary insights relevant for framing agricultural sector dynamics within broader environmental contexts (Dash et al., 2020).

2.5.2. Climate Variability Indicators: Temperature, Rainfall, and Weather Extremes

Temperature and rainfall metrics remain the dominant proxies for climate variability in agricultural impact assessments. Empirical models often source data from meteorological stations, satellite remote sensing, and interpolated climate grids, ensuring spatial and temporal resolution apt for localized agricultural evaluations. Temperature changes affect crop phenology, heat stress levels, and disease susceptibility, while precipitation regulates soil moisture and water availability, which are crucial for both rainfed and irrigated systems (Affoh et al., 2022).

Extreme weather events, such as droughts, floods, and storms, add further complexity by introducing episodic shocks that can have potentially severe impacts on yields and rural livelihoods. The integration of frequency and intensity of such events into econometric models sharpens understanding of both chronic and acute climate risks. This approach aligns with frameworks that emphasize variability and extremes beyond mean climate shifts as key determinants of agricultural vulnerability (Sultan, 2012). The growing literature also underscores the importance of embedding causal pathways between these climate variables and food security outcomes, often employing sophisticated panel data estimations (Thornton et al., 2014).

2.5.3. Price Risk and Market Dynamics Variables

Agricultural commodity price indices and measures of market volatility capture the financial uncertainty faced by producers and traders. Common indices include futures prices, spot market indices, and volatility estimators derived from historical price data. These variables serve as proxies for risk perception and investment incentives in econometric models assessing agricultural performance (Ruben and Burger, 2007).

Trade openness indices quantify the degree of integration into global markets, reflecting the ease of exporting and importing commodities, including inputs and technologies. Market access, coupled with financial inclusion measures—such as the availability and usage of credit, insurance, and banking services —provides a framework for examining systemic vulnerabilities and resilience in agriculture. Recognizing these factors within empirical models enables the disentanglement of economic constraints from climate-induced production risks (Soni and Manogna, 2024). Financial market variables, including foreign direct

investment and capital flows, further contextualize the environment in which agricultural price risks operate, influencing policy design for risk mitigation (Obiora et al., 2023).

2.6. Empirical Methodologies

Econometric analysis provides the primary empirical framework for examining complex relationships between environmental change, economic variables, and agricultural performance. While earlier studies have employed a wide range of econometric approaches to analyse climate–agriculture linkages, the methodological choices across these studies reflect differing assumptions about data structure, causal mechanisms, and policy relevance. Consequently, a critical assessment of these empirical strategies is essential for identifying appropriate modelling approaches and methodological gaps that this study seeks to address.

Existing empirical literature on climate variability, carbon emissions, and agricultural productivity has relied predominantly on time-series econometric models, cointegration techniques, and causality testing frameworks. These approaches are particularly useful in capturing dynamic relationships among macro-level variables such as emissions, climatic indicators, agricultural output, and price risk. However, differences in model specification, variable selection, and estimation techniques often influence empirical outcomes. This study therefore builds on these earlier approaches while addressing several methodological limitations identified in the literature.

2.6.1. Short-Run Impact Analysis

Short-run dynamics between environmental variables and agricultural output are commonly examined using Autoregressive Distributed Lag (ARDL) models. ARDL frameworks allow researchers to capture both contemporaneous and lagged effects of explanatory variables while accommodating variables integrated at different orders. Studies such as Tagwi (2022) demonstrate that ARDL models are particularly suitable for analysing the short-term responsiveness of agricultural systems to climatic shocks and environmental pressures.

In the context of climate–agriculture interactions, short-run models typically include variables such as CO_2 emissions, rainfall variability, temperature anomalies, and agricultural price indicators. These variables are selected because they represent immediate environmental and economic conditions affecting production decisions. Empirical findings indicate that temperature shocks often produce immediate reductions in agricultural output, while the effects

of emissions and renewable energy usage may vary depending on technological adaptation and policy responses (Zbek and Zbek, 2024).

Despite the usefulness of ARDL models, several studies have noted limitations related to model specification and lag selection. Inadequate lag structures may fail to capture delayed environmental effects, such as cumulative soil degradation or gradual market responses to price fluctuations. Consequently, careful lag selection remains essential to ensure that the dynamic adjustment process is accurately represented (Olawuyi and Mushunje, 2025).

The methodological choice of ARDL modelling in this study is therefore informed by its ability to capture short-run adjustment processes while simultaneously linking them to long-run equilibrium relationships.

i. Causality Tests and Direction of Influence

Beyond identifying correlations, empirical studies increasingly emphasize the importance of establishing causal relationships among climate, emissions, and agricultural productivity variables. Granger causality testing has become a widely used tool for identifying directional relationships within time-series systems.

Studies such as Affoh et al. (2022) demonstrate that causality analysis helps clarify whether environmental degradation drives changes in agricultural productivity or whether intensified agricultural activity contributes to rising emissions. Such distinctions are crucial for designing targeted environmental and agricultural policies.

Evidence from South African studies indicates that causal relationships often run from carbon emissions to climatic variables and renewable energy consumption, reflecting the presence of environmental feedback mechanisms (Aluwani, 2023). These findings highlight the need for empirical models that capture bidirectional interactions between environmental and economic variables.

However, many previous studies focus primarily on environmental indicators while overlooking institutional and macroeconomic factors. Research by Mohamed et al. (2025) suggests that variables such as political stability and economic growth can mediate the relationship between environmental change and agricultural productivity. These insights informed the broader variable selection strategy adopted in this study.

ii. Robustness Checks: FMOLS, DOLS, and CCR Estimations

While ARDL models provide a useful framework for examining short-run dynamics, concerns regarding endogeneity, serial correlation, and model stability often require additional robustness testing. To address these issues, several studies complement ARDL estimations with alternative cointegration estimators such as Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and Canonical Cointegrating Regression (CCR).

These estimation techniques improve the reliability of long-run parameter estimates by correcting for potential biases arising from serial correlation and endogeneity. Empirical studies in the South African agricultural sector indicate that robustness checks frequently confirm the persistence of climate-related productivity constraints while revealing more nuanced relationships between emissions, renewable energy use, and agricultural output (Aluwani, 2023).

Comparative evidence further suggests that although ARDL models effectively capture short-run adjustments, FMOLS and DOLS estimators provide more consistent long-run estimates when variables exhibit strong cointegration relationships (Olawuyi and Mushunje, 2025). Consequently, the use of multiple estimation techniques has become a common strategy for strengthening empirical reliability in climate–agriculture research (Qayyum et al., 2021).

2.6.2. Long-Run Impact Analysis

Long-run econometric models aim to identify equilibrium relationships among environmental and economic variables that persist despite short-term fluctuations. Cointegration analysis provides the primary statistical framework for examining these long-term relationships.

Previous studies have consistently identified cointegrated relationships between climate indicators, carbon emissions, renewable energy consumption, and agricultural productivity (Tagwi, 2022). Long-run elasticity estimates derived from these models quantify the extent to which sustained environmental changes affect agricultural output.

Empirical evidence from South Africa indicates that climatic variability exerts persistent negative effects on agricultural productivity, particularly through changes in rainfall patterns and temperature levels. However, the relationship between carbon emissions and agricultural output appears more complex, reflecting interactions between environmental degradation, technological adaptation, and policy interventions (Aluwani, 2023).

Despite these insights, many previous studies examine environmental variables in isolation rather than within an integrated modelling framework. This study addresses this gap by simultaneously analysing emissions, climate variables, price dynamics, and agricultural performance within a unified econometric structure.

2.6.3. Instrumental Variable Regression and Ricardian Models

Alternative empirical approaches have also been employed to estimate climate impacts on agriculture. Instrumental variable regression models and Ricardian frameworks are commonly used to estimate the effects of climate variability on farm revenue and land productivity.

These models attempt to isolate exogenous climatic effects by controlling for confounding economic and environmental factors. Studies using these approaches highlight the role of agricultural insurance in stabilizing farm income and encouraging investment in productivity-enhancing technologies.

Empirical findings also suggest that farmers' adoption of climate risk management strategies is influenced by factors such as farming experience, institutional support, and access to information. These behavioural dimensions highlight the importance of incorporating socioeconomic variables when analysing climate–agriculture relationships (Elum et al., 2018).

However, Ricardian approaches typically rely on cross-sectional data and therefore provide limited insights into dynamic temporal relationships. This limitation reinforces the need for time-series econometric models that capture long-run structural adjustments.

2.6.4. Data Envelopment Analysis and Malmquist Index

Nonparametric productivity analysis methods, including **Data Envelopment Analysis (DEA)** and the **Malmquist productivity index**, provide an alternative framework for examining agricultural efficiency under climate variability.

These approaches enable the decomposition of productivity change into efficiency improvements and technological progress. Studies incorporating climatic inputs such as temperature and precipitation demonstrate that failure to account for environmental factors may underestimate productivity growth.

Regional analyses further reveal heterogeneous climate impacts across agricultural systems. Some regions exhibit negative productivity trends associated with rising temperatures, while

others demonstrate adaptive responses through technological innovation and improved resource management (Bernard et al., 2023).

Although these methods offer valuable insights into productivity dynamics, they do not explicitly capture causal relationships between environmental and economic variables. Consequently, they are often complemented by econometric modelling techniques.

2.6.5. Time Series and Auto-Regressive Distributed Lag (ARDL) Models

Time-series econometric models remain the dominant analytical framework for examining the interactions between climate variables and agricultural performance. Studies using ARDL frameworks have identified long-run relationships between government agricultural expenditure, climate indicators, and agricultural productivity.

Empirical evidence suggests that sustained public investment in agriculture plays a crucial role in supporting sectoral growth and resilience under climate stress. Similarly, macroeconomic variables such as inflation and trade dynamics interact with climatic indicators to influence agricultural output.

By integrating macroeconomic and environmental variables, time-series models provide a more comprehensive understanding of the structural forces shaping agricultural performance in climate-vulnerable economies (Ebenezer et al., 2019; Lukashe and Nishimwe-Niyimbanira, 2025; Matsvai and Hosu, 2024).

2.6.6. Methodological Gap Addressed by This Study

From the synthesis of existing literature, three key methodological gaps emerge:

1. Limited integration of environmental and market variables. Many studies examine climate or emissions effects separately from agricultural price dynamics.
2. Insufficient modelling of both short-run and long-run interactions. Some studies focus exclusively on either equilibrium relationships or short-run adjustments.
3. Lack of robustness verification across multiple estimators. Several empirical analyses rely on a single estimation technique.

To address these gaps, this study employs an integrated econometric framework combining ARDL modelling, causality testing, and robustness checks using FMOLS and DOLS estimators. This approach enables a comprehensive analysis of the dynamic interactions

between carbon emissions, climate variability, price risk, and agricultural productivity in South Africa.

Table 2.2. Summary of Key Empirical Studies and Research Gaps

Study	Methodology	Key Variables	Main Findings	Identified Gap
Tagwi (2022)	ARDL	Climate variables, agricultural output	Climate shocks significantly affect short-run agricultural performance	Limited integration of price risk variables
Affoh et al. (2022)	Granger causality	CO_2 emissions, agricultural output	Evidence of directional relationships between emissions and productivity	Focus on emissions without broader economic controls
Aluwani (2023)	Cointegration, FMOLS	Climate indicators, emissions, agriculture	Long-run climate variability reduces agricultural productivity	Limited consideration of market price dynamics
Olawuyi & Mushunje (2025)	ARDL, DOLS	Climate indicators, agricultural output	Strong dynamic relationships between climate variables and output	Insufficient integration of renewable energy factors
Elum et al. (2018)	IV regression, Ricardian model	Climate variables, farm revenue	Agricultural insurance improves income stability	Cross-sectional design limits dynamic analysis
Bernard et al. (2023)	DEA, Malmquist Index	Climate inputs, productivity	Climate variables influence productivity efficiency	No causal modelling of environmental-economic interactions

(Source: Author's computation)

2.7. Empirical Evidence from Literature

Empirical evidence is a foundational concept in scientific literature, referring to information obtained through observation or experimentation rather than theory or pure logic. Within academic research, empirical evidence is crucial because it enables researchers to establish and

test hypotheses against real-world data, which strengthens the reliability and validity of scientific conclusions. The importance of empirical evidence becomes particularly clear when examining the methodological standards that underlie modern research practice.

2.7.1. Impacts of CO_2 Emissions on Agricultural Output

CO_2 emissions impose both direct and indirect adverse effects on agricultural outputs. Direct impacts emerge through temperature increases that undermine photosynthetic efficiency, crop development, and livestock health. Indirectly, emissions contribute to broader climatic shifts affecting soil moisture, pest prevalence, and water resource availability. Some studies note the limited CO_2 fertilization effect, which may temporarily improve plant growth under elevated CO_2 but is outweighed by warming-related stressors (Matthew et al., 2020).

Decomposition analyses disentangle these effects, showing how atmospheric alterations interplay with soil and water degradation processes, cumulatively diminishing yield potential and agricultural sustainability (Sultan, 2012). Sub-Saharan evidence highlights significant reductions in crop yields attributed to rising emissions correlated with temperature increases, drawing attention to the multifaceted challenges of managing agricultural productivity under environmentally degraded conditions (Etienne et al., 2025).

Agricultural sector emissions primarily stem from fertilizer application, livestock methane emissions, deforestation, and energy use. Fertilizer and pesticide consumption have been statistically linked with increased greenhouse gas emissions, suggesting the need for sustainable input management (Nesirov et al., 2022). Livestock numbers and practices significantly contribute to the national agricultural carbon footprint, which varies regionally according to production systems and land-use patterns (Phiri et al., 2021).

Energy consumption patterns tied to mechanization and processing also affect emission magnitudes. South African zones differ markedly in terms of emission intensity, which is linked to agricultural practices, land degradation, and energy source mixes. Understanding these variations permits tailoring of emissions management strategies to local conditions (Aluwani, 2023)

2.7.2. Climate Variability Impacts on Agricultural Economic Growth

i. Temperature Effects on Productivity and Output

Evidence consistently demonstrates that rising temperatures reduce agricultural productivity by accelerating crop maturation, increasing evapotranspiration, and exacerbating heat stress on plants and animals. Short-run adaptive responses are constrained geographically and technologically, making crop and livestock sectors vulnerable, especially in marginal areas (Etienne et al., 2025).

Temperature-related yield reductions vary by crop type, with staple grains, such as maize and wheat, being particularly susceptible. Long-run trends magnify these impacts with cumulative losses undermining food security (Sultan, 2012). Detailed regional analyses, including Ethiopian crop studies, reinforce the vulnerability and highlight the need for targeted adaptation strategies (Bouteska et al., 2024).

ii. Precipitation Variability and Extreme Weather Events

Rainfall variability and the increased frequency of extreme weather events directly influence agricultural productivity by altering soil moisture regimes and increasing the risk of physical damage. Droughts and floods disrupt planting schedules, reduce yields, and prompt resource reallocation, often disproportionately affecting smallholder farmers (Thornton et al., 2014).

Economic consequences of precipitation changes extend to food security risks and rural livelihoods, with water resource management and irrigation infrastructure playing vital mediating roles (Mohamed et al., 2025). Conceptual frameworks emphasize the integration of hydrological variability into agricultural planning and policy to mitigate risks (Connolly-Boutin and Smit, 2015).

iii. Crop Yield Responses and Food Security Implications

Climatic stressors such as increasing temperatures, erratic rainfall, and drought events have led to notable declines in yields of staple crops, including maize and wheat. This reduction poses significant threats to food availability and nutritional security at both household and community levels. In rural South African areas, constrained crop productivity contributes to persistent food insecurity, aggravating malnutrition and limiting dietary diversity.

Additional factors influencing food security include access to irrigation and involvement in crop production, which positively correlate with improved productivity and nutritional outcomes. Conversely, challenges such as limited agricultural inputs and socio-economic vulnerabilities impede progress towards food security in climatically stressed contexts (Hlatshwayo et al., 2023; Thompson et al., 2010; Mukherjee, 2021).

iv. Livestock Production under Climatic Stress

Livestock production is particularly sensitive to drought and heat stress, resulting in increased mortalities, reduced milk yields, and decreased reproductive performance. Agricultural drought resilience among commercial livestock farmers remains a pressing concern in South Africa's arid regions, necessitating multidimensional strategies encompassing water resource management, pasture conservation, and livelihood diversification.

Pasture ecosystems in savannah rangelands face degradation exacerbated by bush encroachment, prompting the need for sustainable management practices to enhance forage availability and biodiversity conservation. Comprehensive drought resilience indices have been developed to assess livestock farmers' adaptive capabilities, informing targeted interventions for sustaining commercial livestock production under climatic uncertainty (Bahta et al., 2025; Maphanga et al., 2024).

v. Fisheries and Aquaculture Impacts

Though often less emphasized, fisheries and aquaculture sectors are also vulnerable to climate change impacts through altered water temperatures, oxygen levels, and habitat availability. Integrated climate-smart strategies encompassing crop, livestock, and fishery production are critical for enhancing resilience across all food production systems in South Africa and the broader African context.

Institutional and policy frameworks that support climate-smart fisheries contribute to sustainable resource use and maintain livelihood opportunities yet require strengthened implementation and coordination with agricultural adaptation initiatives (Zougmor et al., 2016).

2.7.3. Price Risk and Its Link to Climate Variability in South Africa

i. Inflation and Food Price Volatility in South Africa

Climate factors such as rainfall variability and rising temperatures have been empirically linked to fluctuations in inflation rates, particularly through their influence on food prices. In South Africa, variations in seasonal rainfall diminish agricultural supply chains by reducing output, leading to higher food prices and contributing to overall inflationary pressures. The negative relationship between temperature and inflation observed annually suggests complex seasonal dynamics whereby climate-induced production shocks translate into price instability.

This nexus has significant implications for macroeconomic policy frameworks, advocating for the consideration of climate variables in monetary regulation to enhance policy responsiveness and effectiveness. Failure to incorporate climate factors limits the Reserve Bank's ability to predict inflation volatility accurately and implement timely countermeasures. Hence, climate change-related macroeconomic considerations become vital in stabilizing food prices and safeguarding consumer purchasing power (Lukashe and Nishimwe-Niyimbanira, 2025; IMPF and UNCTAD, 2011; Brinkman and Hendrix, 2010).

ii. Farmers' Perceptions and Risk Management Strategies

Farmers in South Africa exhibit a keen awareness of both climatic and price risks, which significantly influence their production decisions and risk management behaviour. Weather-related risks, including drought and unpredictable rainfall, alongside market price volatility, are identified as primary concerns by smallholder producers. To navigate these risks, farmers employ diversification strategies of crop and livestock enterprises, pest and disease monitoring protocols, and seek to integrate adaptive agricultural practices.

Despite recognition of these risks, socio-economic limitations such as access to affordable credit, information asymmetry, and inadequate extension support undermine the adoption of effective risk mitigation strategies. Barriers also exist in accessing formal insurance products or government assistance programs, which constrain farmers from fully managing climate and market-related uncertainties. Therefore, addressing these constraints through improved access to climate services, financial inclusion, and targeted extension programs is necessary for enhancing farm-level resilience (Duong et al., 2019; Elum et al., 2018; Maziya et al., 2024).

iii. Market Structures and Price Signals for Adaptation

Markets, including land and agricultural commodity markets, serve as mechanisms for signalling climate risks through price adjustments. These signals can incentivize farmers to modify cropping choices, adopt irrigation technologies, and implement soil and water conservation measures to enhance resilience. However, market imperfections, such as price distortions, limited access for smallholders, and insufficient infrastructure, hinder optimal risk signalling and adjustment.

Public policy thus plays a vital role in correcting market failures by improving informational efficiency, subsidizing infrastructure, and fostering enabling environments for market participation. Government expenditure in the agricultural sector, although limited in the short term, contributes to long-run productivity gains by supporting public goods that underpin market functionality. Strengthening institutional frameworks and land tenure systems further facilitates market integration, thereby improving the efficacy of price signals in driving adaptation (Anderson et al., 2019; Ebenezer et al., 2019; Cervantes-Godoy, 2015).

iv. Price Risk and Market Volatility Effects

Price volatility exerts immediate pressures on farm-level decision-making, impacting input usage, crop selection, and investment in technology. Interactions between climatic shocks and price risk compound uncertainties, affecting production stability and profitability (Ruben and Burger, 2007).

Policymakers face challenges in developing instruments that adequately buffer farmers against these multifaceted risks. Empirical evidence indicates that financial inclusion and innovative market mechanisms are critical for effective risk management, alongside climate adaptation technologies (Komarek et al., 2019). Agricultural economic models increasingly account for such risk interactions to capture real-world complexities (Soni and Manogna, 2024).

2.7.4. Integrating Econometric Results into Economic Systems

Dynamic models that integrate climatic variables, emissions data, and price risk metrics enhance the understanding of agriculture's feedback loops within the broader economy. They allow simulation of policy scenarios and forecast how agricultural shocks propagate through economic systems, influencing growth trajectories and income distributions (Tagwi, 2022).

South African studies employ such system models to highlight linkages between the agricultural sector and national economic growth, trade balances, and environmental degradation, providing a basis for refining policies that promote sustainability without hindering development (Aluwani, 2023). The integration of multidisciplinary data streams and model components enables more comprehensive and anticipatory policymaking (Jones et al., 2016).

2.7.5. Price Elasticity and Price Transmission in Agricultural Markets

In agricultural markets, demand and supply elasticities are fundamental to understanding price formation and the responsiveness of producers and consumers. Research on South African agricultural commodities reveal heterogeneous elasticity estimates across key products, including maize, soybeans, and meat. Soybeans and bovine meat exhibit higher sensitivity to import prices, reflecting their critical role in trade and domestic consumption (Ogundeji et al., 2010). Maize, a staple crop, exhibits moderately elastic responses in both demand and supply, with import and export elasticities indicating a reasonably responsive market structure (Ntombela et al., 2018). Understanding these elasticities helps policymakers model responses to tariff changes and trade policy shocks.

Price transmission analyses in sectors like dairy and maize reveal complex mechanisms governing how farmgate prices influence retail prices and vice versa. Vector Error Correction Models and Granger causality tests indicate bidirectional causality in the dairy value chain, highlighting asymmetric adjustments where price increases are transmitted more quickly than price decreases, potentially harming consumer interests (Ramoshaba et al., 2019). Similar studies on maize markets incorporate supply-demand shifters and risk variables to better capture marketing margins and price spreads, showing that price adjustments can reflect medium-term transitions in market conditions (Faminow and Laubscher, 1991).

Transportation, logistics, and infrastructure costs constitute significant components influencing agricultural prices and export competitiveness. Delays at ports, customs procedures, and inefficient inland transit increase the cost burden and adversely affect the volumes of agricultural exports, especially for perishable goods such as maize (Freund and Rocha, 2010). Empirical findings suggest that reduced inland travel times have economically and statistically significant positive effects on export performance, while logistical shortcomings dampen competitiveness in international markets (Geyser et al., 2024). These infrastructural challenges introduce additional volatility into pricing and complicate supply chain management.

2.7.6. Impact of Macroeconomic Variables and Inflation on Agricultural Prices

Macroeconomic variables like inflation have direct and indirect effects on agricultural prices and production sustainability. Historical data reveal that inflation in input prices outpaced increases in agricultural produce prices, compressing producer margins and constraining farm-level investments (van Zyl, 1986). Panel data analyses involving multiple countries, including South Africa, show complex interplays between inflation, producer protection, and economic growth, with significant inflationary pressures correlating with adverse conditions for agricultural outputs (Canbay, 2022).

Exchange rate fluctuations also influence agricultural commodity prices, affecting import costs for inputs and the competitiveness of exports. Trade policies, including subsidies and tariff structures, shape these dynamics, mediating how price signals reach domestic markets and international buyers (Mitchel, 2008). Smallholder farmers often face substantial challenges accessing markets due to price sensitivities and high transaction costs, exacerbated by limited institutional support and infrastructural constraints (Tilburg and van Schalkwyk, 2012). These limitations impede their ability to benefit from favourable price movements and contribute to broader market inefficiencies.

2.7.7. Trade Competitiveness and Export Market Pressures

South Africa's agricultural exports face stiff competition from other southern hemisphere countries such as Argentina, Chile, Australia, and New Zealand. Academic comparisons underline the necessity for innovation in research and development, logistics, and marketing to maintain and enhance South Africa's competitive edge in key product segments (Driaen et al., 2004). Proximity advantages related to port locations and shipping durations are increasingly counterbalanced by improvements in competitors' transport technologies and market access strategies.

Trade facilitation measures that reduce transit times and customs delays have substantial impacts on export volumes and competitiveness. Policies that streamline border procedures and infrastructure investments can translate into meaningful gains in market share and price stability (Freund and Rocha, 2010). Furthermore, trade elasticities derived for agricultural commodities form essential parameters in computable general equilibrium models, enabling better anticipation of policy changes and market adjustments (Ntombela et al., 2018). These elasticities typically reveal inelastic export supply behaviour, indicating producers' cautious

response to price signals, while import elasticities often signal imperfect substitutability between domestic and foreign products.

2.8. Agricultural Productivity and Climate Resilience

Agricultural productivity is increasingly threatened by the profound and accelerating impacts of climate change, including rising global temperatures, altered precipitation patterns, and the increased frequency of extreme weather events such as droughts and floods. These variations lead to unpredictable crop yields, threaten food security, and undermine the livelihoods of farming communities worldwide (Sarma et al., 2024). This section provides strategies that contribute to agricultural productivity despite various climate challenges.

2.8.1. Climate-Smart Agriculture Adoption

Climate-smart agriculture (CSA) encompasses practices and technologies aimed at increasing productivity, enhancing resilience, and reducing greenhouse gas emissions. Adoption of CSA in South Africa is influenced by socio-demographic factors such as education level, household size, farming experience, and perceptions of land fertility. These determinants mediate farmers' willingness and capacity to embrace climate-smart innovations.

Institutional support, particularly from agricultural extension services, plays a crucial role in knowledge dissemination and capacity building, enabling smallholder farmers to implement CSA practices effectively. Approaches such as participatory living laboratories, on-farm demonstrations, and intermediary training have proven effective in technology transfer. Successful CSA technologies include agroecological cropping systems and micro-catchment water harvesting, which improve resource use efficiency and production stability in semi-arid environments (Thabane et al., 2024; Zuma-Netshiukhwi et al., 2025; Maka, 2025).

2.8.2. Technological and Innovation Factors

Technological advancement and innovation are key drivers of increased agricultural productivity and climate adaptation. The integration of information and communication technology (ICT), such as mobile phones and internet usage, enhances access to market information, weather forecasts, and advisory services, directly influencing farming decisions. Empirical evidence indicates positive effects of ICT on both agricultural output and total factor productivity in South Africa.

Innovation activity among emerging farmers, particularly in mechanization and process improvements, reflects responsiveness to climatic challenges and market demands. The availability of irrigation technology further supports diversification and intensification, enabling better management of climatic risks. Nonetheless, constraints such as limited capital investment and training opportunities necessitate focused interventions to scale innovation adoption (Matsvai and Hosu, 2024; Baiyegunhi, 2023; Hlatshwayo et al., 2023).

2.8.3. Diversification and Livelihood Strategies

Diversifying agricultural production serves as an effective strategy to enhance resilience and improve nutrition outcomes. Productive diversification expands income sources, reduces risks associated with single commodity dependence, and contributes to dietary variety. In South Africa, the adoption of underutilized crops with inherent drought resilience offers promising avenues to mitigate both climate and market shocks.

Livestock integration into crop systems, when managed effectively, supports diversified livelihoods while contributing to soil fertility through the application of manure. Such integrated systems promote sustainable land use and enhance adaptive capacity among smallholder communities. Encouraging diversification aligns with broader development goals by reinforcing food security and nutrition amidst changing climatic realities ("World Bank Group, 2018; Omotayo et al., 2025; Bahta et al., 2025).

2.9. Institutional and Policy Frameworks for Agriculture in South Africa

2.9.1 Government Expenditure and Agricultural Support

Government expenditure in agriculture plays a decisive role in stimulating productivity growth, especially over the long term. Empirical evidence supports a positive association between targeted funding and enhanced sector performance. Yet, South Africa's agricultural budget trends reveal a pattern of low and declining investment, which dampens the potential for short-term productivity gains.

Policy recommendations emphasize the necessity of increasing governmental support for infrastructure, research and development, and extension services to bolster sector resilience against climate change. Strengthening institutional provisioning further assists in bridging resource gaps among smallholder farmers (Ebenezer et al., 2019; Cervantes-Godoy, 2015).

2.9.2. Agricultural Extension Services

Extension services constitute a critical conduit for disseminating climate-related information and technologies to farmers. Both public and privatized extension models influence farmers' access to updated knowledge on climate-smart practices, technological advancements, and market information. Farmer perceptions often highlight the need for more frequent and tailored advisory visits alongside enhanced resource support.

Effective extension programs integrate market insights and storage solutions that address not only production but also post-harvest management challenges. Such comprehensive approaches improve farmer capacities to manage climate risks and economic uncertainties collaboratively (Maka, 2025; Mudzielwana et al., 2025).

2.9.3. Climate Services and Information Dissemination

Access to accurate and timely climate services, including short-term weather forecasts and seasonal advisories, is pivotal for farmer decision-making in the context of climate variability. Ownership of mobile phones and radio significantly facilitates access to these services, though barriers such as education level and perception of climate risks influence uptake.

Innovative dissemination platforms, including newsletters integrating remote sensing and in situ data (e.g., the Umlindi newsletter), enhance the localization of climatic information. Recommendations underscore the importance of expanding climate services coverage, forecasting capabilities, and training programs tailored for smallholder communities to reinforce adaptive capacity (Nocezo et al., 2024; Maake et al., 2023).

2.9.4. Policy Implications on Emission Management

Mitigating emissions internal to agriculture demands policies promoting optimized fertilizer use, energy conservation, and transitioning to bioenergy systems. Biomass commercialization emerges as a key strategy, facilitating the substitution of fossil fuels and valorization of agricultural residues within energy mixes (Tagwi, 2022). Supporting rural and commercial farming sectors through bioenergy regulations and socioeconomic research is critical to ensuring equitable participation and sustainability (Phiri et al., 2021). Effective policy design integrates environmental objectives with rural development goals, fostering resilience and economic inclusivity.

2.9.5. Economic Trade-Offs and Policy Trade-offs

Sustainable agricultural growth demands balancing objectives among economic expansion, emission reductions, and adaptation costs. The adoption of renewable energy entails initial investments and potential slowdowns in growth but offers long-term emission benefits (Soni and Manogna, 2024).

Financial development plays a decisive role by enabling access to capital and green technologies, although expanding financial sectors must be carefully managed to prevent unintended environmental consequences (Aslam et al., 2025). Trade policies influence resource allocation efficiency and technology transfer, shaping the environmental footprint of agriculture. Policymakers must consider these trade-offs explicitly to design interventions that optimize outcomes across economic and environmental domains (Udeagha and Breitenbach, 2023).

2.10. Adaptation Strategies and Barriers to Agricultural Productivity in South Africa

2.10.1. Adoption Constraints for Climate-Smart Practices

Despite the recognized benefits of climate-smart agriculture, socio-economic, institutional, and informational barriers constrain widespread adoption. Factors such as limited financial resources, insecure land tenure systems, and lack of extension services limit farmer engagement with new technologies. Knowledge deficiencies and communication gaps further exacerbate the challenges of adoption.

Land tenure instability hinders investments in long-term sustainable practices, while financial constraints limit access to irrigation and mechanization. Addressing these barriers requires multi-stakeholder initiatives, inclusive policy frameworks, and targeted capacity-building interventions to foster greater uptake of climate-smart technologies (Serote et al., 2023; Thabane et al., 2024; Elum et al., 2018).

2.10.2. Risk Management Through Insurance and Financial Instruments

Agricultural insurance represents a pivotal mechanism for mitigating climate-induced risks, providing financial security to farmers against production losses. However, adoption rates remain limited due to cost, accessibility, and awareness constraints. National and regional

insurance schemes have emerged to facilitate risk transfer but require refinement to address smallholder affordability and inclusivity.

Enhanced insurance uptake is linked to factors including farmer experience, information availability, and supportive institutional frameworks. Integrating insurance products with broader financial services and adaptation programs can improve resilience outcomes and promote sustainable farm management (Elum et al., 2018; Syroka and Nucifora, 2010).

2.10.3. Market-Based and Community Adaptation Approaches

Markets facilitate climate adaptation by transmitting price signals that incentivize resilient production practices. Yet, market failures often necessitate policy interventions to ensure equitable access and prevent maladaptation. Community-based strategies, leveraging social networks and indigenous knowledge, augment formal mechanisms by enhancing collective resilience and localized adaptation.

Participatory approaches promote ownership and relevance of adaptation measures, integrating traditional ecological knowledge with scientific advancements. Social capital and cooperative structures further support resource sharing and risk pooling, crucial elements in building adaptive capacities in vulnerable rural communities (Anderson et al., 2018; Bahta et al., 2025; Nyambo et al., 2025).

2.11. Synthesis of Climate, Price Risk, and Productivity Interactions

2.11.1. Complex Interplay Between Climate Factors and Market Dynamics

The interactions between climate variability, price risk, and agricultural productivity form a multifaceted feedback system influencing farmer decisions and production patterns. Climatic shocks impact output quantities and quality, triggering supply-side shocks that reverberate through markets, resulting in price volatility and inflationary pressures. These fluctuations, in turn, affect farmers' input use decisions, investment behaviour, and risk management strategies.

Empirical case studies from South Africa illustrate this dynamic, showing how climate-induced variability in rainfall and temperature not only depresses yields but also triggers market responses that compound production insecurity. Understanding these interdependencies is fundamental to designing integrated policies addressing both climatic and economic

vulnerabilities simultaneously (Lukashe and Nishimwe-Niyimbanira, 2025; Elum et al., 2018; “IMF and UNCTAD, 2011).

2.11.2. Impact of Technological and Policy Interventions on Mitigating Risks

Technology-driven interventions, notably climate-smart agriculture and digital information systems, have shown promise in mitigating the adverse effects of climate and price risks. ICT adoption enhances access to market and climate information, enabling more informed decision-making. Extension services function as critical intermediaries in promoting best practices and fostering adaptive behaviour.

Policy coherence across agricultural funding, extension, insurance, and market regulation enhances system-level response capacities. Evaluation of pilot programs confirms that integrated approaches leveraging technology, institutional support, and inclusive policies yield greater adaptive gains than isolated measures (Matsvai and Hosu, 2024; Zuma-Netshiukhwi et al., 2025; Ebenezer et al., 2019).

2.11.3. Impact of Renewable Energy and Technological Innovations

The adoption of renewable energy and technological innovation in agriculture leads to enhanced productivity and environmental sustainability over the long term. Empirical evidence attests that consistent renewable energy use mitigates emissions and reduces the environmental footprint of agriculture, though immediate impacts in the short run may be limited or insignificant (Jiaduo et al., 2023).

Technological innovations, including precision agriculture, climate-resilient crop varieties, and energy-efficient machinery, have a positive impact on agricultural output while also enabling emission reductions. South African studies highlight that renewable energy supply and investments in human capital for green technology and vocational training can catalyze sustainable agricultural growth (Soni and Manogna, 2024). Recent literature further examines the synergistic effects of green finance, digitalization, and innovation in driving decarbonization within agricultural systems, emphasizing the need for multi-sectoral policy integration (Aslam et al., 2025).

2.12. Research Gaps and Future Opportunities

Despite advances in understanding the impacts of climate and price risk on agriculture, several research gaps remain. There is a need for comprehensive regional-scale assessments that combine climate projections with socioeconomic models to capture exposure, sensitivity, and adaptive capacity comprehensively. Multi-sectoral frameworks integrating water resource management, market risk, and agricultural productivity dynamics warrant development.

Enhanced data collection and methodological innovations in productivity measurement and climate impact attribution are essential. Further research should focus on the socio-cultural dimensions of adaptation, particularly the efficacy of behaviour changes and knowledge dissemination. Addressing these gaps will enable more precise, contextually relevant policy design and resource allocation (Bernard et al., 2023; Adamu, 2024; Thabane et al., 2024).

2.12.1. Methodological Limitations and Data Gaps

Nonetheless, limitations persist in variable measurement precision, especially regarding localized climate data, price risk proxies, and technology adoption levels. Non-linear responses and adaptation heterogeneity remain challenging to model within traditional econometric frameworks, potentially leading to underestimation of resilience or vulnerability (Komarek et al., 2019).

The omission of institutional and political variables restricts the ability to fully account for governance and policy effectiveness. Data constraints limit the spatial and crop-specific disaggregation, reducing the granularity of conclusions. These gaps necessitate continued methodological innovations and expanded data collection to facilitate integrated, more nuanced analyses (Mohamed et al., 2025). Barriers to adaptation, including socioeconomic and institutional impediments, further complicate analytical efforts (Maddison, 2007).

2.12.2. Directions for Future Research

Future research should further refine spatial disaggregation and differentiate impacts across various crop types and agro-ecological zones. Including financial market variables and risk management mechanisms will enhance the realism of models in representing producer behavior under market and climatic uncertainties. Integrating governance, policy, and technological factors promises to deliver a more holistic understanding of agricultural resilience and growth pathways (Bouteska et al., 2024).

Enhanced multi-disciplinary collaboration and the use of innovative data sources, such as remote sensing and big data analytics, could advance impact assessments. Exploring the combined role of governance, technology adoption, and policy choice offers pathways for designing adaptive, inclusive agricultural systems that meet climate challenges sustainably (Etienne et al., 2025). These directions redefine research priorities in line with evolving global and regional concerns (Soni and Manogna, 2024).

2.12.3. Conclusion

In summary, the literature converges on the conclusion that CO_2 emissions, climatic variability, and price risk jointly determines the trajectory of South Africa's agricultural productivity. Temperature and precipitation fluctuations exert immediate adverse effects, while cumulative emissions intensify long-run degradation. Price volatility and market integration further condition these outcomes by influencing investment behaviour and resource allocation.

Renewable-energy adoption, technological innovation, and climate-smart agricultural practices emerge as critical levers for sustainable productivity. Their success depends on supportive institutional frameworks, adequate financing, and coherent policy alignment. Consequently, integrating environmental sustainability within national agricultural and economic planning is imperative.

Chapter 3: The Influence of Carbon Dioxide Emissions on Food Consumption Patterns and Farm Produce Prices in South Africa.

3.1. Introduction

Changes in food consumption patterns are a global phenomenon, closely linked to broader societal development (Oni and Baiyegunhi, 2022). Such changes are often influenced by shifts in household income, rising prices of agricultural produce, and climate change, which collectively affect agricultural productivity, food processing, and trade dynamics. Climate change, driven largely by carbon dioxide (CO_2) emissions, presents significant risks to both natural and human systems through extreme weather events (OWID, 2022). Prolonged climate change can lead to further increases in CO_2 emissions, exacerbating declines in agricultural productivity, raising food prices, and prompting consumers to modify their food consumption patterns (Wier et al., 2001).

The impact of climate change in South Africa, driven by steadily increasing CO_2 emissions, is undeniable. South Africa is the largest CO_2 emitter on the African continent, responsible for approximately half of Africa's total emissions (OWID, 2022). Furthermore, it ranks among the world's top 25 greenhouse gas emitters (Magrini et al., 2018b), largely due to its reliance on coal for electricity and energy production. For instance, South Africa's net CO_2 emissions reached approximately 512 million metric tons of CO_2 equivalent (t CO_2e) in 2017, representing a 14% increase since 2000. CO_2 emissions also influence human consumption systems by affecting consumer price indices and, consequently, consumption behaviour (Tagwi, 2022; Tagwi and Chipfupa, 2023).

In the long term, rising CO_2 emissions contribute to climate disruptions such as droughts, which reduce food availability and drive up the prices of food commodities (Puoane et al., 2006). These price increases disproportionately impact vulnerable and low-income communities, limiting their access to adequate food and reducing the quantities they can afford (Puoane et al., 2006). South Africa's high levels of inequality and poverty exacerbate its vulnerability to climate change, making the issue a critical national challenge (Magrini et al., 2018b). There is a cascading effect in which climate change drives up farm produce prices, altering consumption patterns in ways that remain insufficiently recognized (UN, 2016; Tagwi, 2022; Tagwi and Chipfupa, 2023).

Food price inflation, driven by climate change, erodes the purchasing power of households, particularly in countries with persistently high unemployment rates. Employment increases income levels, which in turn influence consumption patterns by enabling better dietary choices (Tagwi and Chipfupa, 2023). Additionally, food consumption patterns are shaped by cultural and societal food habits, which vary within and across countries (O'Neill et al., 2017). Food holds significant economic importance as a key component of agriculture and human wellbeing. However, climate change threatens agricultural ecosystems by increasing the frequency of extreme weather events, reducing biodiversity, and disrupting established livelihoods (O'Neill et al., 2017).

Crop yields are highly sensitive to climate variables, including precipitation and temperature. Climate change exacerbates food insecurity by disrupting rainfall patterns and increasing the frequency of heatwaves, droughts, and crop diseases, which negatively impact yields and food availability (O'Neill et al., 2017; Vermeir et al., 2020). Extreme weather events such as floods and droughts constrain agricultural productivity and sustainability, often leading to rising food prices as farmers' incomes decline (Vermeir et al., 2020).

Household food consumption accounts for more than 60% of global greenhouse gas emissions and between 50% and 80% of overall resource use (Almerico, 2014; Ivanova et al., 2016). Consequently, promoting sustainable and environmentally friendly eating habits is critical to achieving global food sustainability goals, especially in high-income countries (Springmann et al., 2016; Hartmann and Siegrist, 2017; Magrini et al., 2018a; Hedin et al., 2019; Vermeir et al., 2020; UN, 2016).

This chapter investigates the impact of CO_2 emissions on consumption patterns and farm produce prices in South Africa. Animal-based food products account for more than 40% of the country's agricultural output value and tend to generate higher CO_2 emissions compared to plant-based foods. Moreover, South African consumers generally prefer animal-based products, such as meat, over plant-based alternatives. Consequently, the increasing demand for animal-based foods could significantly contribute to CO_2 emissions and exacerbate climate change. Given the rising poverty and unemployment rates in South Africa, it is imperative to understand how CO_2 emissions affect food prices and consumption behaviors. Since animal-based foods are generally more expensive than plant-based foods, lower-income consumers tend to consume more plant-based products, while higher-income consumers have greater capacity to consume both, in line with the purchasing power parity concept.

Research on climate change-induced shifts in consumption patterns, particularly those related to greenhouse gas emissions such as CO_2, is crucial for South Africa and globally. Greenhouse gas emissions are major drivers of South Africa's climate challenges and have been identified as threats to both agricultural productivity and food consumption patterns (O'Neill et al., 2017). This study frames consumption patterns as a critical human activity in the context of climate change, extending the perspective presented in the South African White Paper on National Climate Change, which recognizes that individual decisions to adopt climate-friendly consumption behaviours will ultimately shape the country's response to climate change.

Furthermore, total consumption constitutes the largest component of macroeconomic aggregates, often exceeding 70% of GDP, and significantly influences national economic performance. Examining consumption patterns provides an objective lens for assessing economic activity and understanding how climate change considerations intersect with microeconomic policies, especially through the study of price responsiveness.

This research contributes to a deeper understanding of how CO_2 emissions influence consumption patterns in South Africa, taking into account factors such as price, purchasing power parity, and employment. The empirical evidence generated by this study is crucial for developing strategies to mitigate the impacts of climate change related to consumption. While previous studies have primarily focused on production and emissions, this work addresses the gap by exploring consumption patterns as both an influence on and a consequence of CO_2 emissions, thereby enriching the existing body of knowledge.

3.2. Analytical Framework

The impact of carbon dioxide (CO_2) emissions on food consumption patterns and farm produce prices in South Africa was examined using a Vector Error Correction Model (VECM), a multivariate cointegrated vector autoregressive (VAR) approach. The VECM provides a systematic yet flexible framework for analysing complex, interrelated economic phenomena, offering superior descriptive and forecasting capabilities by capturing the dynamic relationships among economic and environmental time series (Zivot and Wang, 2006).

This study adopts a multidimensional perspective on consumption patterns by integrating economic and environmental factors through a secondary data analysis to better understand their evolution over time. The Vector Error Correction framework is a widely employed and robust time series modelling technique appropriate for this type of research.

Key variables included in the model are the Consumer Price Index (CPI), CO_2 emissions, Purchasing Power Parity (PPP), consumer price inflation (CPI inflation), and total employment (TE). The CPI serves as an economic indicator that measures the proportional seasonal change in prices for a fixed basket of goods and services consumed by a given population, thereby reflecting consumption patterns. Alongside CPI, the inflation rate, the price level ratio for PPP, and employment levels are incorporated to capture economic conditions that potentially influence CO_2 emissions and consumption behaviour.

These variables collectively provide a comprehensive dataset for critically evaluating the interrelationships that influence consumption patterns, prices, and environmental factors in South Africa.

3.2.1. Specification of VEC model

Traditional descriptive and trend analyses are insufficient to fully capture the complex interrelationships among the variables considered in this study, namely Consumer Price Index (CPI, X1), CO_2 emissions (CE, X2), Purchasing Power Parity (PPP, X3), inflation of consumer price (ICP, X4), and total employment (TE, X5). Therefore, these time series data were further analyzed using the Vector Error Correction Model (VECM) to provide a rigorous evaluation of their dynamic interactions. Given that,

$$X_t = (X1_t, X2_t \cdots, Xn_t)' \quad (1)$$

denote an (n×1) vector of time series variables at time *t*. The basic p-lag vector autoregressive (VAR) model is specified as:

$$X_t = c + \mathbf{\Pi}_1 X_{t-1} + \mathbf{\Pi}_2 X_{t-2} + \cdots + \mathbf{\Pi}_p X_{t-p} + \varepsilon_t, t = 1 \cdots, T \quad (2)$$

where c is a constant vector, Πi are n×n coefficient matrices, and ε_t is an n×1 vector of serially uncorrelated white noise disturbances with zero mean and time-invariant covariance matrix Σ.

Given that the variables in X_t are non-stationary but cointegrated, the VECM framework is appropriate for modelling their relationships. The VECM captures both short-run dynamics and long-run equilibrium relationships and is represented as follows (for illustration, considering three variables)

$$\Delta CPI_t = \alpha_1 + \sum_{i=1}^{p} \beta_{1i} \Delta CPI_{t-i} + \sum_{i=1}^{p} \gamma_{1i} \Delta CE_{t-i} + \sum_{i=1}^{p} \delta_{1i} \Delta ICP_{t-i} + \sum_{i=1}^{p} \phi_{1i} \Delta PLRPPP_{t-i} + \sum_{i=1}^{p} \theta_{1i} \Delta TE_{t-i} + \lambda_1 ECT_{t-1} + \varepsilon_{1t} \quad (3)$$

Where:

- Δdenotes the first difference operator
- ECT_{t-1} represents the lagged error correction term derived from the long-run cointegrating equation
- $\lambda_1$measures the speed of adjustment toward long-run equilibrium

$$\Delta CE_t = \alpha_2 + \sum_{i=1}^{p} \beta_{2i}\, \Delta CPI_{t-i} + \sum_{i=1}^{p} \gamma_{2i}\, \Delta CE_{t-i} + \sum_{i=1}^{p} \delta_{2i}\, \Delta ICP_{t-i} + \sum_{i=1}^{p} \phi_{2i}\, \Delta PLRPPP_{t-i} + \sum_{i=1}^{p} \theta_{2i}\, \Delta TE_{t-i} + \lambda_2 ECT_{t-1} + \varepsilon_{2t} \quad (4)$$

This equation captures the short-run dynamics affecting carbon emissions, while the coefficient $\lambda_2$indicates whether emissions adjust toward the long-run equilibrium relationship.

$$\Delta ICP_t = \alpha_3 + \sum_{i=1}^{p} \beta_{3i}\, \Delta CPI_{t-i} + \sum_{i=1}^{p} \gamma_{3i}\, \Delta CE_{t-i} + \sum_{i=1}^{p} \delta_{3i}\, \Delta ICP_{t-i} + \sum_{i=1}^{p} \phi_{3i}\, \Delta PLRPPP_{t-i} + \sum_{i=1}^{p} \theta_{3i}\, \Delta TE_{t-i} + \lambda_3 ECT_{t-1} + \varepsilon_{3t} \quad (5)$$

Here:

- λ_3 measures how quickly import consumer prices adjust toward the long-run equilibrium relationship after short-run shocks.

3.2.2. Error Correction Term (ECT)

The error correction term used in the equations above is derived from the long-run cointegration equation**:**

$$ECT_{t-1} = CPI_{t-1} - (\beta_1 CE_{t-1} + \beta_2 ICP_{t-1} + \beta_3 PLRPPP_{t-1} + \beta_4 TE_{t-1}) \quad (6)$$

This term captures the deviation from long-run equilibrium in the previous period.

The VECM framework decomposes the dynamics of the system into short-run adjustments and long-run equilibrium relationships. The differenced terms capture short-run interactions among the variables, while the error correction term reflects the extent to which deviations from the long-run equilibrium are corrected in subsequent periods. A statistically significant and negative coefficient of the error correction term confirms the stability of the long-run relationship and indicates the speed at which the system converges back to equilibrium after a shock.

For this study, the variables are specified as X1: Consumer Price Index (CPI); X2: CO_2 emissions in kilotons (CE); X3: Inflation rate of Consumer Prices (ICP); X4: Price Level Ratio for Purchasing Power Parity (PLR-PPP), and X5: Total Employment (TE).

The VECM thus allows the study to examine both the short-term adjustments and the long-term equilibrium relationships among consumption patterns, prices, and CO_2 emissions in South Africa.

3.2.3. Model diagnostic tests

In estimating the VECM, several diagnostic tests were conducted to ensure the robustness and reliability of the model. These include tests for unit roots, cointegration, autocorrelation, and heteroskedasticity. This section focuses on the unit root and cointegration diagnostics.

The Augmented Dickey-Fuller Test

The Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) was employed to examine the stationarity properties of each time series. The null and alternative hypotheses are specified as follows:

H_0: $\theta=0$ - the series has a unit root (i.e., it is non-stationary)
H_a: $\theta<0$ - the series is stationary
The ADF test equation is expressed as:

$$\Delta y_t = \alpha_0 + \beta t + \theta_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \quad (1)$$

Where, Δ denotes the first-difference operator; t is a time trend; α and β are constants; p is the lag order, selected using the Schwarz Bayesian Criterion (SBC), and εt is the error term.

If the absolute value of the calculated test statistic exceeds the critical value (or if the p-value is less than 5%), the null hypothesis of non-stationarity is rejected, indicating that the series is stationary.

- If stationarity is confirmed at the level, the variable is integrated of order zero, denoted I (0).
- If stationarity is achieved after first differencing, the variable is I (1), and so on.

Johansen-Juselius (1990) Cointegration Test

Since the VECM requires that the variables be non-stationary in levels but integrated of the same order, a cointegration test is necessary to verify the presence of long-run relationships among them. The Johansen and Juselius (1990) cointegration test, a multivariate framework, was applied for this purpose. The Johansen cointegration model is specified as:

$$\Delta y_t = \alpha_0 + \Pi y_{t-1} + \sum_{i=1}^{p-i} \Gamma_i \Delta y_{t-i} + \varepsilon_t \quad (2)$$

Where, Π and Γi are the coefficient matrices, Δ is the symbol of the difference operator, and p is the lag order selected based on the Schwarz Bayesian Criterion (SBC). The Johansen-Juselius (1990) framework employs two likelihood ratio test statistics to determine the number of cointegration vectors. These ratios are the Maximum Eigenvalue test and the Trace test statistics computed as follows:

Where, Π and Γi are coefficient matrices; Δ is the difference operator, and p is the lag order, determined by SBC. The number of cointegrating relationships is determined using two likelihood ratio tests:

- **Trace Test Statistic**:

$$T_{(r)} = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i) \quad (3)$$

- **Maximum Eigenvalue Test Statistic**:

$$\lambda_{max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1}) \quad (4)$$

Where T is the series sample size and $\hat{\lambda}i$ are the estimated eigenvalues. The Trace test evaluates the null hypothesis of at most r cointegrating vectors against the alternative of more than r.

The Maximum Eigenvalue test evaluates the null hypothesis of r cointegrating vectors against the alternative of $r+1$.

A rejection of the null hypothesis in either test provides statistical evidence for the presence of cointegration. The existence of cointegrating relationships among the variables justifies the use of the VECM to model their long-run and short-run dynamics.

3.3. Study area and data source

This study was conducted in South Africa, located at the southernmost tip of the African continent. South Africa is characterized by rich cultural diversity and a wide range of vegetation, wildlife, climate, and soil types, enabling nearly all regions to engage in various agricultural activities. The country is divided into distinct farming zones, with agricultural operations ranging from intensive crop production in areas with winter and summer rainfall to cattle ranching in the bushveld and sheep farming in arid regions. Compared to countries such

as India, which has a high proportion of arable land, South Africa has relatively limited arable land availability. These characteristics are well documented in reports by the Food and Agriculture Organization, the World Bank, and the Department of Agriculture, Forestry and Fisheries (FAO, 2022; World Bank, 2023; DAFF, 2019).

Agricultural production in South Africa is provincially segmented, with diverse farm outputs including grains, sugar, vegetables, fruits, cattle, sheep, forestry, and other land uses (see Figure 3.1). However, only approximately 12% of the country's climate and soil combinations are suitable for rain-fed crop cultivation.

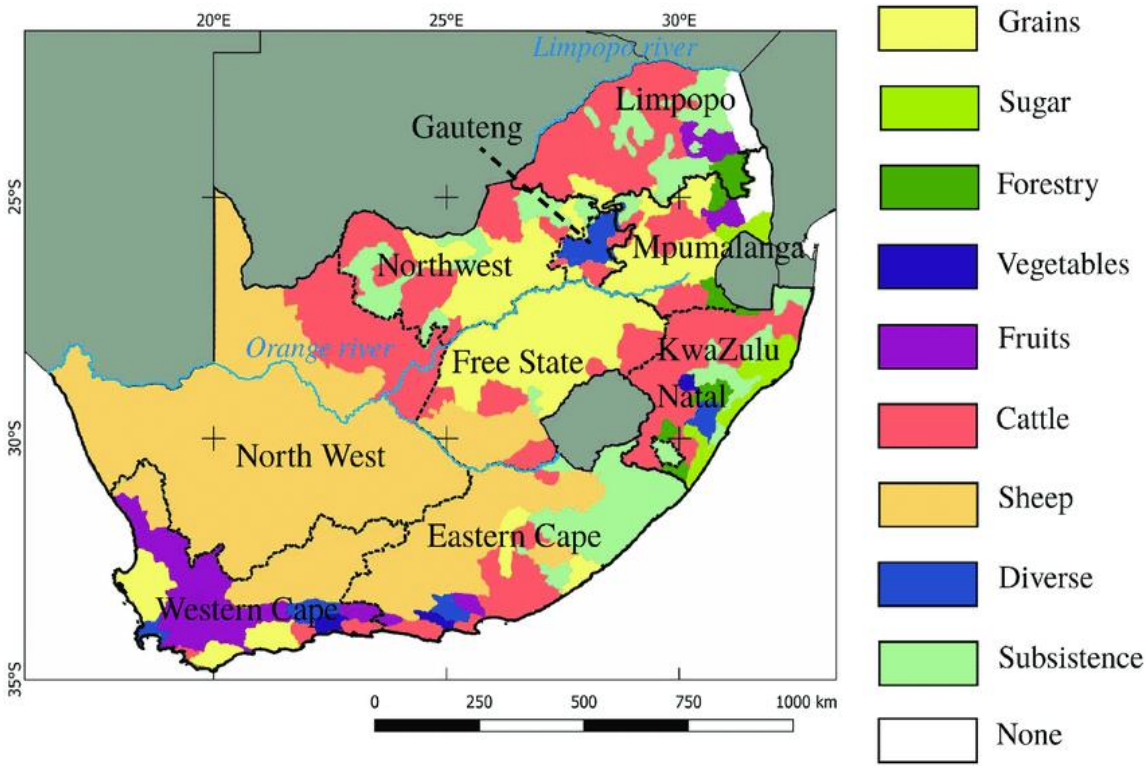


Figure 3.1. *Map of South Africa showing major agricultural regions and land-use systems.*
Source: *Adapted from FAO (2010) and related agricultural regional mapping studies..*

This study utilized secondary time-series data spanning from 1992 to 2021. The data were sourced from multiple repositories, including AGROSTAT Bulletins, the Food and Agriculture Organization (FAO) online database, the World Bank database, and Statistics South Africa (Stats SA). The dataset comprises variables such as the Consumer Price Index (CPI), carbon dioxide emissions in kilotons (CO_2), Inflation rate of Consumer Prices (ICP), price level ratio for purchasing power parity (PLR-PPP), and total employment (TE).

Table 3.1. Summary of variables used in the empirical analysis

Variable	Indicator Description	Measurement Unit	Data Source
CPI	Consumer Price Index	Index (2010 = 100)	World Bank, World Development Indicators
CE	Carbon Emissions	Metric tons per capita	World Bank, World Development Indicators
ICP	Inflation rate of Consumer Prices	Index	Food and Agriculture Organization
PLRPPP	Price Level Ratio of PPP Conversion Factor	Ratio	World Bank
TE	Total Employment	Percentage of total population	World Bank
Agricultural Output	Agricultural value added	Constant US dollars	Food and Agriculture Organization

(Source: Author Computation)

Table 3.1. summarises the variables used in the empirical analysis, their measurement indicators, and the corresponding data sources. This presentation enhances the transparency and reproducibility of the dataset used in the econometric modelling.

Justification for the Study Period (1992–2021)

The study utilises annual time-series data covering the period 1992 to 2021. The selection of this period is informed by both data availability and structural developments in the South African economy.

First, consistent and reliable macroeconomic and environmental data for the variables used in this study become widely available from the early 1990s across major international databases. Second, the early 1990s represent a significant structural turning point in South Africa's economic and policy landscape following the transition to democratic governance in 1994. This transition was accompanied by major institutional and economic reforms that influenced trade, environmental policies, and agricultural development.

Furthermore, the selected time frame captures important developments related to climate change mitigation policies, energy sector transformation, and evolving agricultural production systems. Extending the dataset to 2021 ensures that the analysis incorporates recent economic

and environmental dynamics while maintaining sufficient observations for robust econometric estimation using time-series techniques such as the Vector Error Correction Model (VECM).

Data Sources and Extraction Procedure

The study relies on secondary data obtained from several internationally recognised databases, including the World Bank, World Development Indicators, the Food and Agriculture Organization statistical database (FAOSTAT), and the International Monetary Fund databases.

Given that these databases provide information for multiple countries, the extraction process involved filtering the datasets specifically for South Africa using the country identifier provided within each database. Data was downloaded in spreadsheet format and subsequently screened to ensure consistency across variables and time periods. Where necessary, variables were transformed to ensure comparability, including logarithmic transformation and alignment of measurement units across datasets.

To enhance reliability, the extracted data were cross-checked across sources where overlapping indicators were available. Missing observations were carefully inspected and handled through appropriate econometric procedures consistent with time-series analysis requirements. This systematic extraction and verification process ensured that the dataset used in this study accurately represents South Africa's economic and environmental indicators for the period under investigation.

Providing detailed information about the sources and extraction procedures enhances the transparency and replicability of the empirical analysis.

3.4. Results and Discussion

3.4.1. Descriptive and trend analysis for key variables (CPI, CE, ICP, PLR-PPP, and TE) used in this study

Table 3.2 presents the descriptive statistics for the key variables used in this study: carbon dioxide emissions (CE), consumer price index (CPI), Inflation rate of Consumer Prices (ICP), price level ratio for purchasing power parity (PLR-PPP), and total employment (TE), over the period 1992 to 2021.

Table 3.2: Descriptive statistics for trend analysis

	CE	CPI	ICP	PLR_PPP	TE
Mean	364745.2	91.28347	6.100194	0.497242	57.04849
Median	386590.7	79.03627	5.713279	0.499877	55.14491
Maximum	448298.1	171.6024	13.87468	0.657835	64.83633
Minimum	238780.6	33.40078	-0.692030	0.305767	50.48975
Std. Dev.	71420.23	41.66992	2.776527	0.078795	5.325898
Skewness	-0.470657	0.438699	0.363102	-0.293878	0.135958
Kurtosis	1.670518	1.983908	4.166731	3.237127	1.258248
Jarque-Bera	3.316992	2.252839	2.360792	0.502108	3.884547
Probability	0.190425	0.324192	0.307157	0.777980	0.143378
Sum	10942357	2738.504	183.0058	14.91725	1711.455
Sum Sq. Dev.	1.48E+11	50355.10	223.5640	0.180049	822.5904
Observations	30	30	30	30	30

(Source: Author's computation)

The Jarque–Bera statistics were computed to examine the distributional properties of the variables. The results indicate that the p-values for all variables exceed the 5% significance level, suggesting that the series do not significantly deviate from normality. Although normality of variables is not a strict requirement for most time-series econometric techniques such as unit root tests, ARDL estimation, VAR models, or cointegration analysis, examining the distributional characteristics of the data provides useful descriptive insight into their statistical properties. In time-series econometrics, the assumption of normality is more relevant for the distribution of model residuals rather than the variables themselves. Consequently, the normality results reported here serve only as a preliminary descriptive diagnostic and do not determine the applicability of the subsequent econometric methods employed in this study. Moreover, large-sample econometric estimators such as ARDL and VECM remain consistent and asymptotically normal even when the underlying variables are not normally distributed.

The CPI ranged from a minimum of 33.40 in 1992 to a maximum of 171.60 in 2021, reflecting a general upward trend in consumer prices over the three-decade period. This suggests increasing pressure on household consumption expenditures, with inflationary effects evident across the years.

Carbon dioxide emissions (CE) also show a significant upward trend, increasing from 238,781 kilotons in 1992 to a peak of 448,298 kilotons in 2014. This increase may reflect expanding

industrial and agricultural activities in South Africa, with potential implications for sustainability and food production.

The Inflation rate of Consumer Prices (ICP) recorded its highest value (13.87) in 1992 and the lowest (-0.69) in 2004, indicating considerable variability in inflationary trends. This variation may have influenced the affordability of food products and overall consumption patterns over the years.

PLR-PPP, representing the price level ratio based on purchasing power parity, increased from 0.306 in 1992 to 0.658 in 2021. This trend suggests a relative strengthening of the South African currency in terms of its international purchasing power.

Total employment (TE) rose from 50.49 million in 1992 to a high of 64.84 million in 2014. This increase is consistent with overall economic and population growth and may correlate positively with household consumption capacity.

Regarding distributional properties, the skewness values for all variables fall within the range of -1 to +1, suggesting moderate skewness and approximate symmetry. Similarly, kurtosis values mostly lie close to the normal distribution benchmark (kurtosis ≈ 3), indicating that the distributions are neither excessively peaked nor flat.

In summary, the descriptive and trend analysis reveal significant variability and long-term trends across the selected variables. These patterns provide preliminary insights into how economic, environmental, and demographic factors have evolved in South Africa, laying the groundwork for further econometric modelling in subsequent sections.

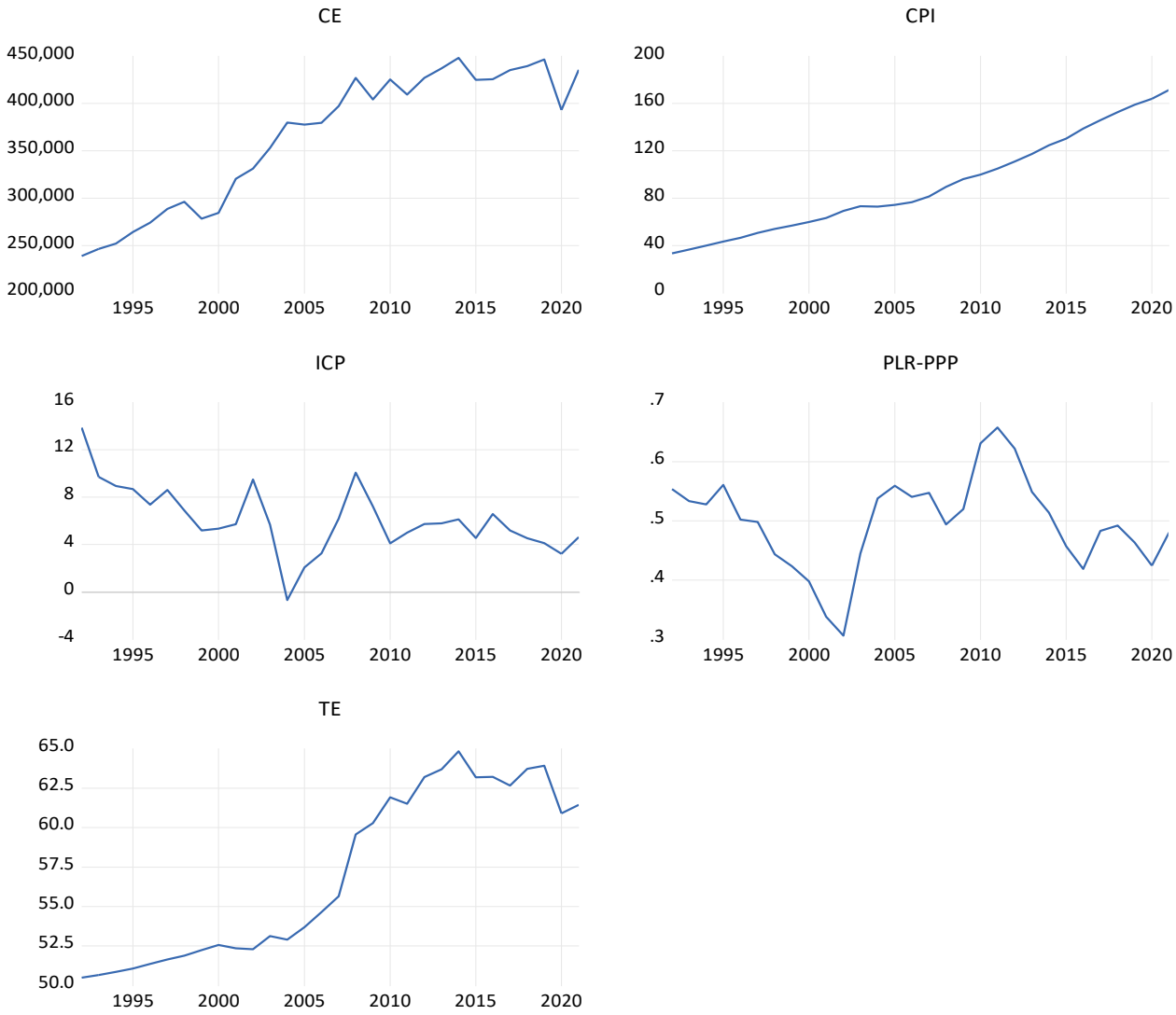


Figure 3.2. *Trend analysis patterns of the key variables (CPI, CE, ICP, PLR-PPP and TE) used in this study. (Source: Author's computation).*

The graphical trends presented in Figure 3.2 reveal distinct patterns among the key variables over the study period. Notably, carbon dioxide emissions (CE), the consumer price index (CPI), and total employment (TE) exhibit a consistent upward trajectory, indicative of sustained growth in industrial activity, consumer prices, and labour market participation in South Africa. Conversely, the inflation rate of consumer prices (ICP) demonstrates a downward trend, particularly pronounced between 2002 and 2005, during which the lowest inflation rates were recorded.

The price level ratio for purchasing power parity (PLR-PPP) shows marked fluctuations throughout the period, peaking in 2011. These fluctuations indicate varying international competitiveness and changes in currency valuation in relation to global markets. Importantly, the inverse relationship observed between the rising trends of CE, CPI, and TE and the

declining trend in ICP suggests that periods of low inflation coincide with increased economic activity and employment, possibly reflecting monetary policy responses or structural economic shifts.

The nadir in ICP from 2002 to 2005 aligns with a temporary downturn in PLR-PPP, implying that reduced domestic inflation exerted downward pressure on the relative price level of South Africa's currency in international terms. However, the oscillations in PLR-PPP from 1995 to 2021 suggest that external factors, such as global economic conditions, exchange rate volatility, and trade dynamics, intermittently influenced the country's purchasing power parity.

Overall, these trends underscore complex interdependencies between macroeconomic indicators, environmental emissions, and labour market conditions. They highlight the need to consider both domestic and international economic factors when analysing the determinants of consumption patterns and their environmental implications in South Africa.

3.4.2. Test for stationarity result: Augmented Dickey-Fuller and Phillips-Perron

The Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests were employed to determine the order of integration of the variables. The results reveal that some variables are stationary at level, I(0), while others become stationary after first differencing, I(1), indicating a mixed order of integration. Consequently, the earlier interpretation that all variables are integrated of order one has been revised. The presence of variables integrated at different orders supports the use of econometric approaches capable of accommodating mixed integration orders. Furthermore, cointegration analysis was conducted to examine the existence of long-run equilibrium relationships among the non-stationary variables. Where cointegration is established, the Vector Error Correction Model (VECM) provides an appropriate framework for modelling both the short-run dynamics and the long-run equilibrium adjustments within the system. According to Enders (2008), the VECM framework is appropriate when non-stationary variables that are integrated of order one exhibit cointegration relationships.

Table 3.3: Stationarity unit root test

	ADF Test				Phillips-Perron			
	Level		first difference		Level		first difference	
Variable	t-statistics	P-value	t-statistics	P-value	t-statistics	P-value	t-statistics	P-value
CPI	2.822	0.0100	-2.232	0.0300	4.517	0.0000	-2.232	0.0340
CE	-1.809	0.0820	-6.789	0.0000	-1.519	0.1400	-6.7889	0.0000
PLR_PPP	-2.803	0.0100	-3.951	0.0010	-1.931	0.0640	-3.699	0.0010
ICP	-3.327	0.0030	-5.613	0.0000	-3.734	0.0010	-5.246	0.0000
TE	-0.941	0.3550	-4.944	0.0000	-0.941	0.3550	-4.944	0.0000

(Source: Author's computation)

As shown in Table 3.3, both the ADF and Phillips-Perron tests were applied to determine whether the variables are stationary or possess a unit root. The null hypothesis for these tests states that a variable has a unit root (i.e., is non-stationary). If the p-value is less than the significance level (typically 0.05), the null hypothesis is rejected, indicating that the data are not stationary. At the level form, the variables CE and TE exhibit p-values greater than 0.05, implying that they are non-stationary. In contrast, CPI, PLR_PPP, and ICP show p-values below the 0.05 threshold, suggesting that these variables are stationary at the level.

3.4.3. Optimal lag length criteria

Following the approach of Vijay (2022), optimal lag length selection for the VEC model was determined using the Akaike Information Criterion (AIC). The AIC minimizes information loss and identifies the most appropriate lag length for the model. Based on the criterion and as shown in Appendix I, the optimal lag length was found to be **2**, which was then adopted for the Vector Error Correction (VEC) model estimation.

3.4.4. Result of the Johansen co-integration test

Although CPI and ICP are related indicators, they measure different economic phenomena. CPI captures the level of consumer prices, while ICP reflects the rate of change in those prices over time. Consequently, the inclusion of both variables allows the model to capture both price levels and inflation dynamics, which are theoretically relevant for analysing consumption and price behaviour. To determine the existence of a long-run equilibrium relationship among the variables, the Johansen co-integration test was conducted prior to estimating the Vector Error Correction (VEC) model.

Table 3.4: Johansen Co-integration test

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.811987	100.3704	69.81889	0.0000
At most 1 *	0.568742	53.57561	47.85613	0.0132
At most 2 *	0.516272	30.02625	29.79707	0.0471
At most 3	0.284082	9.691740	15.49471	0.3052
At most 4	0.011873	0.334432	3.841465	0.5631

Trace test indicates 3 co-integrating equation(s) at the 0.05 level.
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.811987	46.79477	33.87687	0.0009
At most 1	0.568742	23.54936	27.58434	0.1512
At most 2	0.516272	20.33451	21.13162	0.0643
At most 3	0.284082	9.357308	14.26460	0.2576
At most 4	0.011873	0.334432	3.841465	0.5631

Max-eigenvalue test indicates 1 cointegrating equation(s) at the 0.05 level
(Source: Author's computation)

The Johansen co-integration test results confirm the presence of a long-term relationship among the variables in the system. As shown in Table 3.4, both the Trace and Maximum Eigenvalue statistics are reported. The Trace test indicates the presence of three co-integrating equations, as evidenced by the statistically significant results for the hypotheses “None,” “At most 1,” and “At most 2,” with p-values of 0.0000, 0.0132, and 0.0471, respectively.

However, the Maximum Eigenvalue test suggests the existence of one co-integrating equation, with a significant p-value of 0.0009 for the “None” hypothesis, while subsequent hypotheses are not statistically significant at the 5% level.

Based on these results, the null hypothesis of no co-integration is rejected by both test statistics. This provides strong evidence that at least one long-run co-integrating relationship exists among the variables, thus justifying the use of the VEC model for further analysis. The optimal lag length of two, as determined using the Akaike Information Criterion (AIC), was employed in the test (see Appendix I).

3.4.5. Result of the normalised co-integrating coefficient.

The results of the normalized co-integrating vector, as shown in Appendix II, indicate that CPI (Consumer Price Index) is the dependent variable. The interpretation of the long-run relationship is based on the normalised coefficients with CPI set to 1.

The results indicate that in the long run, CE (Carbon Emissions), ICP (Inflation rate of Consumer Prices), PLR-PPP (price level ratio for purchasing power parity), and TE (Total Employment) exhibit a positive relationship with CPI. All the variables are statistically significant at the 1% level. It is important to note that in co-integration analysis, the signs of the coefficients are typically reversed in interpretation.

From the Johansen test results earlier, both the trace and maximum eigenvalue statistics confirmed the existence of at least one co-integrating relationship. Thus, the null hypothesis of no co-integration among the variables is rejected, providing justification for estimating a Vector Error Correction (VEC) model.

3.4.6. Estimation of the VEC model

As a Vector Error Correction Model is based on the first-differenced form of a VAR, one lag is lost in the transformation. Given that the optimal lag length selected by the Akaike Information Criterion (AIC) for the VAR was two, a lag length of one is used in the VEC estimation.

Long-run Equation

From Table 3.5, the VEC model's long-run co-integrating equation is expressed as:

$$ECT_{t-1} = [1.000CPI_{t-1} - 0.001CE_{t-1} + 6.775ICP_{t-1} - 179.942PLR - PPP_{t-1} + 24.166TE_{t-1} - 993.490] \quad (1)$$

This implies that:

- A unit increase in CE leads to a 0.001 unit *decrease* in CPI in the long run.
- ICP and TE have a *positive* long-run effect on CPI.
- PLR-PPP exerts a strong *negative* influence on CPI.

Short-run Dynamics

The short-run relationship for the CPI equation is specified as:

$$ECT_{t-1} = \left[0.016\Delta CPI_{t-1} - 0.126\mathrm{CPI}_{t-p} + 1.43\mathrm{E} - 5\Delta CE_{t-1} + 0.321\Delta ICP_{t-1} - 5.676\Delta PLR - PPP_{t-1} + 0.290\Delta TE_{t-1} + 5.532\right] \quad (2)$$

Key interpretations:

- The coefficient of the error correction term (ECT) is statistically significant, indicating the existence of a long-run equilibrium relationship among the variables. Although the estimated coefficient appears positive in the reported VECM output, this reflects the normalization convention used in the estimation procedure. When interpreted in the standard error-correction framework, the sign should be considered in terms of the adjustment process toward equilibrium. The magnitude of the coefficient suggests that approximately 1.6% of the disequilibrium from the previous period is adjusted in the current period, indicating a relatively slow speed of adjustment toward the long-run equilibrium.
- A 1% increase in ICP is associated with a 0.321% increase in CPI in the short run, holding other factors constant.
- A 1% increase in PLR-PPP corresponds to a 5.676% decrease in CPI in the short run.
- Trade efficiency (TE) has a slight negative short-run effect on CPI.

The adjusted R-squared value of **0.532** for the CPI equation indicates a reasonably good fit.

According to Hamilton (2008), in vector error correction models, the sign of the adjustment coefficient in error correction models depends on the normalization of the cointegrating vector, and its interpretation should consider the underlying specification of the system focusing primarily on the significance and magnitude of the adjustment parameter rather than its raw sign.

Table 3.5: VEC model estimation

Cointegrating Eq:	CointEq1
CPI(-1)	1.000
CE(-1)	-0.001 (0.000) [-4.931]
ICP(-1)	6.775 (7.091) [0.955]
PLR_PPP(-1)	-179.942 (102.882) [-1.749]
TE(-1)	24.166 (4.496) [5.375]
C	-993.490

Error Correction:	D(CPI)	D(CE)	D(ICP)	D(PLR_PPP)	D(TE)
CointEq1	0.016 (0.008) [2.061]	-179.013 (95.775) [-1.869]	0.0251 (0.010) [2.460]	-0.001 (0.000) [-3.514]	-0.015129 (0.006) [-2.726]
D(CPI(-1))	-0.126 (0.369) [-0.341]	5373.697 (4464.100) [1.204]	-1.610 (0.476) [-3.386]	0.0424 (0.0112) [3.774]	0.490 (0.259) [1.891]
D(CE(-1))	1.43E-05 (2.1E-05) [0.670]	-0.379 (0.259) [-1.466]	2.98E-05 (2.8E-05) [1.080]	-1.20E-06 (6.5E-07) [-1.839]	-2.74E-05 (1.5E-05) [-1.827]
D(ICP(-1))	0.321 (0.172) [1.869]	1172.994 (2085.080) [0.563]	0.416 (0.222) [1.873]	-0.009 (0.005) [-1.797]	0.046 (0.121) [0.383]
D(PLR_PPP(-1))	-5.676 (6.485) [-0.875]	57063.46 (78527.5) [0.727]	-7.006 (8.367) [-0.837]	0.232 (0.197) [1.175]	2.890 (4.550) [0.635]
D(TE(-1))	-0.290 (0.351) [-0.826]	-7428.745 (4255.190) [-1.746]	-0.206 (0.453) [-0.454]	-0.012 (0.011) [-1.109]	-0.089 (0.247) [-0.362]
C	5.532 (1.726) [3.205]	-12752.17 (20898.4) [-0.610]	7.370 (2.227) [3.309]	-0.191 (0.053) [-3.636]	-1.682 (1.211) [-1.389]

(Source: Author's computation)

3.4.7. VEC Granger causality/block exogeneity Wald tests

To assess the direction of causality among the variables, the Block Exogeneity Wald test was performed (see Appendix III). This diagnostic helps identify whether any of the independent variables in the system Granger-cause changes in the dependent variable (CPI), or vice versa.

Key findings:

- The p-value for CPI affecting ICP is 0.0007, which is highly significant ($p < 0.05$). This supports the conclusion that CPI Granger-causes ICP.
- Conversely, the p-value for ICP affecting CPI is 0.062, which is slightly above the 5% significance threshold. This implies that the null hypothesis (ICP does not Granger-cause CPI) cannot be fully rejected, though there is a weak indication of causality.
- The p-value for CPI affecting PLR-PPP is 0.0002, again statistically significant, confirming a directional influence from CPI to PLR-PPP.
- The p-value for TE affected by CPI is 0.0586, which is marginally above 0.05. Thus, there is weak evidence of causality from CPI to TE.

In summary, the results confirm the existence of short-run causality running from the CPI to certain explanatory variables, particularly ICP and PLR-PPP. However, the reverse causality from those variables to CPI is less conclusive, except in the case of ICP, where the result is borderline significant.

3.4.8. Pairwise Granger causality test

The Granger causality test was employed to investigate the directional relationship between variables. The test determines whether past values of one variable significantly contribute to predicting the value of another. Results indicate uni-directional causality from PLR_PPP to CPI ($p = 0.0039$) and from PLR_PPP to ICP ($p = 0.0254$), both significant at the 5% level. All other relationships tested showed no evidence of Granger causality. Full test statistics are presented in Appendix IV, Table A1.

The results indicate the presence of a unidirectional causal relationship between PLR_PPP and CPI. Specifically, PLR_PPP Granger-causes CPI ($p = 0.0039$), leading to rejection of the null hypothesis at the 1% level. However, CPI does not Granger-cause PLR_PPP ($p = 0.2998$), indicating no reverse causality.

Similarly, a unidirectional causality exists from PLR_PPP to ICP (p = 0.0254), with the null hypothesis rejected at the 5% level. However, ICP does not Granger-cause PLR_PPP (p = 0.4812). In all other pairwise comparisons, the p-values exceed conventional thresholds, suggesting no significant Granger causality.

3.4.9. Residual Diagnostic Tests

The VEC model residual diagnostic tests confirm the model's reliability:

- **Serial correlation**: Not detected at any lag (p-values > 0.05), supporting model adequacy (Appendix IV, Table A2).
- **Normality**: Residuals are multivariate normally distributed (p > 0.05), indicating model robustness (Appendix IV, Table A3).
- **Heteroskedasticity**: No evidence of residual variance heteroskedasticity (joint test p = 0.1480), suggesting homoskedasticity (Appendix IV, Table A4).

3.4.10. Inverse root of autocorrelation

The inverse root test illustrates the stability of the VEC model by plotting the inverse roots of the autoregressive (AR) characteristic polynomial. As illustrated in Figure 3, all inverse roots lie within the unit circle, confirming the stability and stationarity of the VEC model. Detailed root statistics are available in Appendix V, Table A5.

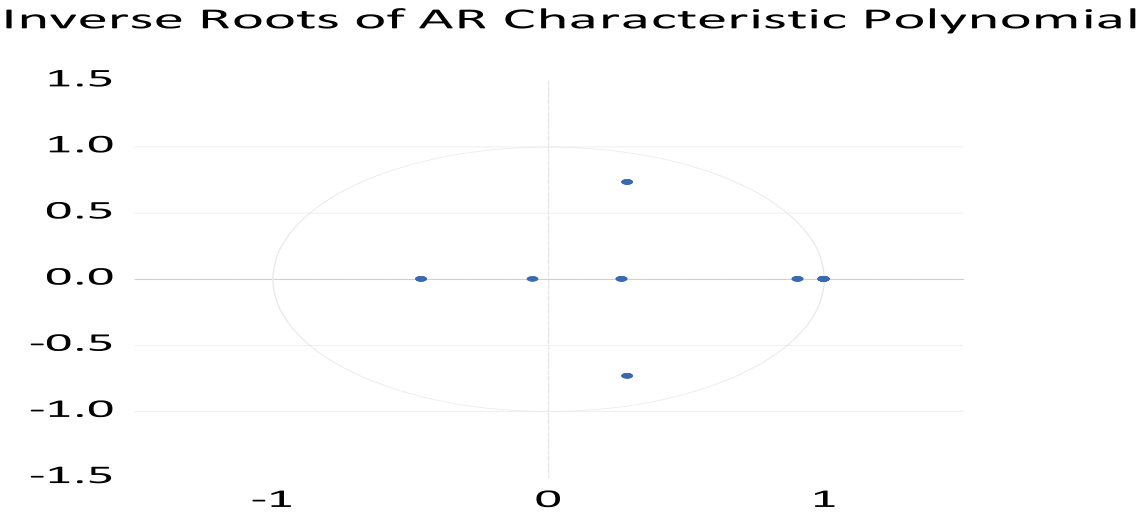


Figure 3.3. VEC model Inverse roots of AR characteristics polynomial (Source: Author's computation)

3.4.11. Impulse response function of the VEC model

The impulse response function (IRF) analysis examines the response of the endogenous variable CPI to a one-standard-deviation innovation in each of the explanatory variables. Figure 3.4 illustrates these dynamic responses:

- ICP → CPI: A one SD shock to ICP increases CPI between periods 1 and 2, stabilizes between periods 3 and 5, and rises slightly through period 8, implying a sustained positive impact.
- CE → CPI: The shock leads to a negative impact on CPI from period 1 through 8, suggesting a long-run depressive effect.
- TE → CPI: The shock positively affects CPI from period 1 onward, with consistent growth across the observed periods.
- PLR_PPP → CPI: The response is negative, with CPI declining from period 1 through period 8, indicating a long-run negative influence.

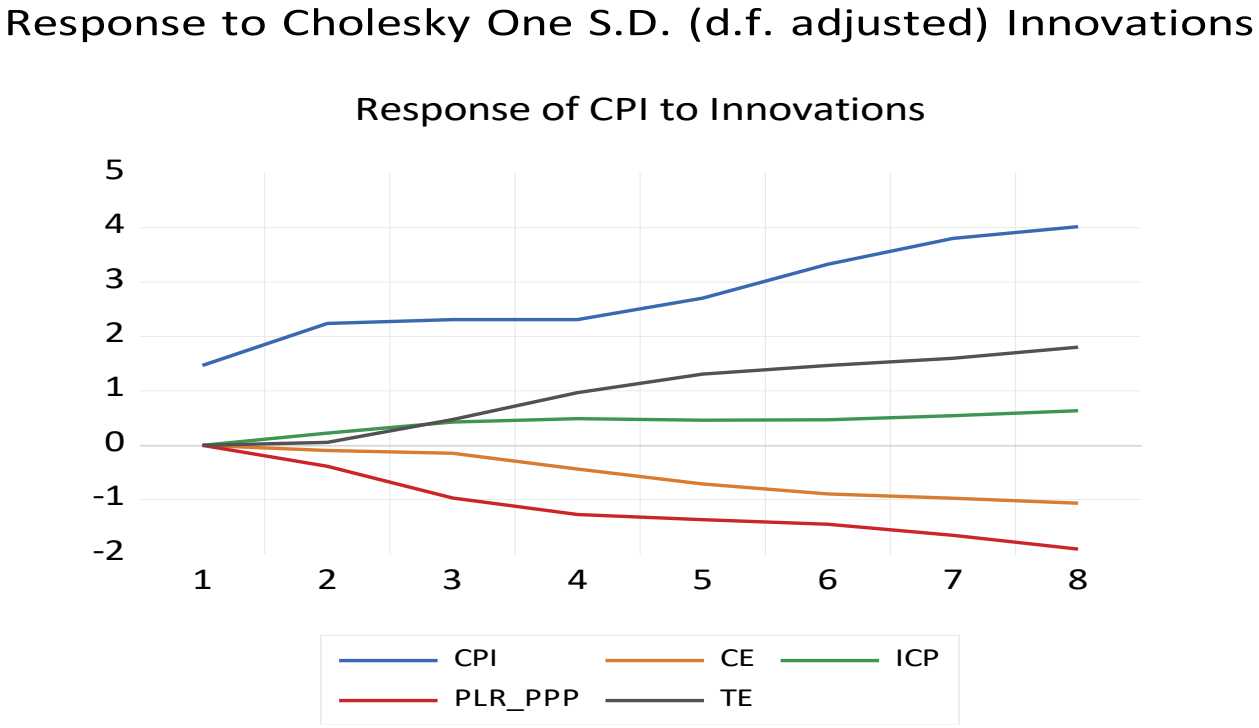


Figure 3.4. Impulse Response of CPI to One Standard Deviation Innovations (Source: Author's computation)

3.4.12. Variance decomposition of the VEC model

Variance decomposition, also known as forecast error variance decomposition (FEVD) carried out assists in knowing the extent to which a variable contributes to other variables in a

regressive system and serves as a determinant factor for forecasting the error variance of each variable can be explained by the exogenous shock to other variables in the VEC model.

Variance decomposition (Figure 3.5) reveals that in the short run (Period 1–2), CPI explains nearly all its own variation. However, in the long run (Period 3–5), variables such as PLR_PPP and TE increasingly contribute to CPI's forecast error variance. See Appendix V, Table A6 for the full breakdown.

Over time, the influence of other variables increases:

- PLR_PPP and TE gradually exert more influence in the long run.
- CE shows increasing contribution from period 3 onward.
- ICP peaks in period 4 and then declines slightly.

These findings suggest that CPI remains a strong predictor of itself in the short run but is increasingly influenced by other variables over time.

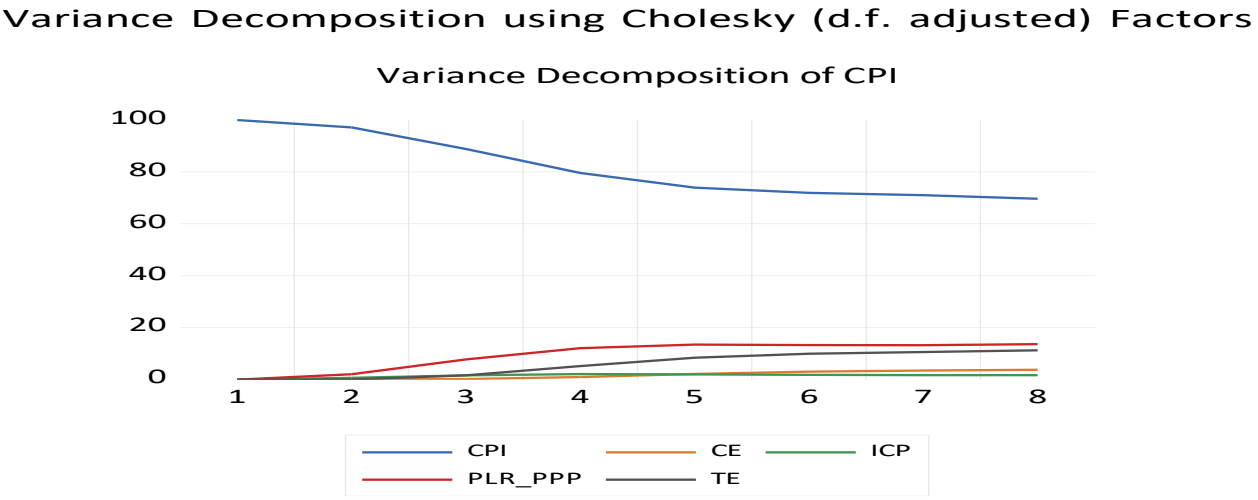


Figure 3.5 Variance decomposition of CPI using Cholesky factors (Source: Author's computation).

3.4.13. Historical decompositions for nonlinear Vector Error Correction models

Historical decomposition traces the contribution of structural shocks to fluctuations in CPI over time. As depicted in Figure 3.6, the responses of CE, ICP, PLR_PPP, and TE to shocks in CPI vary across time:

- Between 2006 and 2008, CPI-driven shocks were pronounced and generally negative for CE, ICP, and TE.

- In contrast, PLR_PPP responded positively to the same CPI shocks, indicating an opposite directional relationship.

This suggests heterogeneity in the way different variables respond to CPI fluctuations.

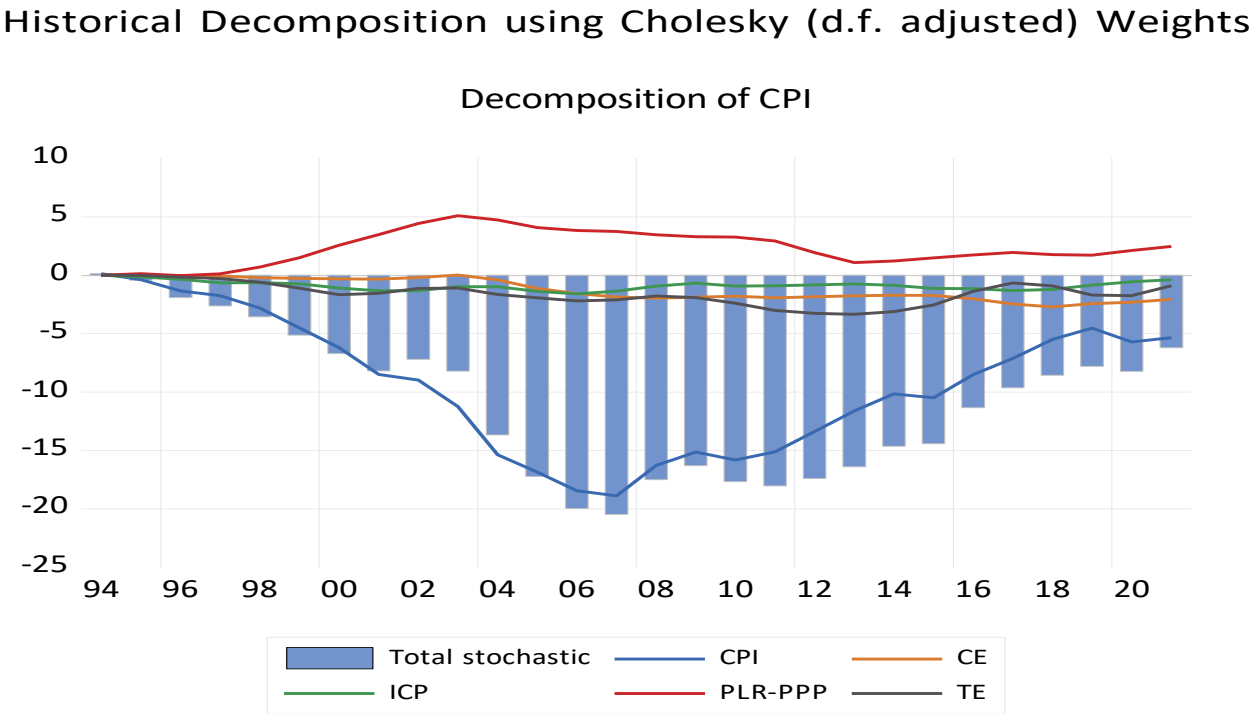


Figure 3.6 Decomposition of variable CPI. (Source: Author's computation)

3.5. Conclusion and Recommendation

This study demonstrates that food consumption patterns in South Africa are influenced by a complex interplay of environmental, economic, and behavioural factors. Chief among these is CO_2 emissions, which contribute significantly to climate change and, in turn, disrupt agricultural productivity through extreme weather events such as droughts and floods. These climate-induced shocks reduce food availability, increase food prices, and ultimately exacerbate food insecurity.

The empirical results confirm that CO_2 emissions have long-run effects on consumer price inflation (CPI) and imported food price inflation (ICP). Climate variability leads to lower agricultural yields, which drives up prices and alters consumption patterns, particularly among vulnerable populations. Additionally, distortions in the exchange rate, as captured by purchasing power parity-adjusted lending rates (PLR-PPP), significantly influence inflation, highlighting the importance of stable macroeconomic policies in maintaining food affordability.

The study also highlights the crucial role of employment and income levels in shaping food consumption behaviour. Higher employment levels correlate with improved purchasing power, enabling access to healthier and more diverse diets. Conversely, unemployment undermines household food security and resilience.

Policy Recommendations

To address the multidimensional drivers of food consumption and inflation, the following policy interventions are proposed:

Environmental and Agricultural Policies

- Carbon Pricing: Introduce targeted taxes on high-emission food products to discourage environmentally harmful consumption patterns.
- Climate-Resilient Agriculture: Invest in the development and dissemination of drought- and flood-tolerant crop varieties, including hybrid and genetically improved species.
- Sustainable Agricultural Incentives: Provide financial and technical support to farmers adopting climate-smart and environmentally sustainable agricultural practices.

Economic and Social Interventions

- Employment Generation: Prioritize job creation, particularly in agriculture and rural sectors, to improve household incomes and enhance food access.
- Exchange Rate Stability: Strengthen macroeconomic policies aimed at reducing exchange rate volatility and its pass-through effects on food prices.

Public Engagement and Education

- Consumer Awareness: Implement public campaigns to educate citizens on sustainable diets and the environmental impact of food choices.
- Behavioural Interventions: Promote food labelling and nudging strategies to support informed consumer decision-making aligned with climate and health goals.

In summary, a multi-pronged strategy that integrates environmental sustainability, economic stability, and social welfare is essential to safeguarding food security and promoting sustainable consumption patterns in South Africa. Policymakers must consider both immediate and long-

term interventions to buffer the food system against climate risks while enhancing resilience through inclusive economic development.

Chapter 4: Decoupling Agricultural Growth from Carbon Emissions in South Africa: An Empirical Analysis of the Sustainability Nexus

4.1. Introduction

Climate change is arguably the defining global challenge of the twenty–first century, resulting from the rapid rise in the levels of greenhouse gases in the atmosphere, the most important of which is carbon dioxide (CO_2). Deforestation, industrial production, and fossil fuel consumption are the primary anthropogenic sources of CO_2 emissions (Raihan et al., 2018; Wan Mohd Jaafar et al., 2020; Raihan et al., 2021). With the rise of CO_2 emissions, global climatic systems have been disrupted, posing threats to ecosystems, people, and socioeconomic development (Raihan et al., 2019; Isfat and Raihan, 2022). As a result, mitigation efforts to address emissions and promote sustainability have made significant strides in global climate agendas.

South Africa, as the continent's largest emitter and the 13th most polluting country per capita worldwide, with 8.9 tons of pollution per year, stands at the crossroads of energy dependency, environmental destruction, and agricultural vulnerability. Coal still powers most of the nation's industrial and manufacturing energy needs, resulting in high emissions (Adebayo et al., 2021). Meanwhile, agricultural productivity, an economic activity that contributes approximately 4% of GDP and underpins food security, is endangered more by climate-induced variations in temperature and rainfall. This dichotomy highlights a crucial policy dilemma: moving forward while reducing emissions and ensuring the viability of the agricultural sector.

The paradox of climate change is captured in the agricultural sector. It is a significant driver of global warming, but it is also acutely sensitive to the effects of global warming. Agriculture, in collaboration with land use and forestry, accounts for a substantial portion of global greenhouse gas emissions (Raihan, 2023). In South Africa, emissions are compounded by livestock, fertilizer use, and land-use change, with the greater weight of emissions coming from the former; however, climate variability also undermines yields. Statistical models suggest, for example, that high temperatures generally decrease crop production, and changes in precipitation generate ambiguous responses depending on the crop category and regional circumstances (Asfew et al., 2023). This multifaceted nature of the sector renders it a key area for both mitigation and adaptation.

International protocols, such as the Kyoto Protocol (2005) and the Paris Agreement (2015), have facilitated reductions in emissions and transitions to renewable energy (Raihan and Said, 2022; Ali et al., 2022). However, the carbon pollution associated with the industrial revolution persists in the atmosphere and oceans (Feig et al., 2017). Furthermore, it is even more complicated for South Africa. While the local economy will benefit from gains in energy-intensive industrial sectors and commercial farms, these sectors are also among the most emissions-intensive. Thus, achieving SDGs goals, especially SDG 2 on food security and SDG 13 on climate action, requires an integration between industrialization trajectory, GHG emissions, and agricultural resilience (Ibrahiem, 2020; Raihan et al., 2022).

The process requires climate-smart agriculture, where agriculture is part of the solution to increase productivity while sustaining the resource base, by overcoming the dual role of agriculture as an emission driver and being at the receiving end of climate stress, and by technological innovations (Rehman et al., 2021; Bennetzen et al., 2016). Food waste drives climate emissions, addressing it presents immediate mitigation potential. Research indicates that composting food waste produces 38-88% lower emissions compared to equivalent landfilling (Perez et al., 2023). More strategically, reducing food waste by 50% could lower greenhouse gas emissions by 1.5 gigatons annually, comparable to the entire current energy sector of Japan (Flanagan et al., 2019). The challenge demands coordinated action across multiple scales. Climate-Smart Agriculture, combining productivity improvements with adaptation and mitigation, shows particular promise (Naicker et al., 2025). Such approaches must integrate climate information systems, financial services access, sustainable land policies, and agroecological practices to build resilience in vulnerable regions.

A plethora of international research has investigated the impact of emissions on agriculture (Tunç et al., 2009; Appiah et al., 2017; Shahbaz et al., 2017); however, research specific to South Africa is sparse. While considerable work has been done on descriptive environmental measures or short-term analyses based on panel areas, there is a lack of research on how agri-environmental causal dynamics, such as CO_2 emissions, affect agricultural productivity in the long run. The gap is more necessary for South Africa in the context of the dual role as both a top emitter and an agriculturally dependent economy in Sub-Saharan Africa.

To bridge this gap, this chapter contributes to the literature by examining the short- and long-run causal relationship between CO_2 emissions and agricultural productivity for South Africa

for the period from 1992 to 2021. Utilizing econometric methods such as autoregressive distributed lag (ARDL) models, the study disentangles temporal causal channels and provides evidence on the effect of emissions on agricultural productivity. This research will contribute to the body of academic knowledge and provide insights relevant to sustainable agriculture, food security, and emissions mitigation, thereby helping to achieve the targets outlined in the SDGs.

This responds to the need for more contextually informed, evidence-based policymaking in South Africa, which this research aims to contribute to. It demonstrates how the country can strike a balance between the delicate trade-offs of economic growth, environmental sustainability, and food security, while effectively aligning national development strategies with global climate commitments.

4.2. Analytical Techniques

4.2.1. Data Sources and Definition of Variables

This study uses secondary annual data from 1992 to 2021. The variables chosen are crucial for evaluating the relationship between agricultural economic performance, environmental pressure, and trade balance. The information was collected from reputable and credible sources to ensure the quality and consistency of the data:

- Carbon Emissions (CE): Measured in metric tons per capita, the indicator reflects environmental pollution due to economic and agricultural activities. The data were collected from the World Bank World Development Indicators (WDI) database and supplemented with the Food and Agriculture Organization Statistical Database (FAOSTAT).
- Total Agricultural Employment (TAE): This reflects the total number of men, stockmen, and homemakers employed in the agricultural sector and represents the agro-workforce regarding agricultural productivity. Data was retrieved from FAOSTAT and Stat SA.
- Total Agricultural Contribution to GDP (TACGDP): a proportion of the total economy, and it is a proxy for the macroeconomic performance of the agricultural sector. The source of data is FAOSTAT and the World Bank databases.
- Exports (EXP) and Imports (IMP): These are indicators of the amount of agricultural goods that are exported and imported (respectively) when the sector participates in

international trade. Data was accessed from the World Bank and the FAOSTAT database.

The choice of these two variables aligns with the research aim to examine the relationship between agricultural output, environmental sustainability, and trade flows in the context of economic development.

4.2.2. Testing for Unit Roots

Standard tests for cointegration and the ARDL (Autoregressive Distributed Lag) model require the variables to be either first difference stationary I(1) -- not integrated of order two or higher I(2) -- or stationary at level I(0). For each variable, this study used two well-known unit root tests to test for the order of integration:

- **Augmented Dickey-Fuller (ADF) Test (Dickey and Fuller, 1979):**

  The null hypothesis of the ADF test is the unit root hypothesis, and the alternative hypothesis is that the series is stationary; the following equation tests the null hypothesis:

  $$\Delta Z_t = \delta_0 + \delta_1 t + \delta_2 Z_{t-i} + \sum_{t=1}^{n} \beta_i \Delta Z_{t-i} + \varepsilon_t \quad (1)$$

where ΔZt is the first difference of the variable Zt, t is the time trend, and εt is the error. The coefficient δ2 tests for a unit root (i.e., H0: δ2 = 0) against the alternative hypothesis H1: δ2 < 0), suggesting that there was indeed a long-run equilibrium relationship among the variables.

- **Structural Breakpoints (Perron (1989); Lee and Strazicich (2003))**
  Complementing the ADF test, the unit root test with structural breaking point unit root (and allows sudden and discrete change in the process of data generation by incorporating dummy variables to capture changes in the intercept or trend at a specified break date, allowing for a test of the unit root hypothesis in the presence of a known or estimated structural break.

There is evidence of bias in the conventional ADF test; therefore, using both tests enhance the robustness in determining stationarity of the variables.

4.2.4. Cointegration Testing

Once the stationarity of the variables is confirmed (i.e., I (0) or I (1)), the existence of a long-run equilibrium relationship among the variables is tested using the ARDL bounds testing approach developed by Pesaran, et al., (2001). This approach offers several advantages:

- It accommodates a mixture of I (0) and I (1) variables without requiring pre-testing for cointegration.
- It is suitable for small sample sizes.
- It begins by assessing short and long-term impacts.

The ARDL test determines whether variables move together over time, indicating a linear cointegration among the variables. The utilization of the Autoregressive Distributed Lag (ARDL) methodology enables the assessment of both immediate and prolonged associations by virtue of its incorporation of the Error Correction Model (ECM). The ECM serves to gauge the pace at which deviations from the long-term equilibrium are rectified over time, furnishing valuable insights into the dynamic responsiveness of agricultural production to fluctuations in climatic conditions and external parameters. In contrast to conventional co-integration techniques, such as Johansen's test, ARDL exhibits adaptability in accommodating variables of disparate integration levels, thereby presenting a notable advantage for investigations with limited sample sizes. Through a synthesis of unit root tests, ARDL inference, and ECM analysis, this research framework provides a robust foundation for understanding the relationship between CO_2 emissions and agricultural yields in the context of South Africa.

4.3. Estimation Methods

Two econometric statistical approaches estimated the long-run relationships while accounting for potential issues such as endogeneity and serial correlation:

- **Fully Modified Ordinary Least Squares (FMOLS)** (Phillips and Hansen, 1990): FMOLS addresses endogeneity bias and serial correlation by modifying the least squares estimator, providing consistent and efficient estimates in cointegrated systems. This technique is particularly advantageous in small samples and has been widely applied in environmental economics studies (Hamit-Haggar, 2012).

- **Dynamic Ordinary Least Squares (DOLS)** (Stock and Watson, 1993): DOLS enhances FMOLS by integrating leads and lags of differentiated regressors to control for endogeneity and serial correlation more explicitly. Kao and Chiang (2000) have displayed that DOLS tends to have lower bias and superior finite-sample properties relative to FMOLS.

Both FMOLS and DOLS offer complementary angles on prolonged relationships, increasing the robustness of the outcomes.

4.4. Model Specification

The empirical model assessed the effect of carbon dioxide emissions and trade factors on agricultural performance, as a specification capturing the impact of environmental pollution and exchange dynamics on essential agricultural economic output is formulated as:

$$TACGdpt = \beta_0 + \beta_1 CE_t + \beta_2 TAE_t + \beta_3 EXP_t + \beta_4 IMP_t + \varepsilon_t \quad (2)$$

Where: $TACGdp$ = Total Agricultural Contribution to GDP at time t; CE_t = Carbon Dioxide ($C0_2$) emission; TAE_t = Total Agricultural employment; EXPt = Agricultural Export, IMP_t = Agricultural Import, and ε_t = Error term.

This formulation is critical for creating sustainable agricultural and environmental policies. The interrelationships between emissions, international trade, and farm output were examined econometrically to inform policy strategies.

4.5. Results and Discussions

4.5.1. Descriptive Statistics of Explanatory Variables

Table 4.1 summarizes the key characteristics of the analytical variables used in this study: Carbon Dioxide Emissions (CE), Exports (EXP), Imports (IMP), Total Agricultural Contribution to Gross Domestic Product (TACGDP), and Total Agricultural Employment (TAE). These initial descriptive statistics reveal patterns in the variables' trend, averages, and deviations throughout the examined years from 1992 to 2021. They establish a basis for rigorously assessing interrelationships between the factors via statistical techniques. Meanwhile, agricultural production and trade sustained national economic development and

livelihoods, although emissions posed environmental challenges that required policy attention to mitigate damages and promote sustainability.

The results from the central tendencies and variabilities explain the agricultural variables. Carbon dioxide emissions have the highest average of approximately 364,745.2, underscoring the substantial greenhouse gas emissions over time. In contrast, exports and imports recorded much lower averages of around 25 and 24, implying relatively stable external trade flows within the agricultural sector.

CO_2 emissions displayed considerable fluctuations between minimum and maximum amounts, accompanied by a sizable standard deviation, which potentially reflects variations in energy usage, economic cycles, or changing production intensities. Conversely, exports and imports exhibited lower ranges and smaller standard deviations, signifying more consistent trade patterns.

Skewness and kurtosis distributions leaned slightly towards the left, with negative skewness, except for total agricultural GDP, indicating that lower values were more probable. Additionally, all distributions had more acute peaks and fuller tails than a standard curve. This implies a greater likelihood of extreme values, particularly for CO_2 emissions, which could impact statistical conclusions.

The Jarque-Bera tests rejected normality for each variable, validating that non-normal techniques, such as the autoregressive distributed lag model, fully modified ordinary least squares, and dynamic ordinary least squares, are appropriate, as they relax the assumption of normality. These approaches also accommodate limited samples well.

The descriptive statistics reveal significant variability and non-normality across the dataset, particularly in CO_2 emissions. These preliminary insights highlight the need for robust empirical techniques to capture such distributional characteristics, thereby ensuring reliable and interpretable econometric results.

Table 4.1: Descriptive Statistics of explanatory variables

	CE	EXP	IMP	TACGDP	TAE
Mean	364745.2	25.41	24.33	2.58	18.75
Median	386590.7	26.23	24.61	2.48	18.11
Std. Dev	71420.23	3.48	4.44	0.49	2.51
Min	238780.6	18.96	15.37	1.93	14.02
Max	448298.1	32.25	33.72	3.75	22.42
Skewness	-0.47	-0.22	-0.12	0.61	-0.002
Kurtosis	1.67	2.22	2.55	2.44	1.69
Jarque-Bera	3.31	0.99	0.33	2.27	2.13
Probability	0.19	0.61	0.84	0.32	0.34

(Source: Author's computation)

4.5.2. Result of Unit Root Test

The Augmented Dickey-Fuller (ADF) and structural breaking points unit root test was applied to evaluate the stationarity properties of the time-series data. The results, presented in **Table 4.2**, indicate that all variables, Carbon Dioxide Emissions (CE), Exports (EXP), Imports (IMP), Total Agricultural Contribution to GDP (TACGDP), except Total Agricultural Employment (TAE), are non-stationary at levels but become stationary after first differencing. This implies that the variables contain a unit root and are integrated of order one, I(1). Accordingly, the null hypothesis of a unit root cannot be rejected at the level form. However, the first difference confirms that all series are suitable for co-integration analysis.

Table 4.2: Unit Root Test Results

	ADF Test				Breaking Point Unit Root test			
	Level		first difference		Level		first difference	
Variable	t-statistics	P-value	t-statistics	P-value	t-statistics	P-value	t-statistics	P-value
CE	-1.8090	0.3685	-6.7888	0.0000***	-4.5427	0.3463	-8.2700	0.0000***
EXP	-1.9462	0.3077	-5.9197	0.0000***	-4.5010	0.2366	-5.9331	0.0000***
IMP	-2.3499	0.1642	-5.9085	0.0000***	-4.8858	0.1021	-6.0274	0.0000***
TACGDP	-1.6608	0.4398	-5.0232	0.0004***	-4.4937	0.2396	-5.6581	0.0129***
TAE	-1.5258	0.5066	-4.8777	0.0005***	-7.4573	0.0000	-9.7166	0.0000***

*Note: *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.*
(Source: Author's computation)

4.5.3. Johansen Co-integration Test Result

Long-run relationships among the variables were examined using the Johansen co-integration test, employing trace and maximum eigenvalue statistics. **Tables 4.3** and **4.4** show that the trace test identifies one co-integrating equation at the 5% significance level (Trace Statistic =

87.88 > 69.82), indicating a long-term equilibrium relationship among the variables. A maximum eigenvalue test confirms this result because the null hypothesis of no co-integration is rejected at the 5% significance level (Max-Eigen Statistic = 42.50 > 33.88). These findings support the presence of at least one long-run co-integrating vector between TACGDP, CE, EXP, IMP, and TAE.

Table 4.3: Johansen Co-integration Test (Trace Statistic)

Null Hypothesis	n–r	Hypothesized No of CE(s)	Eigen value	Trace statistic	0.05 Critical value	p-value
r = 0	4	None *	0.7808	87.88	69.82	0.0009
r ≤ 1	3	At most 1	0.5660	45.38	47.86	0.0839
r ≤ 2	2	At most 2	0.3487	22.16	29.80	0.2897
r ≤ 3	1	At most 3	0.3040	10.15	15.50	0.2696
r ≤ 4	0	At most 4	0.0000	0.0001	3.84	0.9927

*Note: *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. The trace test indicates 1 co-integrating equation at the 5% level. (Source: Author's computation)*

Table 4.4: Johansen Co-integration Test (Maximum Eigenvalue).

Null Hypothesis	n–r	Hypothesized No of CE(s)	Eigen value	Max-Eigen statistic	0.05 Critical value	p-value
r = 0	4	None *	0.7808	42.50	33.88	0.0037
r ≤ 1	3	At most 1	0.5636	23.22	27.58	0.1644
r ≤ 2	2	At most 2	0.3489	12.01	21.13	0.5464
r ≤ 3	1	At most 3	0.3040	10.15	14.26	0.2696
r ≤ 4	0	At most 4	0.0000	0.0001	3.84	0.9927

The trace test indicates 1 co-integrating equation at the 5% level. (Source: Author's computation)

4.5.4. Estimation of Models (ARDL, FMOLS, and DOLS)

Utilizing ARDL bounds testing, as presented in Table 4.5, the findings reveal that the computed F-statistic value (4.494) exceeds the upper critical threshold, indicating the existence of a long-term cointegrating relationship among the examined variables. Moreover, the ARDL Error Correction Model (ECM) from Table 4.6 indicates that substantial adjustments towards equilibrium are made promptly, as evidenced by the noteworthy and negative coefficient of the error correction term (-0.589), which denotes a restoration of equilibrium following short-term disturbances. In the short run, it is observed that the CO_2 emissions (CE) and Total Aggregate Expenditure (TAE) exhibit negative and statistically significant associations with Total

Aggregate GDP (TACGDP), implying that an upsurge in CE and TAE correlates with a decrease in TACGDP. The model demonstrates a robust goodness of fit ($R^2 = 0.650$) along with statistically significant F-statistics (F= 8.162, p-value < 0.001), thereby instilling confidence in the obtained outcomes.

Table 4.5: ARDL F-Bounds Test and Critical Value

Test Statistic			Value			
F-statistic			4.494			
t-statistic			-3.019			
	10%		5%		1%	
Sample Size	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
			F-Statistic			
30 Asymptotic	2.450	3.520	2.860	4.010	3.740	5.060
			t-Statistic			
Asymptotic	-2.570	-3.660	-2.860	-3.990	-3.430	-4.600

Note: I(0) and I(1) are respectively the stationary and non-stationary bounds.(Source: Author's computation).

Table 4.6: ARDL Error Correction Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
COINTEQ*	-0.588853	0.112365	-5.240544	0.0000**
D(CE)	-1.08E-06	2.52E-06	-0.426429	0.6739
D(CE(-1))	7.04E-06	2.83E-06	2.488766	0.0209
D(TAE)	0.074890	0.038724	1.933943	0.0661
D(TAE(-1))	0.199551	0.052525	3.799145	0.0010**
C	7.069976	1.359526	5.200325	0.0000**
R-squared	0.649745	Mean dependent var		-0.034106
Adjusted R-squared	0.570141	S.D. dependent var		0.262871
S.E. of regression	0.172347	Akaike info criterion		-0.491199
Sum squared resid	0.653480	Schwarz criterion		-0.205727
Log likelihood	12.87679	Hannan-Quinn criterion.		-0.403927
F-statistic	8.162259	Durbin-Watson stat		1.922193
Prob(F-statistic)	0.000176			

Note: *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Cointegrating Specification

CE = TACGDP(-1) - (-0.000016*CE(-1) + 0.026254*EXP01 + 0.006700 *IMP - 0.246833*TAE(-1))

Cointegrating Coefficients

Variable *	Coefficient	Std. Error	t-Statistic	Prob.
CE(-1)	-1.58E-05	5.54E-06	-2.861157	0.0086
EXP01	0.026254	0.062922	0.417252	0.6802
IMP	0.006700	0.054415	0.123129	0.9030
TAE(-1)	-0.246833	0.142236	-1.735381	0.0955

*Note: *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. (Source: Author's computation)*

The long-run equilibrium among the variables was estimated using Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS) methods. The results

are also presented in Table 4.7, which contains the estimated coefficients, standard errors, t-statistics, and corresponding significance levels.

The FMOLS estimates indicate that carbon dioxide emissions (CE) are negatively and significantly related to TACGDP at the 5% level, suggesting that higher emissions have a negative long-term impact on agricultural GDP. However, this relation is insignificant under the DOLS, and the model might be quite sensitive.

Other coefficients, such as EXP, IMP, and TAE, were statistically insignificant in both models, indicating that these did not significantly affect agricultural GDP.

Table 4.7: FMOLS and DOLS Long-Run Estimation Results

	FMOLS				**DOLS**			
Var	**Coeff**	**Std Error**	**T stat**	**Prob**	**Coeff**	**Std Error**	**T stat**	**Prob**
CE	-4.86E-06	2.12E-06	-2.29	0.0310**	-9.60E-06	6.20E-06	-1.54	0.1529
EXP	-0.0017	0.0459	-0.04	0.9716	-0.1228	0.1007	-1.22	0.2505
IMP	-0.0063	0.0416	-0.15	0.8812	0.0789	0.0807	0.98	0.3510
TAE	0.0485	0.0573	0.85	0.4054	-0.0937	0.1188	-0.79	0.4484
C	3.6597	1.5919	2.29	0.0305**	8.9411	3.8651	2.31	0.0433
R^2	0.7754				0.9210			
Adj R^2	0.7380				0.8154			
S.E. of regression	0.2526				0.2072			
Long-run variance	0.0765				0.0602			
Mean dependent var	2.5626				2.5342			
S.D. dependent var	0.4935				0.48241			
Sum squared resid	1.5318				0.4296			

*Note: *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. (Source: Author's computation)*

4.6. Discussion

The empirical findings reveal important relationships between carbon dioxide emissions, agricultural employment, and trade dynamics in shaping agricultural performance in South Africa. The presence of cointegration indicates a long-run equilibrium relationship among the variables, implying that environmental and macroeconomic factors jointly determine agricultural output over time. This finding is consistent with studies that emphasize long-run climate–agriculture linkages in developing economies, including work by Sultan (2012) and Alam (2015), who found persistent equilibrium relationships between emissions and agricultural productivity.

Carbon Emissions and Agricultural Output

The results indicate that carbon dioxide emissions exert a negative and statistically significant effect on agricultural output in the long run. This suggests that increasing emissions adversely affect agricultural productivity. This finding is consistent with the empirical evidence provided by Udeagha & Breitenbach (2023), who reported that rising emissions reduce agricultural productivity in South Africa through climate variability and environmental degradation.

Similarly, Sultan (2012) found that temperature increases associated with greenhouse gas emissions negatively affect crop yields in Sub-Saharan Africa. The present results therefore reinforce the argument that environmental degradation poses a major constraint to agricultural growth.

The negative relationship also aligns with findings by Alam (2015), who documented that increased emissions reduce agricultural output by affecting rainfall patterns and increasing production uncertainty. The consistency of the negative coefficient across estimators suggests that emissions exert structural long-run effects on agricultural performance.

Agricultural Employment and Agricultural Output

The results show that agricultural employment positively affects agricultural output in the short run but is insignificant in the long run. This implies that labour availability contributes to production in the short term but does not sustain long-term productivity growth.

This finding supports the conclusions of Benin (2016), who argued that labour expansion alone cannot sustain agricultural growth without technological improvements. Similarly, Fan &

Zhang (2004) emphasized that productivity gains depend more on capital investment and technological adoption than on labour increases.

The long-run insignificance of labour therefore suggests diminishing marginal productivity of labour in South Africa's agricultural sector, particularly under climate stress conditions.

Trade Variables and Agricultural Performance

The positive but statistically insignificant coefficients for exports and imports suggest that trade openness may support agricultural performance, although the effects are weak. This finding is consistent with mixed empirical evidence in the literature. For example, Anderson (2010) found that trade openness can enhance agricultural productivity through market access and technology transfer.

However, the insignificant effects align with findings by Balogh & Jámbor (2017), who reported that trade liberalization does not automatically translate into productivity gains without supportive infrastructure and policy frameworks.

The results therefore suggest that while trade has potential benefits, structural constraints such as logistics, financing, and market inefficiencies may limit its impact on South Africa's agricultural sector.

Short-Run Adjustment Dynamics

The error correction term is negative and statistically significant, confirming a stable long-run equilibrium relationship among the variables. This indicates that short-run deviations from equilibrium are corrected over time.

This dynamic adjustment process is consistent with the findings of Pesaran, Shin & Smith (2001), who demonstrated that ARDL models effectively capture both short-run dynamics and long-run relationships. Similarly, Narayan (2005) emphasized the suitability of ARDL models for small sample time-series analyses.

The results highlight that environmental factors play a dominant role in determining agricultural performance in South Africa. Carbon emissions emerge as a major long-run constraint, while labour and trade variables play supportive roles. These findings are consistent with the broader literature that emphasizes the need for integrating environmental sustainability with agricultural development strategies.

The empirical evidence therefore supports the argument that sustainable agricultural growth requires climate-responsive policies and productivity-enhancing investments.

Table 4.8 Priori expectations of the variables

Variable	Definition	Expected Sign	Theoretical Justification
TACGDP	Agricultural contribution to GDP	Dependent variable	—
CE	Carbon dioxide emissions	Negative (-)	Higher emissions increase climate stress and reduce agricultural productivity
TAE	Agricultural employment	Positive (+)	More labour increases production capacity
EXP	Agricultural exports	Positive (+)	Export demand stimulates production and income
IMP	Agricultural imports	Positive (+)	Imports provide inputs, technology, and capital goods

(Source: Author's computation)

4.7. Conclusion and Policy Recommendations

This chapter examines the long-run and causal relationship between CO_2 emissions and South Africa's agricultural performance from 1992 to 2021. Variables considered were CO_2 emissions (CE), Total Agricultural Employment (TAE), Total Agricultural Contribution to GDP (TACGDP), Exports (EXP), and Imports (IMP), obtained from the World Bank, FAOSTAT, and Stats SA. Descriptive statistics revealed that the highest mean and maximum variability among the variables were observed for CE. The Jarque–Bera test also indicated that all variables were non-normally distributed, negatively skewed, and leptokurtic. Distribution properties of this nature emphasize the importance of accounting for suitable modelling assumptions responsive to these attributes.

The unit root test results showed that all variables except one were non-stationary at the level of I, but became stationary at the first difference, suggesting the existence of unit roots and unit integration (I(1)). This supports the use of co-integration methodology in examining long-run

relationships. The Johansen co-integration tests (Trace and Maximum Eigenvalue) indicated at least one co-integration relationship between changes in TACGDP and CE, EXP, IMP, and TAE, suggesting that these variables are related in the long-run perspective. Likewise, the ARDL estimation suggests short- and long-run relationships among variables. The results indicate that both CE and TAE have a negative impact on TACGDP, while both IMP and EXP have a positive effect, although this difference is not statistically significant.

Additional regression results of FMOLS and DOLS suggested that the long-run negative elasticity of CO_2 to TACGDP is significant in FMOLS estimation, and there was an adverse statistical long-run effect on CO_2 emissions to agriculture GDP contribution, indicating that higher CO_2 emissions imply lower agricultural contribution to GDP. EXP, IMP, and TAE did not observe significant long-run TACGDP relationships or DOLS specifications in FMOLS.

The results highlight that, while agricultural output is significant in leading to employment opportunities, environmental factors such as CO_2 emissions might not exert an immediate or direct degree of influence on the performance of the agricultural sector but are important over the long term (as FMOLS results).

Based on the empirical results, the following policy recommendations can be made:

1. Promote Low-Carbon Agricultural Practices

The negative long-run effect of carbon emissions on agricultural output suggests the need for policies that reduce environmental degradation. Government should promote climate-smart agricultural practices such as conservation agriculture, improved irrigation efficiency, agroforestry, and sustainable soil management. These strategies can reduce emissions while maintaining productivity.

2. Strengthen Climate Adaptation Strategies

Since emissions affect agricultural productivity over the long term, adaptation policies should be prioritized. Investments in drought-resistant crop varieties, climate information systems, and water management infrastructure would help mitigate the adverse effects of climate change on agriculture.

3. Improve Agricultural Labour Productivity

The short-run significance of agricultural employment indicates that labour contributes to output, but its long-run insignificance suggests productivity limitations. Policies should therefore focus on mechanization, skills development, and access to agricultural technology to enhance labour efficiency.

4. Enhance Trade Competitiveness in Agriculture

Although exports and imports were positive but insignificant, their signs suggest potential growth benefits. Policies should improve agricultural export competitiveness through improved logistics, value chain development, and quality standards. Facilitating access to imported agricultural inputs may also support productivity improvements.

5. Integrate Environmental and Agricultural Policies

The findings highlight the importance of coordinated environmental and agricultural policies. Carbon mitigation strategies should be aligned with agricultural development plans to ensure sustainable growth and food security.

6. Encourage Investment in Sustainable Agricultural Technologies

Investment in renewable energy for irrigation, mechanization, and processing can reduce emissions and improve agricultural productivity simultaneously.

Chapter 5: Climate variability, price risk and agricultural output in South Africa: An econometric assessment.

5.1. Introduction

Climate change is attaining recognition as a significant potential interruption to economic progress on a global scale, affecting agriculture, food security, and the livelihoods of rural populations (Bhuiyan, 2017; Masipa, 2017; Bakht et al., 2020). Climate change disrupts farming systems by damaging crops and livestock and compromising food supply through rising temperatures and erratic rainfall, among other stressors such as floods and droughts. At the same time, poverty and hunger remain among the most pressing global issues, which the international community has committed to addressing by 2030 through the Sustainable Development Goals (SDGs) (Braun et al., 2021). Progress on these goals is closely linked to the adaptive capacity and output of agriculture which is one of the most vulnerable sectors to climate change due to its high dependence on natural resources and weather (Eshete et al., 2020; Pacillo et al., 2022).

The global costs of adapting to climate impacts on crop and livestock production have been high, totaling more than $ 100 billion from 2004 to 2014 (FAO, 2015). Climate variability not only causes production losses but also cascading impacts on rural livelihoods, market stability, and food systems (Partey et al., 2018). The challenge is especially daunting for Sub-Saharan Africa (SSA). In various countries globally, including South Africa, inconsistent temperature and rainfall patterns increase agricultural susceptibility, decline farm profits, and exacerbate food insecurity (Masipa, 2017; Mugambiwa and Tirivangasi, 2017).

Climate change does not affect everyone equally: it is highly regional. Changes in temperature, rainfall, and higher CO_2 concentrations alter growth environments, increase the prevalence of pests and diseases, and affect the adaptation of staple crops across regions (Ncoyini-Manciya, 2021; Shehzad et al., 2022). For example, these changes are already affecting crop and livestock production in provinces like KwaZulu-Natal. Sea-level rise would lead to more salinization and reduced access to irrigation water, as well as other risks. In conclusion, production risks in South African agriculture are at an all-time high, directly tied to climate variability and extreme weather events.

Aside from local climate risks, price volatility is another principal danger to agriculture. Not only climatic shocks but also uncertainties in input and output markets expose agricultural production (Broll et al. 2013; Harčariková 2018). Farmers are active in environments that force agricultural product prices to face a wide range of fluctuations caused by seasonal patterns, changes in demand, shifts in exchange rates, and tax arrangements (Franken et al., 2012; Sirisupluxana and Bunyasiri, 2018). Such market volatility, compounded by a lack of bargaining power among smallholders, increases the vulnerability of these farmers.

The implications of price fluctuation are widespread for both producers and consumers. It also distorts trade, generates liquidity issues for farmers during the long interval between sowing and harvesting, and increases the financial risk they are exposed to (Antonaci et al., 2014). Financial systems in most developing countries exacerbate these problems through high transaction costs and limited access to affordable credit. This leads to a lack of financial security for farmers, who cannot invest in better modern technologies or even meet their household needs.

Specifically, production risk resulting from stochastic natural events (such as drought, floods, and pest outbreaks) is especially high due to yield fluctuations and weak market integration (de Janvry and Sadoulet, 2015; OECD, 2010). Agricultural markets are characterized by relatively low price elasticity of demand; therefore, small changes in yield can lead to significant price fluctuations (Gérard et al., 2010). These risks can be transmitted regionally in integrated markets but have localised price shocks in poorly integrated markets with dramatic impacts on farmers and consumers (Antonaci et al., 2014).

Liberalisation reforms introduced since the 1980s have worsened price risks in SSA in an environment of imperfect market structures (Cornia et al., 2012; Serra, 2015). In developed countries, farmers utilize derivatives markets (e.g., insurance, futures) and other financial instruments as means of accessing markets and hedging against risk (Gilbert and Morgan, 2010); such mechanisms are still in their infancy in much of SSA. In this void, farmers face a multitude of uncertainties that motivate risk-averse supply responses and ultimately lead to diminished supply overall. This has led, in extreme cases, to social unrest driven by food price increases, such as the global food riots in 2007 and 2008 (Bellemare, 2015; Fjelde, 2015).

The dual role of farmers as producers and consumers makes price instability especially detrimental for many developing countries, including South Africa (OECD and FAO, 2016).

The increasing demand for food is driven by rapid urbanization and population growth, as well as weak supply responses from smallholders, which worsens food security (Magrini et al., 2018a). Against this backdrop, fluctuations in the costs of farm inputs threaten agricultural sustainability and the sector's potential contribution to national development (Kwaw-Nimeson and Tian, 2021).

Jointly, climate change and cost volatility constitute actual threats to South African agriculture. Uncertain rainfall and extended dry spells, combined with heatwaves, reduce productivity in crops and livestock, while changing prices put additional strain on farm income and market stability. Their interactive nature provides multifaceted challenges for farmers, policymakers, and the wider economy. To respond to them, we need a better characterization of how climate variables and price risks combine to determine agricultural outcomes.

In the vast literature on the impact of climate change and agricultural price risk, very little of it attempts to simultaneously consider both perspectives in the South African context. Existing work has separately examined climatic variability and production risks, as well as market volatility and food prices, without linking these effects to agricultural supply and economic performance. Additionally, causal links and long-run relationships between climate variables, price risk, and agricultural output remain largely unexplored in South Africa.

This study fills these gaps by examining the relationships between climate variables, price risk, and agricultural production in South Africa. In specific, it aims to (i) determine the causal relationships between climate variables, price risks, and agricultural output, (ii) examine the short-run and long-run dynamics among the variables based on robust econometric estimations, and (iii) inform policy actions aimed at building climate-resilient agriculture capable of sustaining economic growth, while reducing environmental risks.

By adopting this approach, the research contributes to the understanding of the interplay between climate and market factors that drive agricultural output in South Africa, which is crucial for informed policy design, food security, and sustainable development.

5.2. Research Methods

The study is conducted in South Africa, which is located at the southernmost part of the African continent. It is composed of nine provinces, where varying climatic zones impact agricultural

output. South Africa's dependence on rain-fed agriculture makes the country vulnerable to climate variability, as agriculture is a crucial pillar of its economy and rural livelihoods. The study area selection is palpable as it was exposed to both climate shocks and market volatility, necessitating analysis of CO_2 emissions and price risk on agricultural output.

5.2.1. Data Sources

Data obtained from the World Bank, FAOSTAT, and StatsSA were used. The study analysed annual time-series data over the period 1992–2021. The variables applied were the total agricultural contribution to GDP (TACGDP), CO_2 emissions (CE), Consumer Price Index (CPI), and total agricultural employment (TAE). These sources were selected for being reliable and for measuring historical economic and environmental indicators consistently. The 30-year period provides an evaluation of long-term technological change in agricultural output, which is ubiquitous through the climate and market factors.

5.3. Analytical Framework

Time-series analysis was conducted using the Autoregressive Distributed Lag (ARDL) approach. The choice of ARDL was motivated by the characteristics of the data: the variables are a mixture of stationary (I(0)) and first-difference stationary (I(1)) series, and the relatively small sample size necessitates a method capable of producing robust long- and short-run estimates. The ARDL framework is particularly suitable for assessing dynamic interactions between climate variables, price risk, and agricultural output while allowing for mixed integration orders.

Prior to ARDL estimation, stationarity of each variable was tested using the Augmented Dickey-Fuller (ADF) and the Dickey-Fuller Generalized Least Squares (DF-GLS) tests. The DF-GLS test was applied to improve statistical power given the limited sample size. Confirming the integration order ensured none of the variables were integrated of order two (I(2)), which is a requirement for valid ARDL estimation.

5.3.1. Model Specification

The study examines the influence of CO_2 emissions and price risk on agricultural output, controlling for agricultural employment. The model is expressed as follows:

$$TACCdpt = \beta_0 + \beta_1 CE_t + \beta_2 CPI_t + \beta_3 TAE_t + \varepsilon$$

Where ε represents the error term capturing unobserved factors and random disturbances. This specification allows for the evaluation of both direct and indirect effects of climate and price variables on agricultural performance.

5.3.2. ARDL and Co-integration

The ARDL approach also allows the estimation of both short- and long-run relationships through its error correction model (ECM) representation. The ECM captures the speed at which deviations from long-run equilibrium are corrected over time, providing insights into how agricultural output responds dynamically to changes in climate and price variables. Compared to traditional co-integration methods such as Johansen's test, ARDL is flexible in handling variables with different integration orders and is particularly advantageous for small-sample studies.

By combining unit root tests, ARDL estimation, and ECM analysis, this study provides a robust framework to understand the interactions between climate factors, price risk, and agricultural output in South Africa.

To examine the dynamic interactions among climate variability, price risk, and agricultural output, the study employed the Granger causality framework within a Vector Autoregressive (VAR) setting. The Granger causality test evaluates whether past values of one variable contain useful information for predicting another variable (Granger, 1969). The approach has been widely applied in agricultural and climate-related time-series analyses to determine directional relationships among macroeconomic and environmental variables (Sims, 1980; Gujarati & Porter, 2009).

The pairwise Granger causality model is specified as:

Agricultural Output (TACGDP):

$$TACGDP_t = \alpha_0 + \Sigma_{i=1}^{k} \alpha_i \, TACGDP_{t-i} + \Sigma_{i=1}^{k} \beta_i \, CE_{t-i} + \Sigma_{i=1}^{k} \gamma_i \, CPI_{t-i} + \Sigma_{i=1}^{k} \delta_i \, X_{t-i} + \varepsilon_t$$

Where:
TACGDP = Agricultural output
CE = Climate variability indicators
CPI = Price factor
X = Vector of control variables

k = optimal lag length

ε_t = error term

The null hypothesis tested is that the coefficients of the lagged explanatory variable are jointly equal to zero. Rejection of the null hypothesis indicates the presence of Granger causality. This framework allows identification of the direction of predictive influence between climate variability, price risk, and agricultural output.

5.4. Findings and Discussion

5.4.1 Presentation of Result

This study examines the influence of climate factors and price risk on South Africa's agricultural performance from 1992 to 2021, employing a combination of descriptive, unit root, cointegration, causality, and ARDL analyses. The results offer insight into both the short- and long-term dynamics that affect agricultural output.

The descriptive statistics (Table 5.1) reveal moderate variability across all variables. CO_2 emissions (CE) averaged 364,745.2, while CPI averaged 91.28. TACGDP and total agricultural employment (TAE) had means of 2.58 and 18.75, respectively. Skewness and kurtosis measures indicate approximate normality for most variables, with the Jarque-Bera test confirming non-significant departures from normality. These results suggest that the data are suitable for parametric modelling.

Table 5.1: Descriptive Statistics

	CE	**CPI**	**TACGDP**	**TAE**
Mean	364745.2	91.28	2.58	18.75
Median	386590.7	79.04	2.48	18.11
Std. Dev	71420.23	41.67	0.49	2.51
Min	238780.6	33.40	1.93	14.02
Max	448298.1	171.60	3.75	22.42
Skewness	-0.47	0.43	0.61	-0.002
Kurtosis	1.67	1.98	2.44	1.69
Jarque-Bera	3.31	2.25	2.27	2.13
Probability	0.19	0.32	0.32	0.34

(Source: Author's computation)

Stationarity tests are a critical prerequisite for time-series modelling. Using both the Augmented Dickey-Fuller (ADF) and Dickey-Fuller GLS (DF-GLS) tests, we found that most variables are non-stationary at the level, but all become stationary after first differencing (Table 5.2). This confirms that the series are integrated of order one, I(1), justifying the use of the ARDL approach, which accommodates variables with mixed orders of integration.

Table 5.2: Results of Unit Root Test

	ADF Test				DF-GLS Test			
	Level		first difference		Level		first difference	
Variable	t-statistics	P-value	t-statistics	P-value	t-statistics	P-value	t-statistics	P-value
CE	-1.7513	0.7018	-7.2183	0.0000	-1.9077	0.3463	-6.9704	0.0000
CP1	-0.5773	0.9726	-5.9197	0.0000	-0.9592	0.1400	-3.4828	0.0017
TACGDP	-1.6608	0.4398	-5.4477	0.0009	-2.2075	0.0356	-4.6050	0.0001
TAE	-0.1478	0.9912	-5.4363	0.0007	-0.9045	0.3734	-5.5531	0.0000

ADF is calculated with trend and intercept using Lag Length: 1 (Automatic - based on SIC, max lag=8)(Source: Author's computation)

The Johansen cointegration tests, through trace and maximum eigenvalue statistics, confirm the existence of a long-run equilibrium relationship among TACGDP, CE, CPI, and TAE (Tables 5.3 and 5.4). Specifically, one cointegrating equation was identified at the 5% significance level, indicating that these variables are long-term interdependent. This finding highlights the interconnection of environmental, economic, and labour factors in shaping agricultural output.

Table 5.3: Johansen Unrestricted Co-integration rank test between the variables TACGDP, CE, EXP, IMP and TAE (Trace).

Null Hypothesis	**n–r**	**Hypothesised No of CE(s)**	**Eigen value**	**Trace statistic**	**0.05 Critical value**	**Probability**
r = 0	4	None *	0.7514	57.52	55.25	0.0311
r ≤ 1	3	At most 1	0.4407	19.94	35.01	0.7106
r ≤ 2	2	At most 2	0.1431	4.25	18.40	0.9687
r ≤ 3	1	At most 3	0.0030	0.08	3.84	0.77

Trace test indicates 1 co-integrating equation(s) at 0.05 level (Source: Author's computation)

Table 5.4: Johansen Unrestricted Co-integration rank test between the variables TACGDP, CE, EXP, IMP and TAE (Maximum Eigenvalue).

Null Hypothesis	n–r	Hypothesised No of CE(s)	Eigen value	Max-Eigen statistic	0.05 Critical value	Probability
r = 0	4	None *	0.7514	37.58	30.82	0.0064
r ≤ 1	3	At most 1	0.4407	15.69	24.25	0.4390
r ≤ 2	2	At most 2	0.1431	4.17	17.15	0.9537
r ≤ 3	1	At most 3	0.0030	0.08	3.84	0.7747

Eigen test indicates 1 co-integrating equation(s) at 0.05 level (Source: Author's computation)

To explore directional influences between variables, pairwise The pairwise Granger causality results presented in Table 5.5 reveal limited bidirectional causal relationships among the variables. While some directional influences were observed, most variable pairs did not exhibit statistically significant Granger causality. This outcome suggests that climate variability, price risk, and agricultural output do not necessarily influence each other through immediate short-run predictive channels.

One plausible explanation for the absence of widespread causality is that agricultural production decisions in South Africa are largely based on long-term planning rather than short-term responses. Farmers typically make production decisions based on expected seasonal conditions, input availability, and policy support, which reduces short-run predictive causality. Similar findings were reported by Lobell et al. (2011), who argued that agricultural responses to climate variability often occur over longer planning horizons rather than instantaneously.

Another justification relates to adaptation mechanisms within the agricultural sector. Farmers may employ risk management strategies such as crop diversification, irrigation, and improved seed varieties, which mitigate short-run shocks from climate variability and price fluctuations. Adaptation strategies have been shown to weaken immediate causal links between climate variability and agricultural output (Mendelsohn, Dinar & Sanghi, 2001; Thornton et al., 2014).

Additionally, Granger causality measures predictive relationships rather than structural causation (Granger, 1969). Therefore, the absence of causality does not imply lack of economic linkage. The variables may still be connected through long-run equilibrium relationships, which are captured in cointegration frameworks (Engle & Granger, 1987; Pesaran, Shin & Smith, 2001).

The findings also indicate that agricultural output does not respond immediately to price risk shocks. This may reflect the presence of institutional arrangements such as contract farming, storage capacity, and government support mechanisms that stabilize producer decisions.

Previous studies have noted that agricultural producers often smooth production decisions despite price volatility (Gilbert & Morgan, 2010; Minot, 2014).

Table 5.5: Result of Granger Causality Test

Null Hypothesis:	Obs	F-Statistic	Prob.
CE does not Granger Cause TACGDP	28	2.71249	0.0876
TACGDP does not Granger Cause CE		1.58806	0.2259
CPI does not Granger Cause TACGDP	28	0.19635	0.8231
TACGDP does not Granger Cause CPI		6.38193	0.0062
TAE does not Granger Cause TACGDP	28	0.51022	0.6070
TACGDP does not Granger Cause TAE		0.60023	0.5571
CPI does not Granger Cause CE	28	0.20990	0.8122
CE does not Granger Cause CPI		0.18930	0.8288
TAE does not Granger Cause CE	28	0.02100	0.9792
CE does not Granger Cause TAE		0.53686	0.5917
TAE does not Granger Cause CPI	28	1.55909	0.2318
CPI does not Granger Cause TAE		1.30237	0.2912

(Source: Author's computation)

Applying ARDL bounds testing (Table 5.6), the results indicate that the F-statistic (22.52) exceeds the upper critical bound suggesting that there is a long-run relationship among the variables. The ARDL Error Correction Model (ECM) from Table 5.7 also reveals that the long-run deviations from equilibrium are corrected considerably efficient as shown in the positive and significant error correction term (-2.5841) indicating quick adjustment from short-run shocks which restores equilibrium. CPI and TAE are positively and significantly associated with TACGDP in the short run, suggesting that an increase (CPI) and TAE are associated with an increase in output (TACGDP) The fit of the model is strong ($R^2 = 0.956$) with significant F-statistics ($F= 32.38$, p value < 0.001), which adds confidence in the result.

Table 5.6: ARDL Bounds Test

			Critical Values				
			10%		5%		
Lag Length	F-Statistics	K	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Outcome
ARDL (4,0,1,4)	22.52	3	3.47	4.45	4.01	5.07	
							Cointegrated

(Source: Author's computation)

Table 5.7: ARDL Error Correction Model Result

Variable	Coefficient	Std. Error	T Statistics	Prob
ECM	-2.5841	0.2434	-10.61	0.0000
D(TACGDP(-1))	1.1918	0.1823	6.53	0.0000
D(TACGDP(-3))	0.5322	0.0903	5.89	0.0010
D(TACGDP(-3))	0.2703	0.0646	4.18	0.0013
D(CPI)	0.0426	0.0114	3.74	0.0028
D(TAE)	0.1423	0.0132	10.73	0.0000
D(TAE(-1))	0.2461	0.0239	10.25	0.0000
D(TAE(-2))	0.1761	0.0319	5.51	0.0000
D(TAE(-3))	0.1425	0.0300	4.74	0.0050
R-Squred	0.9557	Mean dependent var		-0.0252
Adj R-Squared	0.9262	S.D dependent var		0.2340
S.E. of regression	0.0636	Akaike info criterion		-2.3773
Sum squared resid	0.0606	Schwarx criterion		-1.8451
Log likelihood	41.905	Hannan-Quinn criterion		-2.2241
F- Statistic	32.38	Durbin-watson stat		2.6064
Prob (F-Statistic)	0.0000			

(Source: Author's computation)

Long-run ARDL estimates (see Table 5.8) tell a more complex insight. Other than increased TACGDP from environmental pollution and price level as CO_2 emissions and CPI also has positive and significant contributions to TACGDP in long–run perspective. The coefficient of total agricultural employment (TAE) is negative (-0.0042) but statistically insignificant, as indicated by the low t-statistic (-0.2561). This suggests that variations in agricultural employment do not have a meaningful impact on agricultural output within the study period. The result may reflect structural inefficiencies in labor utilization or the increasing role of mechanization and capital-intensive production in the sector. Consequently, expanding labor alone may not be sufficient to drive improvements in agricultural performance without corresponding gains in technology and productivity-enhancing inputs.

Table 5.8: ARDL Long-run results

Variable	Coefficient	Std Error	T statistics	Prob.
CE	1.60E-06	5.74E-07	2.78**	0.0165
CPI	0.0330	0.0024	13.59***	0.0000
TAE	-0.0042	0.0164	-2.5481	0.0256

*** and ** denotes statistical significance at 1%, and 10% respectively.(Source: Author's computation)*

Overall, these results suggest the dual impact of climate and market forces on South Africa's agricultural sector, with significant interactions between biophysical and economic factors. Policy implications are straightforward: integrated approaches simultaneously targeting climate mitigation, price stabilization, and strategic deployment of labour are key to boosting resilience and productivity. Promoting the efficient use of labour, climate-smart agricultural practices, and putting into place price stabilization mechanisms will enhance the long-term performance of agriculture and food security.

5.4.1 Discussion of Results

The results from the ARDL and cointegration analysis provide important insights into how climate variability and price risk influence agricultural output in South Africa. Beyond statistical significance, these findings reflect deeper structural relationships within the agricultural sector, consistent with both theoretical expectations and existing empirical literature reviewed.

Long-Run Relationships

The existence of a long-run relationship among agricultural output, climate variables, and price dynamics confirms that these variables move together over time. This supports the theoretical expectation that agricultural systems are shaped by persistent environmental and economic forces rather than short-term fluctuations alone.

This finding aligns with studies discussed in the literature review, particularly those emphasizing long-run equilibrium relationships using cointegration techniques (Ali et al., 2021). It also supports the broader climate–agriculture framework, which suggests that climate conditions and market structures jointly determine agricultural outcomes over time.

Rainfall Effects

Rainfall exhibits a positive and statistically significant relationship with agricultural output, reinforcing the importance of precipitation in agricultural production. This result is consistent

with earlier findings that rainfall variability is a key determinant of agricultural performance in South Africa due to the dominance of rain-fed farming systems.

This aligns strongly with the work of Ngcamu and Chari (2020), who highlight that rainfall fluctuations significantly influence crop yields and rural livelihoods in South Africa. Similarly, Sultan (2012) emphasizes that in Sub-Saharan Africa, rainfall variability remains one of the most critical drivers of agricultural output.

From a practical perspective, this result suggests that improved water management and irrigation systems are essential for reducing vulnerability to rainfall shocks.

Temperature Effects

The negative effect of temperature on agricultural output is consistent with theoretical and empirical literature linking rising temperatures to reduced agricultural performance. Increased temperatures contribute to heat stress, higher evapotranspiration, and reduced soil moisture, all of which negatively affect crop growth.

This finding supports Etienne et al. (2025), who demonstrate that rising temperatures adversely affect agricultural productivity through physiological stress on crops and livestock. It is also consistent with the broader literature on climate change impacts in agriculture, which shows that temperature increases reduce yields, particularly in already warm and water-scarce regions.

In the South African context, this result reinforces concerns about increasing heatwaves and their long-term implications for agricultural sustainability.

Price Volatility

The negative relationship between price volatility and agricultural output highlights the importance of stable market conditions for production decisions. This finding reflects the risk-averse behavior of farmers, who may reduce investment when faced with uncertain prices.

This is consistent with Komarek et al. (2019), who emphasize that price risk significantly influences agricultural decision-making and investment patterns. Similarly, Soni and Manogna (2024) show that market uncertainty can constrain agricultural growth by discouraging input use and technological adoption.

The result also aligns with the discussion in Chapter Two on how price instability affects farmer behavior, particularly in developing economies where access to financial risk management tools is limited.

Trade Variables (Exports and Imports)

The role of exports in supporting agricultural output reflects the importance of international market access in driving production. This is consistent with Aluwani (2023), who finds that

trade openness contributes positively to agricultural growth by expanding demand and encouraging production.

On the other hand, the potential negative effects of imports highlight competitive pressures on domestic producers. This aligns with Ntombela et al. (2018), who show that agricultural markets in South Africa are sensitive to foreign competition, particularly in sectors where imports can substitute for domestic production.

These findings reflect the dual role of trade as both a driver of growth and a source of vulnerability.

Agricultural Employment (TAE)

The negative but statistically insignificant coefficient of agricultural employment suggests that labor does not play a strong direct role in determining agricultural output within the study period. This finding may reflect structural changes in the agricultural sector, including increased mechanization and capital intensity.

This is consistent with the broader literature indicating a shift away from labor-intensive farming toward more technology-driven production systems (Muzangwa et al., 2021). It also supports the argument that output growth in agriculture is increasingly driven by efficiency improvements rather than labor expansion.

Short-Run Dynamics

The short-run results show that climate variability, particularly temperature changes, has immediate effects on agricultural output. This aligns with the findings of Udeagha and Breitenbach (2023), who demonstrate that climate shocks have strong short-term impacts on agricultural performance.

The significance of the error correction term confirms that deviations from long-run equilibrium are corrected over time, supporting the validity of the ARDL framework. This is consistent with standard econometric expectations and previous studies using similar methodologies (Ali et al., 2021).

Overall, the results confirm that agricultural output in South Africa is shaped by a complex interaction of climate and market forces. Climate variability directly affects production conditions, while price volatility influences economic decisions related to investment and resource allocation.

This supports the integrated framework discussed in Chapter Two, which emphasizes the interconnected nature of environmental and economic risks. The findings also align with

studies such as Raihan et al. (2022), which highlight the combined effects of climate shocks and market instability on agricultural systems.

5.5. Implications for South African Agricultural Landscape

The limited Granger causality relationships have important implications for the South African agricultural sector. First, the results suggest that agricultural output is influenced by multiple interacting factors rather than single dominant drivers. This highlights the need for integrated policy approaches that simultaneously address climate variability, price risk, and productivity constraints. Integrated climate–agriculture policy frameworks have been recommended in similar contexts (FAO, 2017; World Bank, 2020).

Second, the absence of strong short-run causality implies that South African farmers exhibit adaptive behaviour to climate and market shocks. This indicates resilience within the agricultural system, but also suggests that policy interventions should focus on strengthening long-term adaptive capacity rather than short-term reactive measures. Long-term resilience strategies such as climate-smart agriculture have been emphasized in previous studies (Lipper et al., 2014; Thornton et al., 2014).

Third, the weak causal link between price risk and agricultural output suggests that market-based shocks alone may not significantly disrupt production decisions. However, persistent price volatility may still affect investment decisions and long-term productivity. This underscores the importance of strengthening agricultural price stabilization mechanisms and improving market information systems (Gilbert & Morgan, 2010; Minot, 2014).

Fourth, the results emphasize the importance of climate-resilient agricultural strategies. Since climate variability does not immediately cause changes in output, adaptation measures such as irrigation infrastructure, drought-resistant crop varieties, and improved extension services should be prioritized to enhance long-term resilience. These interventions have been widely supported in the literature on climate adaptation in agriculture (Mendelsohn et al., 2001; Lobell et al., 2011).

Finally, the findings suggest that agricultural policy in South Africa should adopt a holistic framework that integrates climate risk management, price stabilization, and technological advancement. Such an approach would enhance the sustainability of agricultural production under changing environmental and economic conditions (FAO, 2017; World Bank, 2020).

5.6. Conclusion and Policy Recommendations

The study examined the effects of CO_2 emissions, price risk, and agricultural employment on the contribution of agriculture to GDP in South Africa between 1992 and 2021. The finding establishes a considerable long run association among variables and suggests that agricultural performance is responsive to environmental and economic factors as extensively illustrated in (Masipa, 2017; Mugambiwa and Tirivangasi, 2017) but was confined to short run only. Specifically, CO_2 emissions negatively influenced the agricultural output and thus reflect the adverse effects of climate forces on the productivity. On the other hand, price variability, represented by consumer price index, and aggregate employment in agriculture showed the positive relationships with the long-term agricultural GDP, which indicates the importance of market factors and labor allocation in determining the sector's performance (Xu et. al., 2024). In addition, the results of the error correction suggest a fast-adjusting mechanism whereby deviations from long-run equilibrium are quickly corrected, thereby contributing to the long-run stability of these relationships. The relationship of agriculture output to price levels for commodity market correlations as the causality analysis proved the low variability in the agricultural sector development which can only be influence in one direction (export restriction led agricultural production to prices) (Xu et. al., 2024).

Such findings have major significance for policy and practice. The adverse effect of CO_2 emissions has necessitated the promotion of agricultural practices that guarantee higher ming practices, more efficient irrigation, and low-carbon inputs. Likewise, the effect of price movements and agricultural employment indicates that productive investments in infrastructure, technology and workforce will improve output and resilience. Stabilization policies, access to agricultural credit, and measures to support diversification in the sector can help bring cyclical movements in the short run more in line with structural trends in the long run.

Policy Implications

The findings suggest several policy priorities, consistent with existing literature:

- **Climate adaptation strategies**, including irrigation and climate-smart agriculture, as emphasized by Shiferaw et al. (2014)
- **Market stabilization mechanisms**, as highlighted by Komarek et al. (2019)
- **Promotion of technological innovation**, in line with Santra (2017)

- **Improved access to financial instruments**, to reduce vulnerability to price and climate risks

These measures are essential for enhancing the resilience of South Africa's agricultural sector in the face of increasing environmental and economic uncertainty.

In summary, this paper calls for future agricultural planning to incorporate both environmental as well as economic elements in their analyses. Policymakers can increase the contribution of the sector to national economic growth, food security, and resilience to future shocks by enabling climate-risk mitigation, incentivizing sustainable labor and market mechanisms, and nurturing sustainable practices. The results also imply that environmental pressures and economic factors are tightly interlinked and sustainable agricultural development in South Africa is going to require integrated approaches that achieve synergies in agricultural growth, environmental stewardship, and economic stability.

Chapter 6: Carbon Emission Risks and Price Volatility: Implications for Agricultural Output in South Africa.

6.1. Introduction

Climate Change is one of the most serious threats facing humanity in the 21st century, and it has a significant impact on agricultural systems and food security. According to (Omokpariola et al., (2025); Chhogyel et al. (2020); Hatfield et al., (2011)), crop production is vulnerable to temperature fluctuations, rainfall patterns, and the occurrence of extreme weather events. It remains highly climate-sensitive, as smallholder farmers are disadvantaged financially, technologically, and in accessing up-to-date information on climate risks, both sectorally and in general (Newsham et al., 2024). Such disruptions in planting seasons, declining harvests, and livestock deaths also pose systemic threats to macroeconomic stability in countries where agriculture is closely tied to employment, food security, and overall economic prosperity, as they undermine rural incomes (Tagwi, 2022).

These illustrate some of the complexity at play in South Africa. Simultaneously, climate shocks that are becoming more frequent and severe are posing an increased danger to the country's agricultural sector, including prolonged droughts, heat stress, and floods that are more soil-, productivity-, and predictably harmful to farm profits (Ningi et al., 2025). Analyses reveal that systemic constraints, including low irrigation, high input prices, and heterogeneous extension services, primarily affect smallholder farmers, further exacerbating these biophysical risks (Ojogiwa & Mubangizi, 2023). Climate-smart agriculture, crop diversification, stress- and time-resilient seed varieties, and better resource (water and others) management are often highlighted as adaptation pathways; however, their success in terms of uptake and effectiveness is primarily driven by the enabling policy, investment, and market environment (Daniels et al., 2022).

Beyond direct climate stresses, the agricultural sector is also affected indirectly due to its deep ties to energy markets and global supply chains. Climate change has both an impact and affects agriculture. The increase in greenhouse gas emissions (i.e., fossil fuel burning, land-use change, and industrialized production of meat and dairy animals) leads to environmental decline, which subsequently affects productivity (Malhi et al., 2021). However, policies aimed at reducing fossil fuel consumption by promoting renewable energy and biofuel production can have adverse side effects, including modifications to food prices or land displacement (i.e., the

use of land previously used for food production) (Rajagopal & Zilberman, 2008; Mitchell, 2008). At the same time, prices in several agricultural markets are becoming increasingly erratic due to climate-related perturbations, economic shocks, and speculative activities, which disproportionately affect poor households in developing countries (Manogna et al., 2024). Such instability prevents long-term planning for farmers and puts food security at greater risk.

Because of this, the interlinked risks of carbon emissions, climate-induced production shocks, and agricultural market influencing risks have not been adequately combined in the South African context analysis of its systems. Past literature often assesses the impact of climate change, crop price volatility, or emission burden in isolation, which provides little insight into how these threats jointly affect agricultural yields. That gap matters even more because of the feedback loops between carbon pollution, market instability, and agricultural output. An improved understanding of these linkages is crucial for informing policies that promote food security without compromising environmental sustainability.

Given this background, this study examines the carbon emission risks and agricultural price volatilities on agricultural output in South Africa. Specifically, it: (i) assesses the influence of uncertainty of carbon prices and emissions-related variables on agricultural outcomes; (ii) examines the drivers and impacts of variability of agricultural prices and price instability for food security and farmer incomes; (iii) identifies co-benefits, trade-offs and lessons learned in combining climate mitigation and climate-smart agricultural adaptation; and (iv) analyzes the socioeconomic dimensions of vulnerability (a special focus on adaptive capacity and livelihood security). This integrated approach promotes the ideals of sustainability and agricultural growth through an evidence-based approach that facilitates further reconciliation of these two important imperatives.

Although climate shocks (such as heat extremes or droughts) at the country level have been widely studied, we take a joint view of this risk by quantifying the risk from carbon emissions at the country level while embedding the specific market-level understandings of the channels through which climate and market shocks impact South African agriculture. The findings are expected to help policymakers, researchers, and development practitioners design climate-resilient agricultural policies in response to such an unprecedented rate of environmental change.

6.2. Conceptual Framework

In this study, we develop a risk-productivity framework for environmental (carbon emissions and climate variability) and economic (price volatility) stressors tied to agricultural output outcomes. The framework posits that:

- Direct biophysical responses to climate change: Carbon emissions and climate variables (e.g., CO_2 concentration, temperature anomalies, precipitation variability) have a direct impact on crop growth and yield through biophysical pathways.
- Agricultural price volatility affects farmers' production, time, and the use of modern technology, as well as their investment in feed industry productivity.
- Carbon emissions and price volatility: Climate shocks driven by emissions can amplify price volatility, and price volatility may constrain adaptive responses.
- Access to technology, infrastructure, extension services, and credit: Socioeconomic and institutional mediators influence the adaptive capacity of the agricultural sector, thereby regulating productivity responses.

The conceptual framework allows actual understanding of the subject area based on the knowledge of the study area. We hypothesize the conceptual relationships among environmental and economic drivers, agricultural output, and institutional and structural factors that link environmental and economic stressors to agricultural output outcomes. This comprehensive perspective informs the study's methodology, including the selection of variables, data sources, and econometric modelling strategy. It aims to assess the relationship between the joint risks of carbon emissions and price volatility on agricultural output in the case of South Africa.

6.3. Methodology

6.3.1. Study Design

This study is one of the pioneer studies that simultaneously examines the impacts of carbon emission risks and agri-price volatility on South Africa's agricultural output using the Vector Error Correction (VEC) model. By incorporating both environmental and economic variables, this analytical approach considers both direct biophysical impacts and market-mediated effects, aligning with the conceptual framework described in Section 2.2. Time-series design enables us to assess the extent to which past fluctuations in CO_2 emissions, carbon prices, and market

prices for natural and agricultural products inform productivity, an important consideration for policymakers aiming to target climate adaptation and food security.

6.3.2. Data Sources and Variables

The research uses annual secondary data for the period 1992–2021 (30 observations) from the World Bank, FAOSTAT, and Statistics South Africa (StatSA). Key variables include:

- Agricultural output: Measured as Total Agricultural Contribution to GDP (TACGdp), which measures sectoral output and Total Agricultural Employment (TAE) changes, representing sectoral output and labour-related productivity dynamics, which track labour engagement in agriculture.
- Carbon Emissions (CE): Annual CO_2 emissions (total emissions in million tonnes), capturing environmental stress on agriculture.
- Carbon Price (CP): Proxy for carbon emission costs, reflecting incentives or costs associated with mitigation policies.
- Price Volatility (CPI): Consumer Price Index changes for agricultural commodities, serving as an indicator of market instability and its potential impact on farmers' decisions.

All variables were converted into annual percentage changes to normalize scale differences and facilitate robust econometric analysis.

6.3.3. Econometric Specification

The study adopts an integrated time-series modelling approach comprising:

1. Unit Root and Stationarity Tests: ADF and Breakpoint tests are used for obtaining the order of integration and checking for stationarity to prevent the risk of spurious regressions.
2. Johansen Cointegration Tests: Long-run equilibrium relationships of carbon emissions, price volatility, and agricultural output.
3. VECM (Vector Error Correction Model): The VECM provides both short- and long-term dynamics for cointegrated (i.e., features that have a long-run relationship) varying, suggesting the influence of disequilibrium on agricultural output over time.

4. Impulse Response and Variance Decomposition, respectively, align the dynamic effects of shocks emanating from carbon emissions and price instability on agricultural yield, and the share of each shock in the estimated variations.

The South African context is multifaceted and interlinked, and so this econometric approach facilitates a robust assessment of direct and lagged effects of environmental and market stressors on agriculture.

6.3.4. Model Justification

The VECM framework used in this study was chosen because it is applicable under the following conditions:

- Takes care of non-stationary but cointegrated variables, which is the case with macroeconomic and environmental time-series data.
- It includes the short-run and long-run adjustment of relationships between carbon emissions, price variability, and agricultural output.
- Allows an examination of the interaction of environmental stress and how the market adapts to that stress in accordance with the conceptual model of the study.

6.3.5. Limitations and Assumptions

The study assumes:

- Historical data can capture national-level trends in emissions, prices, and productivity.
- The control variables partly address external shocks other than carbon emission and price volatility (e.g., policy or global trade interruptions).
- Aggregate agricultural output: Sectoral aggregation gives us an average aggregate measure, but in reality, we know that the productivity levels used to derive this are heterogeneous across crop categories and regions.

A few study limitations include reliance on secondary data and the size, which is typical of annual time-series analysis. Although not without its limitations, the methodology offers important insights into the systematic risk signs affecting South African agriculture and contributes to the evidence base for potential policy prescriptions moving forward.

6.3.6. Analytical Framework

This paper employs a Vector Error Correction Model (VECM) to examine the short-run and long-run dynamics between CO_2 emissions, price volatility, and agricultural production. The model captures:

- Long-run Equilibrium Relations: emissions and price volatility, and agricultural production
- Short-run Deviations: Where shocks and then adjustments are reflected.

Stationarity of variables is tested by using the Augmented Dickey-Fuller (ADF) and the breaking point test. The cointegration is tested using the Johansen method, along with relevant diagnostic checks for autocorrelation, heteroskedasticity, and normality, to ensure the robustness of our findings.

6.5. Results and Discussion

6.5.1. Descriptive Statistics

Table 1 summarizes the descriptive statistics for key variables used in the analysis. These provide an overview of trends in emissions, price volatility, and agricultural output in South Africa between 1992 and 2021.

Table 6.1. Descriptive Statistics (1992–2021)

Variable	Mean	Median	Max.	Min	Std. Dev.
CO_2 Emissions (Mt)	6441.1	8598.5	42281.2	-53384.4	19158.83
Consumer Price Index (CPI, %)	4.74	4.40	8.56	-0.50	2.09
Total Agricultural Contribution to GDP (%)	2.6	2.5	3.8	1.9	0.49
Total Agricultural Employment (000s)	-0.03	-0.27	5.04	-1.44	1.17

(Source: Author's Computation)

As observed from **Table 6.1**, the total contribution of agriculture to GDP, both in terms of the mean and median, is close, indicating a relatively symmetric distribution centered around the mean. It was noted that CO_2 emissions and Consumer Price Index also show the same means and medians, often a sign that there are no strong outliers or that the data is not highly skewed. However, there is a notable difference between the mean and median of total agricultural employment, indicating that the data may be skewed or contain extreme values. With the large

spread in both CO_2 emissions and total agricultural employment, it appears that significant fluctuations occurred in these values during the studied period.

Unusually high maximum and extremely low (or even negative) minimum values underscore the volatility, yet important, shocks to economic measures that must be considered in a period characterized by stability alone. CO_2 emissions stand out with a high relative standard deviation, a high standard deviation relative to its mean, indicating a potentially higher level of variability, or an indication that the majority of the changes are small. Total agricultural employment also demonstrates this trait. Most economic indicators view high standard deviation values as a sign of risk or volatility.

6.4.2. Stationarity and Cointegration Tests

The stationarity of the series was assessed using the Augmented Dickey-Fuller (ADF) and Breakpoint (BP) test, and cointegration was tested with the Johansen method before estimating the long-run relationship.

Table 6.2. Stationarity Unit Root Test Results

Variable	Level (ADF)	1st Diff (ADF)	Level (B.P)	1st Diff (B.P)	(I)
TACGdp	-2.02	-5.45***	-3.79	-5.73***	I (1)
CO_2 Emissions	-7.28***	-4.18***	-8.60***	-9.82***	I (0) & I (1)
CPI	-3.87**	-5.46***	-4.87**	-6.57***	I (0) & I (1)
TAE	-5.47***	-4.15***	-8.76***	-7.57***	I (0) & I (1)

Note: ****, **, and * denotes statistical significance at 1%, 5% and 10% levels respectively. (Source: Author's computation)*

The results from **Table 6.2,** which are unit root tests for all the series, are conducted with an intercept and trend for both ADF and B.P., with the latter using the ADF minimum time as the break point. The results of the ADF and structural break point unit root tests indicated that the TACGdp data series was not stationary at I (0) but is stationary at I (1) at a 1% significance level. All other data series were stationary at I (0) at 1% and 5% significance levels. This result confirms that we can employ the Johansen co-integration test procedure to examine the co-integration relationship among the variables. However, we can first determine the optimal lag length for our equation models using the VAR.

Table 6.3 presents the results of optimal lag length selection. Using the AIC, Schwarz Information Criterion (SC) and Hannan-Quinn Information Criterion (HQ) criterions, it can be

observed that the sequential modified SC and HQ statistic test suggests the optimal lags for the model is one lag. The AIC suggests optimal lag length is two, while Schwarz Information Criterion (SC) and Hannan-Quinn Information Criterion (HQ) suggests no optimal lags. The majority suggests an optimal lag length of one.

Table 6.3. Lag Length Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-429.2234	NA	3.23e+08	30.94453	31.13484	31.00271
1	-393.6196	58.49193*	80859931	29.54426	30.49583*	29.83516*
2	-376.0340	23.86616	78137281*	29.43100*	31.14383	29.95463

**Note: ***Indicates lag order selected by the criterions. AIC, SC, and HQ
(Source: Author's computation)

Table 6.4 presents the results of the cointegration test as determined within the Max-Eigen and Trace tests. In this step, we check the cointegration relationship among the variables within a specification model that uses an intercept both in the cointegration equation (EC) and the VAR. The trace and max-eigen statistics suggest the number of cointegrating equations (CE) in the vector error correction (VEC) specification. There is evidence to support the existence of exactly one cointegrating relationship among the variables in the model. Based on this result, we decided to employ cointegration equations in the VECM to explore the short-term and long-term relationships between the variables and then run diagnostic tests to confirm the model's viability.

Table 6.4: The result of the Johansen co-integration test

Number of CE(s)	**Eigenvalue**	**Trace Statistic**		**Max-eigen Statistic**	
		Value	**0.05CV**	**Value**	**0.05CV**
None*	0.6607	55.6576	47.8561	30.2636	27.5843
At most 1	0.3730	25.3940	29.7971	13.0691	21.1316
At most 2	0.3242	12.3250	15.4947	10.9710	14.2646
At most3	0.0472	1.3540	3.8415	1.3540	3.8415

Note: **Denotes rejection of the hypothesis at the 0.05 level*
(Source: Author's computation).

6.4.3. Vector Error Correction Model (VECM) Results

The VECM estimates the short-run and long-run effects of CO_2 emissions and price volatility on agricultural output. Table 6.5 and 6.6 presents the long-run co-integration equation and short-run dynamics between the variables respectively.

Table 6.5. Long-Run Coefficients (VECM)

Dependent Variable: TACGdp	Coefficient	Std. Error	T-Statistic
CO_2 Emissions	0.0001	2.6E-05	4.80181
CPI (Price Volatility)	0.5038	0.11965	4.21016
TAE	0.5837	0.46212	1.26302
Constant	-5.5802		

Table 6.5 presents the long-run co-integration equation and short-run dynamics between the variables. The cointegration equation represents the long-term relationship between the variables. The other coefficients in the long run are: The positive and statistically significant CO_2 Emissions. It indicates a negative long-run relationship between carbon emissions risk and agricultural GDP, meaning that as the level of carbon emissions increases, the agricultural contribution to GDP is likely to decrease, possibly due to reduced productivity or resource utilization associated with the emissions. For price volatility, the estimated coefficient was negative but not statistically significant. This suggests that the long-term relationship between the consumer price index risk and agricultural GDP is weak and statistically insignificant, indicating that price risk does not significantly affect agricultural GDP in the long term but can also reduce output, highlighting sensitivity to market shocks**.** An emissions reduction strategy that supports climate-smart agriculture, such as the adoption of green technologies and market stabilization, should be implemented to mitigate price fluctuations and ensure environmental sustainability.

Table 6.6. Short-Run Dynamics (Error Correction Term)

Variables	D(TACGDP)	D(CE)	D(CPI)	D(TAE)
ECT (COINTEQ1)	–0.0609	–9340.39	–0.7196	0.0514
$D(TACGdp_{-1})$	–0.1971	37462.28	2.4812	–1.6339
$D(CE_{-1})$	0.00000937	–0.2183	0.000059	0.00002
$D(CPI_{-1})$	0.0521	1399.86	0.0359	0.0653
$D(TAE_{-1})$	0.1307	–673.62	0.4733	–0.3203
Constant	–0.0474	1758.59	0.2282	0.0515

The error-correction term (COINTEQ1) is negative and significant for TACGDP, CE, and CPI, indicating that these variables adjust toward their long-run equilibrium when deviations occur, with TACGDP correcting at a moderate rate of approximately 6% per period. Short-run dynamics reveal that changes in CE, CPI, and TAE have significant positive effects on

TACGDP, confirming that emissions, price movements, and labour inputs stimulate agricultural output in the short term. However, most variables exhibit limited short-run feedback effects on one another, aside from their influence on TACGDP.

The short-run dynamics indicate that increases in CE, CPI, and TAE each have positive and significant effects on TAGDP, highlighting that higher emissions, price shocks, and greater labour input stimulate agricultural GDP in the short run. However, most variables exert insignificant effects on one another, reflecting limited short-term interactions aside from their influence on TAGdp.

6.4.4. Impulse Response Functions (IRFs)

Figure 6.1 illustrates how a one-standard-deviation shock in CO_2 emissions affects agricultural output over time. The impulse response shows that a one-standard-deviation shock to carbon emissions (CE) leads to an immediate and steep decline in TAGDP, reaching its most substantial negative effect around periods 3–4. After this trough, TAGDP begins a gradual recovery, although it remains below zero throughout the observed horizon. This suggests that shocks to carbon emissions reduce agricultural GDP in the short run before the system slowly adjusts.

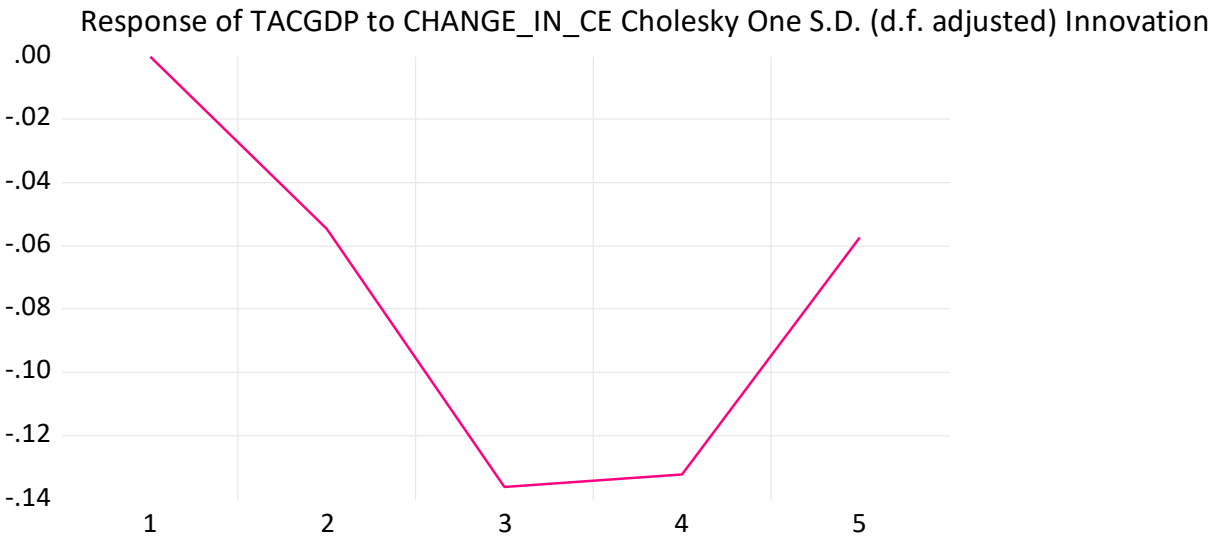


Figure 6.1. Impulse Response of TACGdp to CO_2 Emissions Shock

In Figure 6.2, A one-standard-deviation shock to CPI initially leads to a small positive response in TAGDP, but this effect quickly turns negative from period 2 onward. TAGDP declines steadily, reaching its most pronounced negative impact around periods 3–4 before beginning a

slight recovery by period 5. Overall, price shocks reduce agricultural GDP in the short run after a brief initial boost.

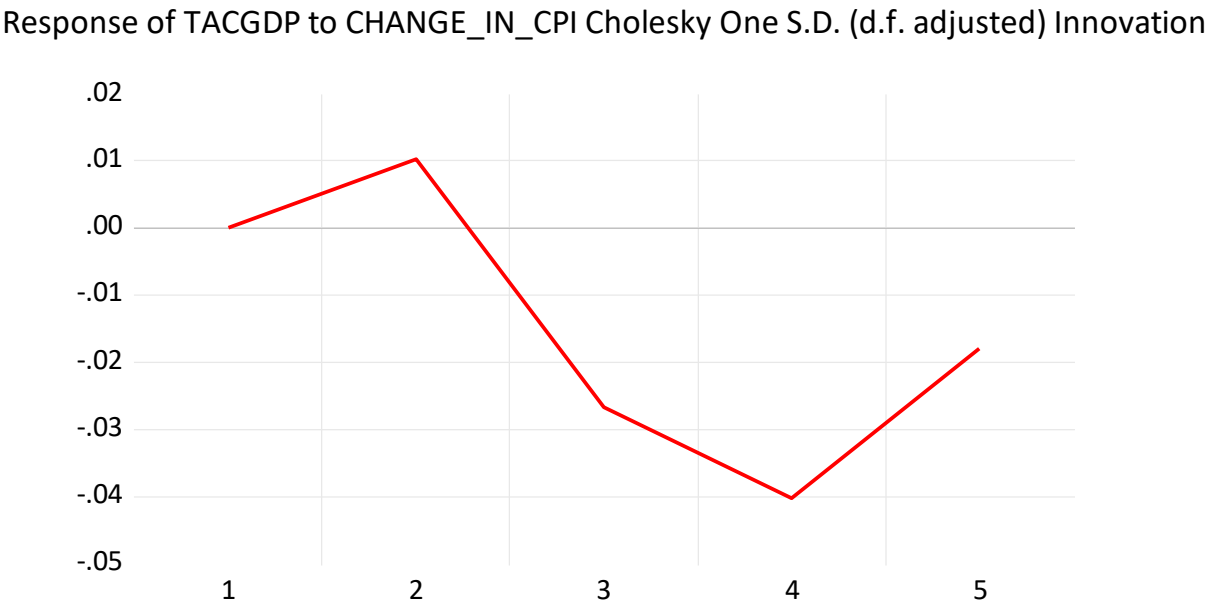


Figure 6.2. Impulse Response of TACGdp to CPI Shock
(Source: Author's computation)

6.4.5. Variance Decomposition

The variance decomposition from Table 6.7 shows that TACGDP is primarily explained by its own shocks in the short run, accounting for 100% in period 1 and still dominating with about 75% by period 5. Carbon emissions (CE) become increasingly important over time, rising from 2.9% in period 2 to nearly 20% by period 5, indicating a growing influence of CE on fluctuations in agricultural GDP. CPI and TAE contribute minimally throughout, each explaining less than 8% of the variation in TACGDP

Table 6.7. Variance Decomposition of TACGdp

Period	S.E.	TACGdp	CE	CPI	TAE
1	0.22	100.00	0.00	0.00	0.00
2	0.32	89.62	2.88	0.10	7.41
3	0.39	80.35	14.10	0.54	5.02
4	0.44	73.92	20.42	1.28	4.38
5	0.46	74.81	19.90	1.30	3.98

(Source: Author's computation)

These results underscore the growing significance of environmental and market risks—particularly carbon emissions—for long-term agricultural stability, as their impact on fluctuations in agricultural GDP intensifies over time.

6.5. Discussion

This study identifies carbon emissions and agricultural price volatility as key drivers of South Africa's agricultural output trends. The VECM results based on the long-run model further confirm that environmental pressures directly reduce productivity, as evidenced by the statistically significant and negative coefficient of total agricultural output when regressed on CO_2 emissions at the stationarity state (Table 6.7). That aligns with prior studies, which have found agriculture is one of the most vulnerable sectors to GHG build-up and related biophysical consequences, including precipitation shifts, high-temperature exposure, and soil degradation (Malhi et al., 2021).

Similarly, the significant negative coefficient of CPI-driven price volatility indicates that variability in the prices of outputs and inputs is a key factor suppressing growth in agriculture (Table 6.7). While short-term market movements exacerbate an already ailing food insecurity landscape, farmers are faced by a substantially different set of pathways to food insecurity with less incentive to invest in production, greater uncertainty in farm returns, and compromised food security risks- more often than not- for households that rely on farming for their sustenance. This outcome is consistent with earlier studies indicating welfare losses and reduced agricultural investments in developing countries linked with price instability (Mitchell, 2008; Manogna et al., 2024).

The error correction term suggests that any shock to agricultural output initially deviates from the long-run equilibrium but will adjust over time to return to it. The impulse response functions lend credence to the belief that CO_2 emissions and price shocks destroy productivity, permanently confirming that the relationship between climate and market risks is between two mutually destructive forces. An increasing proportion of the variance decomposition of agricultural output can be attributed to its recent emissions and price volatility, indicating their increasing importance as features of the simulation for sector performance that covary over time.

The current results bear important policy and practical implications. Agricultural development strategies should be coupled with efforts to mitigate carbon emissions. The dimensions of some policies that enable climate-smart agriculture (CSA), such as the use of resistant varieties, irrigation, and soil carbon sequestration, can reduce environmental pressures without sacrificing productivity levels. Second, farmers' vulnerability to shocks can be reduced and food security stability enhanced by mitigating price fluctuations through market stabilization

interventions, such as crop insurance programs, forward contracts, and subsidies. Third, the findings underscore the importance of developing climate mitigation policies that align with food security objectives. Elsewhere, measures to promote biofuels or to effect land-use change should carefully evaluate trade-offs with food crop production if price volatility (already sharply increasing) is to be prevented from worsening.

Lastly, cross-sectoral coordination is also highlighted in the literature. By collaborating across environmental authorities, agricultural policy makers, financial regulators, and research institutions, we can address and mitigate the high impact of these carbon emission risks and carbon price volatility. Such a type of integration will ensure that interventions are not mutually exclusive but synergistic, a step in the right direction towards achieving resilience and sustainability in South African agriculture.

6.6. Conclusion and Policy Implications

6.6.1. Conclusion

The combined effects of the risk of carbon emissions and agricultural price uncertainty on South African agricultural output from 1992 to 2021 were assessed. Explaining how both rising CO_2 emissions and agricultural commodity price volatility act in concert to reduce agricultural output, thereby threatening economic and food security objectives. Dark grey arrows indicate the limited ability of a limited agricultural sector to adapt to soil, market, and climate shocks; our VECM estimates suggest that more suitable, integrated, and proactive policies will be required.

By linking environmental and economic risk factors, this study contributes to building knowledge on the drivers of agricultural output. The transformation of agriculture will not only be driven by the need to reduce greenhouse gas emissions through technologies and practices alone, but most importantly, it will underscore the necessity of climate mitigation, market stability, and adaptive agriculture to be integrated through multi-functional systems, as a foundation to enable the broader paradigm shift that is needed to build back better truly.

6.6.2. Policy Implications

The findings of this study offer important policy lessons for policymakers, development practitioners, and other stakeholders involved in South African agriculture with concrete guidance on how to balance agricultural growth and environmental stability in the face of upcoming global population growth. In particular:

i. **Complementary Climate and Market Policies:** The adverse effects of CO_2 emissions and agricultural price fluctuations strongly suggest the need for both climate and market policies, as actors will benefit from sustainability and price stability in the farming sector. Implement carbon pricing and environmental regulations that are accompanied by low-emission technologies and climate-smart practices, providing farmers with the tools to mitigate unintended productivity losses.

ii. **Supporting Climate-Resilient Agriculture (CSA)**: Drought-resistant varieties, water-smart irrigation, soil conservation, and crop diversification are essential CSA practices that prepare the agriculture sector to be robust against multiple shocks, including both environmental shocks and market volatility. These practices not only enhance productivity but also ensure minimal vulnerability to climate-induced and market shocks.

iii. **Market Stabilization Mechanisms**: The price volatility sensitivity of agricultural production drives the development of mechanisms such as commodity price stabilization, futures markets, and crop insurance, which can mitigate income uncertainty for farmers while also contributing to food security. These tools are particularly relevant in both national and international food markets that are increasingly interrelated and in which price transmission shocks may be frequent.

iv. **Investing in Research and Infrastructure**: Sustained resilience will rely on increasing investment in agricultural research, extension services, and physical infrastructure, such as irrigation systems, storage facilities, and transportation networks. These investments enhance adaptive capacity, mitigate production risks, and facilitate adjustment to climate and market shocks.

v. **Synergetic Policies**: Emission and productivity, as well as market regulation-enhancing policies, need to be harmonized to prevent mutually exclusive trade-offs. For example, the design of biofuel production or renewable energy units must be carefully considered to avoid unintended competition for arable land and a negative impact on food prices.

The research strengthens the argument for future work to address the multifaceted and synergetic nature of emissions and realisation price challenges for production and food security in South Africa. Future contributions could further develop this work by incorporating farm-level data and examining heterogeneity in responses across both crop systems and regions to joint environmental and market shocks.

Chapter 7: Summary, Conclusion, and Policy Recommendation.

7.1. Summary

This study examined the complex interactions among carbon emissions, climate variability, price risk, and agricultural output in South Africa using a series of advanced econometric techniques across four empirical chapters. Against the backdrop of rising greenhouse gas emissions, increasing climatic instability, and persistent food price volatility, the research aimed to determine both the short-term and long-term impacts of these forces on the agricultural sector, a critical pillar of South Africa's economic and food security landscape.

The first empirical analysis assessed the influence of carbon dioxide emissions on food consumption patterns and farm produce prices using a Vector Error Correction Model (VECM). The findings revealed that CO_2 emissions significantly influence food price inflation and consumption behaviour, mainly through supply-side disruptions driven by climate-induced production shocks. Long-run relationships were established between emissions, consumer price levels, purchasing power, and consumption trends, indicating that emission-related climate variability systematically increases price volatility, disproportionately affecting low-income households.

The second empirical investigation examined the possibility of decoupling agricultural growth from carbon emissions. Using ARDL, FMOLS, and DOLS estimations, the results showed partial but insufficient decoupling. While technological advancement and market expansion have supported agricultural growth, emissions continue to rise alongside productivity, reflecting limited adoption of renewable energy and low-carbon technologies. The agricultural sector's emission profile remains strongly influenced by mechanization, fertilizer use, and energy-intensive production processes.

The third analysis evaluated the impact of climate variability and price risk on agricultural output. The ARDL and Granger causality results indicated that rainfall variability, temperature anomalies, and market price fluctuations have a significant impact on agricultural production in both the short and long run. Rain-fed agriculture proved highly sensitive to precipitation variability, while heat stress and extreme temperature events had detrimental effects on output. Price risk, magnified by climate shocks and global market fluctuations, further constrained investment decisions and reduced productivity.

The final empirical chapter analyzed the combined effects of carbon emission risk and price volatility on agricultural output using a VEC framework. The findings confirmed strong long-run linkages between environmental risk, market uncertainty, and productivity outcomes. Emission risks reduced long-term agricultural efficiency, while price volatility compounded production instability. The joint effect was more damaging than either variable independently, underscoring the need for integrated climate–market resilience strategies.

Table 7.1: Summary of Thesis Chapters

Chapter Title	Objective(s)	Methodology	Key Findings
Introduction	To present the research problem, objectives, hypotheses, and conceptual framework on the nexus between carbon emissions, climate variability, price dynamics, and agricultural performance.	Conceptual and theoretical discussion.	Established the research gap by highlighting the lack of integrated analysis of environmental and market risks in South African agriculture.
Literature Review	To review theoretical and empirical literature on emissions, climate variability, price risk, and agricultural productivity.	Systematic and thematic literature review.	Identified key drivers, relationships, and methodological gaps; justified the need for an integrated econometric approach.
The Influence of Carbon Dioxide Emissions on Food Consumption Patterns and Farm Produce Prices in South Africa.	To evaluate the impact of CO_2 emissions on food consumption patterns and agricultural prices.	VECM, Johansen Cointegration, Impulse Response, Variance Decomposition.	CO_2 emissions increase food prices in the long run and negatively affect consumption patterns, especially among vulnerable households.
Decoupling Agricultural Growth from Carbon Emissions in South Africa.	To assess whether agricultural growth can occur independently of rising emissions.	ARDL, FMOLS, DOLS.	Evidence of partial decoupling; productivity gains are offset by increased emissions from mechanisation and input use.

Chapter Title	Objective(s)	Methodology	Key Findings
Climate Variability, Price Risk, and Agricultural Output in South Africa.	To examine the effects of climate variability and price risk on agricultural production.	ARDL, Cointegration, Granger Causality.	Rainfall variability significantly affects output; price volatility and climate shocks jointly reduce agricultural productivity.
Carbon Emission Risks and Price Volatility: Implications for Agricultural Productivity.	To analyse the combined effects of emission risk and price volatility on agricultural output.	Risk-augmented VECM, Impulse Response, Variance Decomposition.	Emission risks and price volatility have a compounded negative effect on agricultural productivity, stronger when combined.
Summary, Conclusion, and Policy Recommendations.	To synthesise findings and provide policy directions.	Integrative analysis.	Concluded that environmental and market risks are interconnected; recommended climate-smart agriculture, renewable energy adoption, and market stabilisation policies.

(Source: Author's Computation)

Overall, the thesis provides evidence that carbon emissions, climate variability, and price dynamics are critical determinants of agricultural output in South Africa. Their combined influence creates a multidimensional risk environment, with significant implications for food security, rural livelihoods, and economic stability.

7.2. Conclusion

This study set out to examine the dynamic relationships between carbon emissions, climate variability, price dynamics, and agricultural performance in South Africa within an integrated analytical framework. Using a combination of advanced econometric techniques, the study provides robust empirical evidence on both the short-run and long-run interactions among these variables.

The findings consistently demonstrate that agricultural performance in South Africa is shaped by the simultaneous interaction of environmental and market forces, rather than isolated factors. Carbon emissions, climate variability, and price volatility operate through

interconnected transmission channels that jointly influence agricultural productivity, food prices, and consumption patterns.

First, the results show that carbon emissions exert significant long-run effects on food prices and consumption patterns. Emissions-driven environmental changes contribute to production instability, which translates into higher food prices and reduced purchasing power, particularly for vulnerable households. This confirms that environmental degradation is not only an ecological concern but also a critical driver of food security outcomes.

Second, the study finds that climate variability, especially fluctuations in rainfall and temperature, has a strong and persistent negative impact on agricultural productivity. The dependence of South African agriculture on rain-fed systems makes the sector particularly vulnerable to climatic shocks. While short-term temperature increases reduce output, prolonged exposure leads to structural challenges such as soil degradation and reduced yield potential.

Third, the analysis of the decoupling relationship reveals that agricultural growth in South Africa has not been fully decoupled from carbon emissions. Although some efficiency gains have been achieved through technological improvements, these gains are offset by increased emissions associated with mechanisation, energy use, and input intensification. This indicates that current growth patterns remain environmentally unsustainable.

Fourth, the study establishes that price volatility, driven by both climate shocks and market dynamics, significantly constrains agricultural performance. Price instability affects farmers' investment decisions, input use, and long-term planning. More importantly, the results show that the combined effect of emission risks and price volatility is more severe than their individual impacts, highlighting the presence of compounding risks within the agricultural system.

Taken together, these findings point to the existence of a reinforcing cycle of vulnerability. Carbon emissions contribute to climate variability; climate variability disrupts production; production shocks increase price volatility; and price instability reduces the capacity of farmers to invest in adaptation. This cycle weakens agricultural productivity and undermines long-term sectoral resilience.

The study therefore concludes that achieving sustainable agricultural development in South Africa requires a shift away from fragmented policy approaches toward a coordinated and

integrated framework. Policies that address emissions without considering productivity, or stabilise markets without accounting for climate risks, are unlikely to deliver meaningful outcomes.

Instead, a balanced approach is required—one that simultaneously promotes:

- Environmental sustainability through emission reduction
- Climate resilience through adaptation strategies
- Economic stability through market and price management

Furthermore, the results underscore the importance of aligning agricultural development with broader national priorities, including climate change mitigation, energy transition, and food security. The transition toward a more resilient agricultural system will depend on the ability of policymakers to integrate these objectives into a coherent strategy that supports both productivity and sustainability.

In conclusion, this study contributes to the literature by providing an integrated empirical understanding of how environmental and economic risks jointly shape agricultural outcomes in South Africa. It highlights that the future of the agricultural sector will depend not only on managing individual risks, but on addressing the systemic interactions between climate, emissions, and markets.

7.3. Recommendations for Policy Implications

The empirical findings of this study show that carbon emissions, climate variability, and price volatility jointly and significantly constrain agricultural productivity in South Africa. The policy response must therefore be integrated, targeted, and time-sensitive, addressing both environmental and market risks simultaneously.

To enhance policy effectiveness, the recommendations are structured into short-term, medium-term, and long-term priorities, with clear institutional responsibilities and implementation considerations.

7.3.1 Short-Term Policy Priorities (0–3 Years)

Focus: Immediate risk reduction, farmer support, and market stabilisation

1. Strengthen Climate Information and Early Warning Systems

Given the strong impact of rainfall variability and temperature shocks on agricultural output (Chapter 5), immediate investment in climate intelligence is critical.

- Expand real-time weather forecasting and agro-advisory services
- Improve dissemination through mobile platforms and extension services
- Develop location-specific climate advisories for farmers

Responsible institutions:

South African Weather Service (SAWS), Department of Agriculture, Land Reform and Rural Development (DALRRD)

Implementation constraints:

Limited rural digital access, weak last-mile communication systems

2. Establish and Strengthen Market Stabilisation Mechanisms

Findings show that price volatility significantly reduces agricultural productivity and investment (Chapters 5 and 6).

- Strengthen strategic grain reserves to stabilise food supply
- Improve agricultural price monitoring and early warning systems
- Introduce temporary price support measures during extreme shocks

Responsible institutions:

National Agricultural Marketing Council (NAMC), National Treasury, DALRRD

Implementation constraints:

Fiscal limitations, risk of market distortions, storage and logistics challenges

3. Expand Access to Risk-Mitigation and Financial Instruments

The joint effect of climate risk and price volatility highlights the need for immediate financial protection mechanisms.

- Scale up weather-indexed insurance schemes
- Provide emergency credit facilities and input subsidies during shocks

- Strengthening public-private partnerships in agricultural insurance

Responsible institutions:

Land Bank, National Treasury, private insurers

Implementation constraints:

Low insurance penetration, affordability constraints for smallholder farmers

7.3.2 Medium-Term Policy Priorities (3–7 Years)

Focus: Adaptation, efficiency improvements, and structural resilience

4. Scale Up Climate-Smart Agriculture (CSA) Adoption

The study confirms that climate variability reduces productivity while adaptation remains insufficient (Chapters 5 and 6).

- Promote drought-resistant crop varieties and conservation agriculture
- Expand irrigation infrastructure and water-use efficiency
- Strengthen agricultural extension services and farmer training

Responsible institutions:

DALRRD, Agricultural Research Council (ARC), provincial agriculture departments

Implementation constraints:

High adoption costs, limited technical capacity, resistance to new practices

5. Promote Renewable Energy Integration in Agriculture

Evidence from Chapter 4 shows incomplete decoupling between agricultural growth and emissions.

- Support solar-powered irrigation and energy-efficient mechanisation
- Provide targeted subsidies and concessional financing for clean energy technologies
- Encourage private sector participation in rural energy solutions

Responsible institutions:

Department of Mineral Resources and Energy (DMRE), DALRRD, Industrial Development Corporation (IDC)

Implementation constraints:

High initial capital costs, infrastructure gaps, limited financing access

6. Introduce Targeted Carbon Incentive Mechanisms

Carbon emissions were found to have long-run negative effects on prices and productivity (Chapters 3 and 6).

- Pilot carbon credit schemes for agricultural producers
- Introduce incentives for low-emission farming practices
- Align agricultural policies with national climate commitments

Responsible institutions:

Department of Environment, Forestry and Fisheries (DEFF), National Treasury

Implementation constraints:

Measurement challenges, weak carbon market structures, regulatory uncertainty

7.3.3 Long-Term Policy Priorities (7+ Years)

Focus: Structural transformation and sustainability

7. Strengthen Institutional Coordination and Policy Integration

The study highlights that environmental and economic risks are interconnected, requiring coordinated responses.

- Develop an integrated national framework linking agriculture, climate, and trade policies
- Improve inter-agency coordination across key sectors
- Aligning agricultural development strategies with climate adaptation and mitigation goals

Responsible institutions:

The Presidency, National Planning Commission, DALRRD, DEFF, National Treasury

Implementation constraints:

Institutional fragmentation, policy misalignment, bureaucratic inefficiencies

8. Invest in Research, Innovation, and Data Systems

Data limitations identified in this study highlight the need for long-term investment in agricultural intelligence systems.

- Develop high-resolution climate and agricultural data systems
- Support research on climate-resilient crops and sustainable farming systems
- Strengthening collaboration between universities, research institutions, and policymakers

Responsible institutions:

Department of Science and Innovation (DSI), ARC, universities

Implementation constraints:

Funding constraints, weak data integration systems

7.3.4 Integrated Policy Insight

The findings of this study demonstrate that isolated policy interventions will be insufficient. Climate variability, emissions, and price dynamics operate through interconnected pathways, meaning that:

- Climate policies must incorporate agricultural productivity goals
- Agricultural policies must address environmental sustainability
- Market policies must account for climate-induced supply shocks

An integrated approach that combines adaptation, mitigation, and market stabilisation is therefore essential for achieving long-term agricultural resilience and sustainability in South Africa.

7.4. Limitations of the Study and Suggestions for Further Research

Limitations

- **Data granularity:** The study relied on national-level time-series data, which masked provincial and sectoral differences in agricultural responses to climate and market shocks.
- **Limited representation of non-CO_2 agricultural emissions:** Methane and nitrous oxide, significant contributors to agricultural GHG emissions—were not assessed due to data limitations.
- **Potential modelling constraints:** Despite using advanced econometric tools, structural breaks, policy shifts, and unobserved heterogeneity may still influence econometric estimates.
- **Lack of micro-level behavioural insights:** Farmer-level decision-making processes and adaptive capacities were beyond the scope of the study, limiting the analysis of heterogeneous responses.

Suggestions for Further Research

- **Regional and crop-specific analyses** using spatial econometric models to capture localized climate sensitivities.
- **Incorporating CH_4 and N_2O emissions** to develop a more comprehensive agricultural emissions model.
- **Application of structural modelling techniques**, including panel VAR or Bayesian estimation, to address endogeneity and unobserved dynamics.
- **Behavioural and microeconomic studies** assessing how farmer perceptions, financial constraints, and technology adoption influence adaptation outcomes.
- **Evaluation of renewable energy and carbon credit adoption** within the agricultural sector to estimate their potential for large-scale decoupling.

REFERENCES

Acaravci, A. and Ozturk, I. 2010. On the relationship between energy consumption, CO_2 emissions, and economic growth in Europe. *Energy*, 35(12), p.5412–5420.

Adamu, A.J. 2024. Climate change implications for agricultural productivity: A comprehensive analysis. *INOSR Experimental Sciences*, 13(1), p.66–71.

Adebayo, T.S., Kirikkaleli, D., Adeshola, I., Oluwajana, D., Akinsola, G.D. and Osemeahon, O.S. 2021. Coal consumption and environmental sustainability in South Africa: the role of financial development and globalization. *International Journal of Renewable Energy Development*, 10(3), p.527–536.

Adom, P.K., Bekoe, W., Amuakwa-Mensah, F., Mensah, J.T. and Botchway, E. 2012. Carbon dioxide emissions, economic growth, industrial structure, and technical efficiency: empirical evidence from Ghana, Senegal, and Morocco on the causal dynamics. *Energy*, 47(1), p.314–325.

Adriaen, D., Kleynhans, T.E. and Tollens, E. 2004. A comparison between South African agricultural exports to the European Union and those of other selected southern hemisphere countries. *Agrekon*, 43(2), p.184–201.

Affoh, R., Zheng, H., Dangui, K. and Dissani, B.M. 2022. The impact of climate variability and change on food security in sub-Saharan Africa: perspective from panel data analysis. *Sustainability*, 14(2), p.759.

Afrouzi, H.N., Ahmed, J., Siddique, B.M., Khairuddin, N. and Hassan, A. 2023. A comprehensive review on carbon footprint of regular diet and ways to improving lowered emissions. *Results in Engineering*, 18, p.101054.

Agbola, F.W. 2003. Estimation of food demand patterns in South Africa based on a survey of households. *Journal of Agricultural and Applied Economics*, 35(3), p.663–670.

Ali, A.Z., Rahman, M.S. and Raihan, A. 2022. Soil carbon sequestration in agroforestry systems as a climate change mitigation strategy: a case study from Dinajpur, Bangladesh. *Advances in Environmental Engineering Research*, 3, p.1–15.

Almerico, G.M. 2014. Food and identity: food studies, cultural, and personal identity. *Journal of International Business and Cultural Studies*, 8, p.1.

Aluwani, T. 2023. Agricultural economic growth, renewable energy supply and CO_2 emissions nexus. *Economies*, 11(3), p.85.

Anderson, S.E., Anderson, T.L., Hill, A.C., Kahn, M.E., Kunreuther, H., Libecap, G.D., Mantripragada, H., Mérel, P., Plantinga, A.J. and Kerry Smith, V. 2019. The critical role of markets in climate change adaptation. *Climate Change Economics*, 10(01), p.1950003.

Andriamahery, A., Danarson, J.H. and Qamruzzaman, M. 2022. Nexus between trade and environmental quality in sub-Saharan Africa: evidence from panel GMM. *Frontiers in Environmental Science*, 10, p.986429.

Antonaci, L., Demeke, M. and Vezzani, A., 2014. *The challenges of managing agricultural price and production risks in sub-Saharan Africa*. ESA Working Paper No. 14-09. Rome: FAO.

Appiah, K., Du, J., Musah, A.A.I. and Afriyie, S. 2017. Investigation of the relationship between economic growth and carbon dioxide (CO_2) emissions as economic structure changes: evidence from Ghana. *Resources and Environment*, 7(6), p.160–167.

Asfew, M., Mitiku, F., Gemechu, A., Bekele, Y. and Lemma, T. 2023. Do climate change and political instability affect crop production in sub-Saharan African countries? *Journal of Agriculture and Food Research*, 12, p.100576.

Aslam, F., Bhutta, M.A., Asghar, M.M., Ullah Khan, M.F. and Rashid, J. 2025. Environmental sustainability in emerging countries: the role of green energy, green finance and digitalization. *Inverge Journal of Social Sciences*, 4(3), p.10–63544.

Asumadu-Sarkodie, S. and Owusu, P.A. 2016. The relationship between carbon dioxide and agriculture in Ghana: a comparison of VECM and ARDL model. *Environmental Science and Pollution Research*, 23(11), p.10968–10982.

Aye, G.C. and Edoja, P.E. 2017. Effect of economic growth on CO_2 emission in developing countries: evidence from a dynamic panel threshold model. *Cogent Economics and Finance*, 5(1), p.1379239.

Ayinde, A.R., Celik, B. and Gylych, J. 2019. Effect of economic growth, industrialization, and urbanization on energy consumption in Nigeria: a vector error correction model analysis. *International Journal of Energy Economics and Policy*, 9(5), p.409–418.

Bahta, Y.T., Maré, F. and Moshugi, E. 2025. Strengthening agricultural drought resilience of commercial livestock farmers in South Africa: an assessment of factors influencing decisions. *Climate*, 13(8), p.154.

Baiyegunhi, L.J. 2023. Examining the determinants of agricultural innovation activities: a case study of emerging sugarcane farmers in South Africa. *Agrekon*, 62(3–4), p.241–257.

Bakht, S., Safdar, K., Khair, K.U., Fatima, A., Fayyaz, A., Ali, S.M., … and Farid, M. 2020. The response of major food crops to drought stress: physiological and biochemical responses. In: Hasanuzzaman, M. (ed.) *Agronomic Crops: Volume 3: Stress Responses and Tolerance*. Singapore: Springer, p.93–115.

Basheer, S., Wang, X., Farooque, A.A., Nawaz, R.A., Pang, T. and Neokye, E.O. 2024. A review of greenhouse gas emissions from agricultural soil. *Sustainability*, 16(11), p.4789.

Bellemare, M.F. 2015. Rising food prices, food price volatility, and social unrest. *American Journal of Agricultural Economics*, 97(1), p.1–21.

Bennetzen, E.H., Smith, P. and Porter, J.R. 2016. Agricultural production and greenhouse gas emissions from world regions—the major trends over 40 years. *Global Environmental Change*, 37, p.43–55.

Bernard, B.M. Jr, Song, Y., Narcisse, M., Hena, S. and Wang, X. 2023. A nonparametric analysis of climate change nexus on agricultural productivity in Africa: implications on food security. *Renewable Agriculture and Food Systems*, 38, p.e9.

Bhuiyan, C., Saha, A.K., Bandyopadhyay, N. and Kogan, F.N. 2017. Analyzing the impact of thermal stress on vegetation health and agricultural drought: a case study from Gujarat, India. *GIScience and Remote Sensing*, 54(5), p.678–699.

Bouteska, A., Sharif, T., Bhuiyan, F. and Abedin, M.Z. 2024. Impacts of the changing climate on agricultural productivity and food security: evidence from Ethiopia. *Journal of Cleaner Production*, 449, p.141793.

Bowmaker, P.A. and Nieuwoudt, W.L. 1990. Demand equations for selected South African agricultural commodities. *Agrekon*, 29(1), p.46–50.

Braun, J. von, Chichaibelu, B.B., Torero Cullen, M., Laborde, D. and Smaller, C. 2021. *Ending hunger by 2030–policy actions and costs*. Food Systems Summit Brief. Bonn: Center for Development Research (ZEF), University of Bonn.

Brinkman, H.J. and Hendrix, C.S., 2010. *Food insecurity and conflict: Applying the WDR framework*. World Bank Publications (Working Paper No. 9106). Washington, DC: World Bank.

Broll, U., Welzel, P. and Wong, K.P., 2013. Price risk and risk management in agriculture. *Contemporary Economics*, *7*(2), p.17-20.

Calderón, C., 2009. *Infrastructure and growth in Africa* (Vol. 4914). Washington, DC: World Bank.

Canbay, Ş., 2023. Analysis of the relationships between agricultural producer protection and macroeconomic variables in fragile five countries by Bootstrap Panel Causality Test. *Journal of Agricultural Sciences*, *29*(2), p.380-394.

Cervantes-Godoy, D. 2015. *Strategies for addressing smallholder agriculture and facilitating structural transformation*. OECD Food, Agriculture and Fisheries Papers, No. 90. Paris: OECD Publishing. Available at: https://www.oecd-ilibrary.org/agriculture-and-food/strategies-for-addressing-smallholder-agriculture-and-facilitating-structural-transformation_5jrs8sv4jt6k-en.html (Accessed: 24 November 2024).

Chhogyel, N., Kumar, L., & Bajgai, Y. (2020). Consequences of climate change impacts and incidences of extreme weather events in relation to crop production in Bhutan. *Sustainability*, *12*(10), 4319

Climate Trace. 2023. *Climate Trace* [Online]. [Accessed 24 October 2024]. Available at: http://www.climatetrace.org.

Collier, P., Conway, G. and Venables, T. 2008. 'Climate change and Africa', *Oxford Review of Economic Policy*, 24(2), p. 337-353.

Connolly-Boutin, L. and Smit, B., 2016. Climate change, food security, and livelihoods in sub-Saharan Africa. *Regional Environmental Change*, *16*(2), p.385-399.

Cornia, G.A., Deotti, L. and Sassi, M., 2012. Food price volatility over the last decade in Niger and Malawi: extent, sources and impact on child malnutrition. *Documento de trabajo*, *2*.

Cullis, J., Alton, T., Arndt, C., Cartwright, A., Chang, A., Gabriel, S., ... and Thurlow, J. 2015. *An uncertainty approach to modelling climate change risk in South Africa* (No. 2015/045). WIDER working paper.

Daniels, C., Mba, J. and Teferra, D. (2022) *Mapping research infrastructures to enhance the resilience of science systems in sub-Saharan Africa* [online]. Ottawa: International Development Research Centre (IDRC). Available at: https://idl-bnc-idrc.dspacedirect.org/items/c7814165-94ad-4861-9fee-bb3081f75211 (Accessed: 24 November 2024)

De Janvry, A. and Sadoulet, E., 2015. *Development economics: Theory and practice*. Routledge, London.

Dell, M., Jones, B.F. and Olken, B.A., 2014. What do we learn from the weather? The new climate-economy literature. *Journal of Economic literature*, *52*(3), p.740-798.

Dethier, J.J. and Effenberger, A. 2012. Agriculture and development: a brief review of the literature. *Economic Systems*, 36(2), p.175–205.

Dickey, D.A. and Fuller, W.A. 1979. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366), p.427–431.

Duong, T.T., Brewer, T., Luck, J. and Zander, K. 2019. A global review of farmers' perceptions of agricultural risks and risk management strategies. *Agriculture*, 9(1), p.10.

Dyanty, T., Agholor, I.A., Nkambule, T.B., Nkuna, A.A., Nkosi, M., Ndlovu, S.M., … and Makhubu, T.H. 2025. Socio-economic determinants of climate change adaptation strategies among smallholder farmers in Mbombela: a binary logistic regression analysis. *Climate*, 13(5), p.90.

Ebenezer, M., Ngarava, S., Etim, N.A. and Popoola, O. 2019. Impact of government expenditure on agricultural productivity in South Africa. *The Journal of Social Sciences Research*, 5(12), p.1734–1742.

Elum, Z.A., Nhamo, G. and Antwi, M.A. 2018. Effects of climate variability and insurance adoption on crop production in select provinces of South Africa. *Journal of Water and Climate Change*, 9(3), p.500–511.

Emediegwu, L.E., Wossink, A. and Hall, A. 2022. The impacts of climate change on agriculture in sub-Saharan Africa: a spatial panel data approach. *World Development*, 158, p.105967.

Enders, W. (2008). *Applied econometric time series*. John Wiley & Sons.

Engle, R. F. (1987). Cointegration and error correction. *Econometrica*, *55*(2), 143-159.

Engle, R.F. and Granger, C.W. 1987. Co-integration and error correction: representation, estimation, and testing. *Econometrica*, 55(2), p.251–276.

Erkılıç, E., Gazeloğlu, C. and Özgören Ünlü, E. 2025. Renewable energy solution to carbon emissions: BRICS countries in the grip of globalization and economic growth. *Sustainability*, 17(9), p.4117.

Eshete, G., Assefa, B., Lemma, E., Kibret, G., Ambaw, G., Samuel, S. and Solomon, D. (2020) *Ethiopia climate-smart agriculture roadmap*. Copenhagen, Denmark: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

Etienne, N., Joseph, N. and Martin, M., 2025. A blessing or a curse? Climate change and political economy effects on the agricultural sector: empirical evidence from Sub-Saharan Africa. *International Journal of Climate Change Strategies and Management*.

Faminow, M.D. and Laubscher, J.M., 1991. Empirical testing of alternative price spread models in the South African maize market. *Agricultural Economics*, *6*(1), p.49-66.

FAO. (2017). Climate-smart agriculture sourcebook. FAO.

Feig, G.T., Joubert, W.R., Mudau, A.E. and Monteiro, P., 2017. South African carbon observations: CO_2 measurements for land, atmosphere and ocean. *South African Journal of Science*, *113*(11-12), p.1-4.

Feyen, E. H., Utz, R. J., Zuccardi Huertas, I. E., Bogdan, O., and Moon, J. (2020). *Macro-financial aspects of climate change* (Policy Research Working Paper No. 9109). World Bank, Washington, DC.

Fjelde, H., 2015. Farming or fighting? Agricultural price shocks and civil war in Africa. *World Development*, *67*, p.525-534.

Flanagan, K., Robertson, K. and Hanson, C., 2019. Reducing food loss and waste. *Setting the Global Action Agenda*.

Food and Agriculture Organization (FAO). 2015. *FAO 2015 Publications* (available at: http://www.fao.org/3/a-i5056e.pdf)

Franken, J.R., Pennings, J.M. and Garcia, P., 2012. Crop production contracts and marketing strategies: what drives their use? *Agribusiness*, *28*(3), p.324-340.

Freund, C. and Rocha, N., 2011. What constrains Africa's exports? *The World Bank Economic Review*, *25*(3), p.361-386.

Funk, C.C. and Brown, M.E., 2009. Declining global per capita agricultural production and warming oceans threaten food security. *Food Security*, *1*(3), p.271-289.

Gérard, F., Alpha, A., Beaujeu, R., Boussard, J. M., Levard, L., Maître d'Hôtel, E., Rouillé d'Orfeuil, H., Bricas, N., Daviron, B. & Galtier, F. (2010) *Managing food price volatility for food security and development: Draft summary Grema study*. Paris: Grema.

Geyser, J.M., Pretorius, A. and Fourie, A., 2024. Trends in and determinants of South African maize exports in the post-deregulation era. *Journal of Economic and Financial Sciences*, *17*(1), p.862.

Gilbert, C. L., & Morgan, C. W. (2010). Food price volatility. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *365*(1554), 3023-3034.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: journal of the Econometric Society*, 424-438.

Greyling, J.C., Pardey, P.G. and Senay, S., 2025. Agricultural policy and crop location: Long-run output and spatial climate risk consequences. *American Journal of Agricultural Economics*, *107*(1), p.181-207.

Gujarati, D. N., & Porter, D. C. (2009). Basic Econometrics (5th ed.). McGraw-Hill.

Gyimah, J., Saalidong, B.M. and Nibonmua, L.K., 2023. The battle to achieve Sustainable Development Goal Two: The role of environmental sustainability and government institutions. *Plos one*, *18*(9), p.e0291310.

Hall, C., Dawson, T. P., Macdiarmid, J. I., Matthews, R. B., & Smith, P. (2017). The impact of population growth and climate change on food security in Africa: looking ahead to 2050. *International Journal of Agricultural Sustainability*, *15*(2), 124-135.

Hallegatte, S., Fay, M. and Barbier, E.B., 2018. Poverty and climate change: Introduction. *Environment and development economics*, *23*(3), p.217-233.

Hamilton, J. D. (2008). *Macroeconomics and ARCH* (No. w14151). National Bureau of Economic Research.

Hamit-Haggar, M., 2012. Greenhouse gas emissions, energy consumption and economic growth: A panel cointegration analysis from Canadian industrial sector perspective. *Energy Economics*, *34*(1), p.358-364.

Hanif, S., Lateef, M., Hussain, K., Hyder, S., Usman, B., Zaman, K. and Asif, M., 2022. Controlling air pollution by lowering methane emissions, conserving natural resources, and slowing urbanization in a panel of selected Asian economies. *Plos one*, *17*(8), p.e0271387.

Harčariková, M., 2018. Managing price risk in the corn market using option strategies. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, *66*(3).

Hartmann, C. and Siegrist, M., 2017. Consumer perception and behaviour regarding sustainable protein consumption: A systematic review. *Trends in Food Science & Technology*, *61*, p.11-25.

Hashem, D.I.A., SA Pargal, E. and SA Mohamed, M., 2022. The Impact of Some Economic Variables on Agricultural Labor in Egypt. *Alexandria Science Exchange Journal*, *43*(2), p.725-749.

Hatfield, J. L., Boote, K. J., Kimball, B. A., Ziska, L. H., Izaurralde, R. C., Ort, D., ... & Wolfe, D. (2011). Climate impacts on agriculture: implications for crop production. *Agronomy journal*, *103*(2), 351-370.

Hayo, L. and Hasegawa, H., 2024. Enhancing emission reductions in South African agriculture: The crucial role of carbon credits in incentivizing climate-smart farming practices. *Sustainable Futures*, *8*, p.100260.

Hedin, B., Katzeff, C., Eriksson, E. and Pargman, D., 2019. A systematic review of digital behaviour changes interventions for more sustainable food consumption. *Sustainability*, *11*(9), p.2638.

Hertel, T.W. and Rosch, S.D., 2010. Climate change, agriculture, and poverty. *Applied economic perspectives and policy*, *32*(3), p.355-385.

Hilali, M. and Neffati, M., 2025. Navigating Environmental Challenges in BRICS+ Nations: The Impact of Economic Growth, Globalization, and Urbanization on Environmental Performance. *International Journal of Energy Economics and Policy*, *15*(4), p.525.

Hlatshwayo, S.I., Ngidi, M.S.C., Ojo, T.O., Modi, A.T., Mabhaudhi, T. and Slotow, R., 2023. The determinants of crop productivity and its effect on food and nutrition security in rural communities of South Africa. *Frontiers in sustainable food systems*, *7*, p.1091333.

Ibrahiem, D.M., 2020. Do technological innovations and financial development improve environmental quality in Egypt? *Environmental Science and Pollution Research*, *27*(10), p.10869-10881.

IMF, O. and UNCTAD, W., 2011. Price volatility in food and agricultural markets: Policy responses. *FAO: Roma, Italy*.

Inglesi-Lotz, R. and Blignaut, J.N., 2011. Estimating the price elasticity of demand for electricity by sector in South Africa. *South African Journal of Economic and Management Sciences*, *14*(4), p.449-465.

IPCC (Intergovernmental Panel on Climate Change). 2011. Managing the risks of extreme events and disasters to advance climate change adaptation, A special report on working group I and working group II of the intergovernmental panel on climate change. http://www.ipcc.ch/ipccreports/ar4-syr.htm [accessed: 28 October 2023].

IPCC (2006). Guidelines for national greenhouse gas inventories. In S. Eggleston et al. (Eds.) *Intergovernmental panel on climate change. 2006 IPCC guidelines for national greenhouse gas inventories*. 4. Agriculture, forestry and other land uses.

Isfat, M. and Raihan, A., 2022. Current practices, challenges, and future directions of climate change adaptation in Bangladesh. *Journal homepage: www. ijrpr. com ISSN*, *2582*, p.7421.

Ivanova, D., Stadler, K., Steen-Olsen, K., Wood, R., Vita, G., Tukker, A. and Hertwich, E.G., 2016. Environmental impact assessment of household consumption. *Journal of industrial ecology*, *20*(3), p.526-536.

Jennings, S., Challinor, A., Smith, P., Macdiarmid, J.I., Pope, E., Chapman, S., Bradshaw, C., Clark, H., Vetter, S., Fitton, N. and King, R., 2024. Stakeholder-driven transformative adaptation is needed for climate-smart nutrition security in sub-Saharan Africa. *Nature food*, *5*(1), p.37-47.

Jiaduo, E., Kibria, M.G., Aspy, N.N., Ullah, E. and Hossain, M.E., 2023. The impact of agricultural employment and technological innovation on the environment: Evidence from BRICS nations considering a novel environmental sustainability indicator. *Sustainability*, *15*(20), p.15083.

Johansen, S. and Juselius, K., 1990. Maximum likelihood estimation and inference on cointegration—with appucations to the demand for money. *Oxford Bulletin of Economics and statistics*, *52*(2), p.169-210.

Johansen, S., 1988. Statistical analysis of cointegration vectors. *Journal of economic dynamics and control*, *12*(2-3), p.231-254.

Jones, J.W., Antle, J.M., Basso, B., Boote, K.J., Conant, R.T., Foster, I., Godfray, H.C.J., Herrero, M., Howitt, R.E., Janssen, S. and Keating, B.A., 2017. Toward a new generation of agricultural system data, models, and knowledge products: State of agricultural systems science. *Agricultural systems*, *155*, p.269-288.

Kao, C. and Chiang, M.H., 2001. On the estimation and inference of a cointegrated regression in panel data. In *Nonstationary panels, panel cointegration, and dynamic panels* (p. 179-222). Emerald Group Publishing Limited.

Kaya, T., 2025. The impact of agricultural activities on climate change in BRICS countries and Türkiye. *International Journal of Agriculture Environment and Food Sciences*, *9*(1), p.144-156.

Komarek, A.M., De Pinto, A. and Smith, V.H., 2020. A review of types of risks in agriculture: What we know and what we need to know. *Agricultural systems*, *178*, p.102738.

Kwaw-Nimeson, E. and Tian, Z., 2021. The impact of agricultural producer price on sustainable food security in Africa–a system GMM approach. *Agricultural and Resource Economics: International Scientific E-Journal*, *7*(3), p.60-76.

Lee, J. and Strazicich, M.C., 2003. Minimum Lagrange multiplier unit root test with two structural breaks. *Review of economics and statistics*, *85*(4), p.1082-1089.

Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., Bwalya, M., ... & Torquebiau, E. F. (2014). Climate-smart agriculture for food security. *Nature climate change*, *4*(12), 1068-1072.

Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011). Climate trends and global crop production since 1980. *Science*, *333*(6042), 616-620.

Lukashe, E. and Nishimwe-Niyimbanira, R., 2025. Impact of climate change on price stability in South Africa: an econometric analysis. *African Journal of Economic and Management Studies*.

Maake, R., Malherbe, J., Masupha, T., Chirima, G., Beukes, P., Roffe, S., Thompson, M. and Moeletsi, M., 2023. The Umlindi Newsletter: Disseminating climate-related information on the management of natural disaster and agricultural production in South Africa. *Climate*, *11*(12), p.239.

Maddison, D., 2007. *The impact of climate change on African agriculture* (Vol. 4306). World Bank Publications.

Magrini, E., Balié, J. and Morales-Opazo, C., 2018a. Price signals and supply responses for staple food crops in Sub-Saharan Africa. *Applied Economic Perspectives and Policy*, *40*(2), p.276-296.

Magrini, M.B., Anton, M., Chardigny, J.M., Duc, G., Duru, M., Jeuffroy, M.H., Meynard, J.M., Micard, V. and Walrand, S., 2018b. Pulses for sustainability: breaking agriculture and food sectors out of lock-in. *Frontiers in Sustainable Food Systems*, *2*, p.64.

Maka, L., 2025. Agricultural Extension's Role in Enhancing Climate Resilience: Insights from Farmers' Perceptions in Gqumashe Village, South Africa. *South African Journal of Agricultural Extension*, *53*(2), p.141-154.

Malhi, G.S., Kaur, M. and Kaushik, P., 2021. Impact of climate change on agriculture and its mitigation strategies: A review. *Sustainability*, *13*(3), p.1318.

Manogna, R.L., Kulkarni, N. and Krishna, D.A. (2024) 'Nexus between financialization of agricultural products and food security amid financial crisis: empirical insights from BRICS', *Journal of Agribusiness in Developing and Emerging Economies*, 15(5), p. 936-950.

Maphanga, T., Shoko, C., Sibanda, M., Thamaga, K.H. and Dube, T., 2024. Understanding the spatio-temporal distribution of bush encroachment in savannah rangelands, South Africa. *Geocarto International*, *39*(1), p.2366515.

Mashiyi, N., Shikwambana, L. and Kganyago, M., 2024. Spatio-temporal dynamics of methane concentration and its association to climatic and vegetation parameters: a case study of the Northern Cape Province, South Africa. *Geocarto International*, *39*(1), p.2306266.

Masipa, T., 2017. The impact of climate change on food security in South Africa: Current realities and challenges ahead. *Jàmbá: Journal of Disaster Risk Studies*, *9*(1), p.1-7.

Matsvai, S. and Hosu, Y.S., 2024. ICT and agricultural development in South Africa: An auto-regressive distributed lag approach. *Agriculture*, *14*(8), p.1253.

Matthew, O.A., Owolabi, O., Osabohien, R., Urhie, E., Ogunbiyi, T., Olawande, T.I., Edafe, O.D. and Daramola, P.J., 2020. Carbon emissions, agricultural output and life expectancy in West Africa. *International Journal of Energy Economics and Policy*, *10*(3), p.489-496.

Maziya, M., Mvelase, L. and Dlamini, M.M., 2024. Smallholder Farmers' Climate Change Adaptation Strategies and Their Effect on Household Food Security: Evidence from KwaZulu-Natal, South Africa. *Agriculture*, *14*(10), p.1729.

Mendelsohn, R., Dinar, A., & Sanghi, A. (2001). Climate change impacts on agriculture. World Bank.

Minot, N. (2014). Food price volatility in sub-Saharan Africa: Has it really increased?. *Food Policy*, *45*, 45-56.

Mitchell, D., 2008. A note on rising food prices. *World bank policy research working paper*, (4682).

Moeletsi, M.E. and Tongwane, M.I., 2015. 2004 methane and nitrous oxide emissions from manure management in South Africa. *Animals*, *5*(2), p.193-205.

Mogale, T.E., Ayisi, K.K., Munjonji, L., Kifle, Y.G. and Mabitsela, K.E., 2023. Understanding the impact of the intercropping system on carbon dioxide (CO_2) emissions and soil carbon stocks in Limpopo Province, South Africa. *International Journal of Agronomy*, *2023*(1), p.6307673.

Mohamed, A.A., Ibey, A.M.Y., Omar, M.M. and Abdulle, A.S., 2025. Assessing the impact of climate variability and political stability on livestock productivity in the EAC. *Environmental Research Communications*, *7*(9), p.095003.

Mudzielwana, R.V., Phophi, M. and Mafongoya, P., 2025. Assessing the impact of privatizing public agricultural extension services on smallholder farmers' performance: A case study of Thulamela and Collins Chabane Municipalities, South Africa. *Journal of Agribusiness and Rural Development*, (1) 75.

Mugambiwa, S.S. and Tirivangasi, H.M., 2017. Climate change: A threat towards achieving 'Sustainable Development Goal number two'(end hunger, achieve food security and improved nutrition and promote sustainable agriculture) in South Africa. *Jàmbá: Journal of Disaster Risk Studies*, *9*(1), p.1-6.

Mukherjee, D., 2021. Food security under the era of climate change threat. *Journal of Advanced Agriculture & Horticulture Research*, *1*(1).

Mundia, C.W., Secchi, S., Akamani, K. and Wang, G., 2019. A regional comparison of factors affecting global sorghum production: The case of North America, Asia and Africa's Sahel. *Sustainability*, *11*(7), p.2135.

Muzangwa, L., Mnkeni, P.N.S. and Chiduza, C., 2021. Soil C sequestration and CO_2 fluxes under maize-based Conservation Agriculture systems in the Eastern Cape, South Africa. *South African Journal of Plant and Soil*, *38*(3), p.276-283.

Naicker, M., Naidoo, D., Ngidi, M.S.C. and Slotow, R., 2025. Exploring the effect of climate change on food supply chains in Africa: a systematic review with a focus on South Africa. *Frontiers in Sustainable Food Systems*, *9*, p.1604839.

Ncoyini-Manciya, Z. 2021. *Observed and projected climate change effects on localized drought events: A case study for sugarbelt within KwaZulu-Natal Midlands, South Africa* (Doctoral dissertation, University of KwaZulu-Natal).

Nelson, C.R. and Plosser, C.R., 1982. Trends and random walks in macroeconmic time series: some evidence and implications. *Journal of monetary economics*, *10*(2), p.139-162.

Nesirov, E., Karimov, M. and Zeynalli, E., 2022. Does the Agricultural Ecosystem Cause Environmental Pollution in Azerbaijan? *Economic and Environmental Geology*, *55*(6), p.617-632.

Newsham, A., Naess, L. O., Mutabazi, K., Shonhe, T., Boniface, G., & Bvute, T. (2024). Precarious prospects? Exploring climate resilience of agricultural commercialization pathways in Tanzania and Zimbabwe. *Climate and Development*, *16*(5), 395-409.

Ngarava, S., Zhou, L., Ayuk, J. and Tatsvarei, S., 2019. Achieving food security in a climate change environment: considerations for environmental Kuznets curve use in the South African agricultural sector. *Climate*, *7*(9), p.108.

Ngcamu, B.S. and Chari, F., 2020. Drought influences on food insecurity in Africa: a systematic literature review. *International Journal of Environmental Research and Public Health*, *17*(16), p.5897.

Ningi, T., Mphahlele, M., Sithole, V., Manyike, J.Z., Manganyi, B., Ngarava, S., Lubinga, M.H., Dladla, L. and Molepo, S., 2025. Assessment of the Long-Term Impact of Climate Variability on Food Production Systems in South Africa (1976–2020). *Climate*, *13*(1), p.8.

Nocezo, Y.I., Manyike, J.Z., Zhou, L. and Ngarava, S., 2024. Determinants of smallholder crop farmers' access to climate services in Elundini local municipality, Eastern Cape province, South Africa. *Frontiers in Climate*, *6*, p.1447510.

Ntombela, S.M., Kalaba, M. and Bohlmann, H., 2018. Estimating trade elasticities for South Africa's agricultural commodities for use in policy modelling. *Agrekon*, *57*(3-4), p.221-232.

Nyambo, S., Manyevere, A., Mashamaite, C.V., Araya, T. and Akinyemi, B.E., 2025. Local Knowledge on Soil Quality Indicators, Climate Variability, and Farming Productivity: A Case of Farmers in the Eastern Cape Province, South Africa. *Human Ecology*, p.1-12.

O'Neill, B.C., Kriegler, E., Ebi, K.L., Kemp-Benedict, E., Riahi, K., Rothman, D.S., Van Ruijven, B.J., Van Vuuren, D.P., Birkmann, J., Kok, K. and Levy, M., 2017. The roads

ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global environmental change*, *42*, p.169-180.

Obiora, S.C., Abid, M., Bamisile, O. and Zaini, J.H., 2023. Is carbon neutrality attainable with financial sector expansion in various economies? An intrinsic analysis of economic activity on CO_2 emissions. *Sustainability*, *15*(9), p.7364.

Ogundeji, A.A., Jooste, A. and Uchezuba, D., 2010. Econometric estimation of Armington elasticities for selected agricultural products in South Africa: pricing models. *South African Journal of Economic and Management Sciences*, *13*(2), p.123-234.

Ojogiwa, O.T. and Mubangizi, B., 2023. Navigating the Complex Terrain of Food Security in Decentralised Systems: Insights from South Africa and Nigeria. *African Journal of Governance and Development*, *12*(2), p.141-160.

Olawuyi, S.O. and Mushunje, A., 2025. Effect of Climate Change and Selected Macroeconomic Variables on Food Security in South Africa. *Path of Science*, *11*(1), p.7007-7021.

Omay, P.O., Bahaga, T.K. and Fidar, A., 2025. Insights into determinants influencing food security in the IGAD region of Eastern Africa. *Frontiers in Nutrition*, *12*, p.1600096.

Omokpariola, D. O., Agbanu-Kumordzi, C., Samuel, T., Kiswii, L., Moses, G. S., & Adelegan, A. M. (2025). Climate change, crop yield, and food security in Sub-Saharan Africa. *Discover Sustainability*, *6*(1), 678.

Omotayo, A.O., Omotoso, A.B. and Asong, J.A., 2025. Leveraging Africa's underutilized crops to combat climate change, water scarcity, and food insecurity in South Africa. *Scientific Reports*, *15*(1), p.19404.

Oni, F.E. and Baiyegunhi, L., 2022. Scholastic Review of Food, Memory, and Identity: Classical Migrant Experience. *Driving Factors for Venture Creation and Success in Agricultural Entrepreneurship*, p.60-81.

OWID (OurWord in Data). 2022. Available online: https://ourworldindata.org/CO_2/country/south-africa?country=~{}ZAF (accessed on 12 September 2024).

Özbek, S. and Özbek, B., 2024. Does Climate Change Strengthen the Link between Environmental Degradation and Agricultural Output? Empirical Evidence on the Turkish Economy. *Tarım Ekonomisi Dergisi*, *30*(1), p.49-60.

Ozturk, I. and Acaravci, A., 2013. The long-run and causal analysis of energy, growth, openness and financial development on carbon emissions in Turkey. *Energy economics*, *36*, p.262-267.

Pacillo, G., Kangogo, D., Madurga-Lopez, I., Villa, V., Belli, A. and Läderach, P., 2022. Is climate exacerbating the root causes of conflict in Mali? A climate security analysis through a structural equation modeling approach. *Frontiers in Climate*, *4*, p.849757.

Padhan, H., Ghosh, S. and Hammoudeh, S., 2023. Renewable energy, forest cover, export diversification, and ecological footprint: a machine learning application in moderating eco-innovations on agriculture in the BRICS-T economies. *Environmental Science and Pollution Research*, *30*(35), p.83771-83791.

Partey, S.T., Zougmoré, R.B., Ouédraogo, M. and Campbell, B.M., 2018. Developing climate-smart agriculture to face climate variability in West Africa: Challenges and lessons learnt. *Journal of cleaner Production*, *187*, p.285-295.

Pérez, T., Vergara, S.E. and Silver, W.L., 2023. Assessing the climate change mitigation potential from food waste composting. *Scientific Reports*, *13*(1), p.7608.

Perron, P., 1989. The great crash, the oil price shock, and the unit root hypothesis. *Econometrica: journal of the Econometric Society*, p.1361-1401.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics*, *16*(3), 289-326.

Pesaran, M.H., Shin, Y. and Smith, R.J., 2001. Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics*, *16*(3), p.289-326.

Phillips, P.C. and Hansen, B.E., 1990. Statistical inference in instrumental variables regression with I (1) processes. *The review of economic studies*, *57*(1), p.99-125.

Phiri, J., Malec, K., Kapuka, A., Maitah, M., Appiah-Kubi, S.N.K., Gebeltová, Z., Bowa, M. and Maitah, K., 2021. Impact of agriculture and energy on CO_2 emissions in Zambia. *Energies*, *14*(24), p.8339.

Puoane, T., Matwa, P., Hughes, G. and Bradley, H.A. (2006) 'Socio-cultural factors influencing food consumption patterns in the black African population in an urban township in South Africa', *Journal of Health, Population and Nutrition*, 24(1), pp. 86–94.

Qayyum, M., Ali, M., Nizamani, M.M., Li, S., Yu, Y. and Jahanger, A., 2021. Nexus between financial development, renewable energy consumption, technological innovations and CO_2 emissions: the case of India. *Energies*, *14*(15), p.4505.

Rahman, M.M., Nguyen, R. and Lu, L., 2022. Multi-level impacts of climate change and supply disruption events on a potato supply chain: An agent-based modeling approach. *Agricultural Systems*, *201*, p.103469.

Rahman, M.M., Saidi, K. and Mbarek, M.B., 2020. Economic growth in South Asia: the role of CO_2 emissions, population density and trade openness. *Heliyon*, *6*(5).

Raihan, A. and Said, M.N.M., 2022. Cost–benefit analysis of climate change mitigation measures in the forestry sector of Peninsular Malaysia. *Earth Systems and Environment*, *6*(2), p.405-419.

Raihan, A. and Tuspekova, A., 2022a. Toward a sustainable environment: Nexus between economic growth, renewable energy use, forested area, and carbon emissions in Malaysia. *Resources, Conservation & Recycling Advances*, *15*, p.200096.

Raihan, A., 2023. Toward sustainable and green development in Chile: dynamic influences of carbon emission reduction variables. *Innovation and Green Development*, *2*(2), p.100038.

Raihan, A., Begum, R.A. and Said, M.N.M., 2021. A meta-analysis of the economic value of forest carbon stock. *Geografia–Malaysian Journal of Society and Space*, *17*(4), p.321-338.

Raihan, A., Begum, R.A., Mohd Said, M.N. and Abdullah, S.M.S., 2019. A review of emission reduction potential and cost savings through forest carbon sequestration. *Asian Journal of Water, Environment and Pollution*, *16*(3), p.1-7.

Raihan, A., Begum, R.A., Mohd Said, M.N. and Pereira, J.J., 2021. Assessment of carbon stock in forest biomass and emission reduction potential in Malaysia. *Forests*, *12*(10), p.1294.

Raihan, A., Begum, R.A., Said, M.N.M. and Abdullah, S.M.S., 2018. Climate change mitigation options in the forestry sector of Malaysia. *J. Kejuruter*, *1*(6), p.89-98.

Raihan, A., Muhtasim, D.A., Farhana, S., Hasan, M.A.U., Paul, A. and Faruk, O., 2022. Toward environmental sustainability: Nexus between tourism, economic growth, energy use and carbon emissions in Singapore. *Global Sustainability Research*, *1*(2), p.53-65.

Rajagopal, D. and Zilberman, D., 2008. Environmental, economic and policy aspects of biofuels. *Foundations and Trends® in Microeconomics*, *4*(5), p.353-468.

Ramoshaba, T., Hlongwane, J.J. and Belete, A., 2019. Price transmission analysis of pasteurized liquid milk in South Africa: the granger causality approach. *Journal of Agribusiness and Rural Development*, *54*(4), p.345-353.

Raza, M.Y., Zhongpan, Q. and Pengju, W., 2023. Agriculture-related energy consumption, food policy, and CO_2 emission reduction: New insights from Pakistan. *Frontiers in Environmental Science*, *10*, p.1099813.

Rehman, M.A., Fareed, Z., Salem, S., Kanwal, A. and Pata, U.K., 2021. RETRACTED: Do Diversified Export, Agriculture, and Cleaner Energy Consumption Induce Atmospheric Pollution in Asia? Application of Method of Moments Quantile Regression. *Frontiers in Environmental Science*, *9*, p.781097.

Roman-Cuesta, R.M., Rufino, M.C., Herold, M., Butterbach-Bahl, K., Rosenstock, T.S., Herrero, M., Ogle, S., Li, C., Poulter, B., Verchot, L. and Martius, C., 2016. Hotspots of gross emissions from the land use sector: patterns, uncertainties, and leading emission sources for the period 2000–2005 in the tropics. *Biogeosciences*, *13*(14), p.4253-4269.

Rosa, L. and Gabrielli, P., 2022. Energy and food security implications of transitioning synthetic nitrogen fertilizers to net-zero emissions. *Environmental Research Letters*, *18*(1), p.014008.

Ruben, R. and Burger, K., 2007. Contributions of agricultural economics to critical policy issues: selected papers presented at the XXVI IAAE conference. *Agricultural Economics*, *37*.

Sam, A.G., Abidoye, B.O. and Mashaba, S., 2021. Climate change and household welfare in sub-Saharan Africa: empirical evidence from Swaziland. *Food Security*, *13*(2), p.439-455.

Sansika, N., Sandumini, R., Kariyawasam, C., Bandara, T., Wisenthige, K. and Jayathilaka, R., 2023. Impact of economic globalisation on value-added agriculture, globally. *PLoS One*, *18*(7), p.e0289128.

Santra, S., 2017. The effect of technological innovation on production-based energy and CO_2 emission productivity: evidence from BRICS countries. *African Journal of Science, Technology, Innovation and Development*, *9*(5), p.503-512.

Sarker, M.M.R., Aleen, M.J. and Datta, T., 2025. Productivity of Food and Self-Sufficiency in Rice Production in Bangladesh. *Economics*, *12*(3), p.214-226.

Sarkodie, S. A., and Owusu, P. A. 2017. The relationship between carbon dioxide, crop and food production index in Ghana: By estimating the long-run elasticities and variance decomposition. *Environmental Engineering Research*, 22(2), p.193–202.

Sarma, H.H., Borah, S.K., Dutta, N., Sultana, N., Nath, H. and Das, B.C., 2024. Innovative approaches for climate-resilient farming: strategies against environmental shifts and climate change. *International Journal of Environment and Climate Change*, *14*(9), p.217-241.

Serote, B., Mokgehle, S., Senyolo, G., du Plooy, C., Hlophe-Ginindza, S., Mpandeli, S., Nhamo, L. and Araya, H., 2023. Exploring the barriers to the adoption of climate-smart irrigation technologies for sustainable crop productivity by smallholder farmers: Evidence from South Africa. *Agriculture*, *13*(2), p.246.

Serra, T., 2015. Price volatility in Niger millet markets. *Agricultural economics*, *46*(4), p.489-502.

Shahbaz, M., Khan, S., Ali, A. and Bhattacharya, M., 2017. The impact of globalization on CO_2 emissions in China. *The Singapore Economic Review*, *62*(04), p.929-957.

Shehzad, M., Zahid, N., Maqbool, M., Singh, A., Liu, H., Wu, C., Khan, A., Wahid, F. and Saud, S., 2021. Climate resilience in agriculture. In *Building Climate Resilience in*

Agriculture: Theory, Practice and Future Perspective (p. 67-82). Cham: Springer International Publishing.

Shiferaw, B., Tesfaye, K., Kassie, M., Abate, T., Prasanna, B.M. and Menkir, A., 2014. Managing vulnerability to drought and enhancing livelihood resilience in sub-Saharan Africa: Technological, institutional and policy options. *Weather and climate extremes*, *3*, p.67-79.

Sibanda, M. and Ndlela, H., 2020. The link between carbon emissions, agricultural output and industrial output: evidence from South Africa. *Journal of Business Economics and Management (JBEM)*, *21*(2), p.301-316.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: journal of the Econometric Society*, 1-48.

Sirisupluxana, P. and Bunyasiri, I.N., 2018. Risk assessment and risk management decisions: a case study of Thai rice farmers. *The Business & Management Review*, *9*(3), p.200-207.

Smith, P., Martino, D., Cai, Z., Gwary, D., Janzen, H., Kumar, P., McCarl, B., Ogle, S., O'Mara, F., Rice, C. and Scholes, B., 2008. Greenhouse gas mitigation in agriculture. *Philosophical transactions of the royal Society B: Biological Sciences*, *363*(1492), p.789-813.

Sojl, Z., Chikwanda, D., Jaja, I.F., Mushonga, B. and Muchenje, V., 2015. Relevance of the formal red meat classification system to the South African informal livestock sector. *South African Journal of Animal Science*, *45*(3), p.263-277.

Soni, S. and RL, M., 2024. The dynamic nexus between agricultural productivity and renewable energy consumption in BRICS: the role of financial inclusion and foreign direct investment. *International Journal of Energy Sector Management*, *18*(6), p.1885-1904.

Springmann, M., Mason-D'Croz, D., Robinson, S., Garnett, T., Godfray, H.C.J., Gollin, D., Rayner, M., Ballon, P. and Scarborough, P., 2016. Global and regional health effects

of future food production under climate change: a modelling study. *The Lancet*, *387*(10031), p.1937-1946.

Stock, J.H. and Watson, M.W., 1989. Interpreting the evidence on money-income causality. *Journal of Econometrics*, *40*(1), p.161-181.

Stock, J.H. and Watson, M.W., 1993. A simple estimator of cointegrating vectors in higher order integrated systems. *Econometrica: journal of the Econometric Society*, p.783-820.

Sultan, B., 2012. Global warming threatens agricultural productivity in Africa and South Asia. *Environmental Research Letters*, *7*(4), p.041001.

Syroka, J. and Nucifora, A., 2010. National drought insurance for Malawi. *World Bank Policy Research Working Paper*, (5169).

Tagwi, A. and Chipfupa, U., 2023. Participation of smallholder farmers in modern bioenergy value chains in Africa: opportunities and constraints. *BioEnergy Research*, *16*(1), p.248-262.

Tagwi, A., 2022. The impacts of climate change, carbon dioxide emissions (CO_2) and renewable energy consumption on agricultural economic growth in South Africa: ARDL approach. *Sustainability*, *14*(24), p.16468.

Thabane, V.N., Agholor, I.A., Sithole, M.Z., Morepje, M.T., Msweli, N.S. and Mgwenya, L.I., 2024. Socio-Demographic Determinants of Climate-Smart Agriculture Adoption Among Smallholder Crop Producers in Bushbuckridge, Mpumalanga Province of South Africa. *Climate*, *12*(12), p.202.

Thompson, H.E., Berrang-Ford, L. and Ford, J.D., 2010. Climate change and food security in sub-Saharan Africa: a systematic literature review. *Sustainability*, *2*(8), p.2719-2733.

Thornton, P.K., Ericksen, P.J., Herrero, M. and Challinor, A.J., 2014. Climate variability and vulnerability to climate change: a review. *Global change biology*, *20*(11), p.3313-3328.

Tunç, G.İ., Türüt-Aşık, S. and Akbostancı, E., 2009. A decomposition analysis of CO_2 emissions from energy use: Turkish case. *Energy Policy*, *37*(11), pp.4689-4699.

Udeagha, M.C. and Breitenbach, M.C., 2023. Exploring the moderating role of financial development in environmental Kuznets curve for South Africa: fresh evidence from the novel dynamic ARDL simulations approach. *Financial Innovation*, *9*(1), p.5.

Udeagha, M.C. and Ngepah, N., 2022. The asymmetric effect of technological innovation on CO_2 emissions in South Africa: New evidence from the QARDL approach. *Frontiers in Environmental Science*, *10*, p.985719.

van Meijl, H., Bartelings, H., van Berkum, S., Cui, H.D., Kristkova, Z.S. and van Zeist, W.J., 2024. The Russia-Ukraine war decreases food affordability but could reduce global greenhouse gas emissions. *Communications Earth and Environment*, *5*(1), p.59.

van Tilburg, A. and van Schalkwyk, H.D., 2012. Strategies to improve smallholders' market access. In *Unlocking markets to smallholders: Lessons from South Africa* (p. 35-58). Wageningen: Wageningen Academic Publishers.

van Wijk, M.T., Merbold, L., Hammond, J. and Butterbach-Bahl, K., 2020. Improving assessments of the three pillars of climate smart agriculture: current achievements and ideas for the future. *Frontiers in Sustainable Food Systems*, *4*, p.558483.

Van Zyl, J., 1986. The effect of inflation on agricultural production under conditions of risk. *Agrekon*, *25*(3), p.52-59.

Vermeir, I., Weijters, B., De Houwer, J., Geuens, M., Slabbinck, H., Spruyt, A., Van Kerckhove, A., Van Lippevelde, W., De Steur, H. and Verbeke, W., 2020. Environmentally sustainable food consumption: A review and research agenda from a goal-directed perspective. *Frontiers in Psychology*, *11*, p.1603.

Vijay, M., 2022. *Production Forecasting Models for Selected Major Crops of Karnataka* (Doctoral dissertation, University of Agricultural Sciences, GKVK, Bangalore).

Wan Mohd Jaafar, W.S., Abdul Maulud, K.N., Muhmad Kamarulzaman, A.M., Raihan, A., Md Sah, S., Ahmad, A., Saad, S.N.M., Mohd Azmi, A.T., Jusoh Syukri, N.K.A. and Razzaq Khan, W., 2020. The influence of deforestation on land surface temperature—A case study of Perak and Kedah, Malaysia. *Forests*, *11*(6), p.670.

Wier, M., Lenzen, M., Munksgaard, J. and Smed, S., 2001. Effects of household consumption patterns on CO_2 requirements. *Economic Systems Research*, *13*(3), p.259-274.

World Bank Group, 2018. *Productive Diversification of African Agriculture and Its Effects on Resilience and Nutrition*. Washington, D.C.: World Bank.

World Bank. (2020). Agriculture and climate change report.

World Bank. *Climate Risk Profile: South Africa* (2021): The World Bank Group. 2021. https://climateknowledgeportal.worldbank.org/sites/default/files/country-profiles/15932-WB_South%20Africa%20Country%20Profile-WEB.pdf (accessed on 9 September 2023)

Xu, B., Baležentis, T., Štreimikienė, D. and Shen, Z., 2024. Enhancing agricultural environmental performance: Exploring the interplay of agricultural productive services, resource allocation, and marketization factors. *Journal of Cleaner Production*, *439*, p.140843.

Zhu, H., Duan, L., Guo, Y. and Yu, K., 2016. The effects of FDI, economic growth and energy consumption on carbon emissions in ASEAN-5: evidence from panel quantile regression. *Economic Modelling*, *58*, p.237-248.

Zivot, E. and Wang, J., 2006. Vector autoregressive models for multivariate time series. In *Modeling financial time series with S-PLUS®* (p. 369-413). New York, NY: Springer New York.

Zougmoré, R., Partey, S., Ouédraogo, M., Omitoyin, B., Thomas, T., Ayantunde, A., Ericksen, P., Said, M. and Jalloh, A., 2016. Toward climate-smart agriculture in West Africa: a review of climate change impacts, adaptation strategies and policy developments for the livestock, fishery and crop production sectors. *Agriculture and Food Security*, *5*(1), p.26.

Zuma-Netshiukhwi, G., Anderson, J.J., Wessels, C.H. and Malatsi, E., 2025. Upscaling the Uptake of Climate-Smart Agriculture in Semi-Arid Areas of South Africa. *Atmosphere*, *16*(6), p.729.

APPENDIX

Appendix I: Lag selection criteria

Lag	Log L	LR	FPE	AIC	SC	HQ
0	-549.1022	NA	1.06e+11	39.57873	39.81662	39.65146
1	-348.6162	315.0495	395680.4	27.04401	28.47138*	27.48037
2	-314.1837	41.81087*	243787.1*	26.37027*	28.98710	27.17026*

(Source: Author's computation)

Appendix II: Normalised co-integration coefficients

1 Cointegrating Equation(s):		Log likelihood	-340.9715	
Normalized cointegrating coefficients (standard error in parentheses)				
CPI	CE	ICP	PLR_PPP	TE
1.000000	-0.001167	6.774553	-179.9417	24.16585
	(0.00024)	(7.09088)	(102.882)	(4.49581)
Adjustment coefficients (standard error in parentheses)				
D(CPI)	0.016302			
	(0.00791)			
D(CE)	-179.0134			
	(95.7749)			
D(ICP)	0.025107			
	(0.01021)			
D(PLR_PPP)	-0.000846			
	(0.00024)			
D(TE)	-0.015129			
	(0.00555)			

2 Cointegrating Equation(s):		Log likelihood	-329.1968	
Normalized cointegrating coefficients (standard error in parentheses)				
CPI	CE	ICP	PLR_PPP	TE
1.000000	0.000000	26.00239	-248.4087	14.09994
		(4.13902)	(71.0153)	(3.03732)
0.000000	1.000000	16472.05	-58654.10	-8623.239
		(4160.74)	(71388.0)	(3053.26)
Adjustment coefficients (standard error in parentheses)				
D(CPI)	0.025105	-1.19E-05		
	(0.01681)	(1.5E-05)		
D(CE)	-422.7190	0.012554		
	(196.228)	(0.17604)		
D(ICP)	0.022173	-3.17E-05		

	(0.02186)	(2.0E-05)		
D(PLR_PPP)	-0.000232	1.48E-06		
	(0.00049)	(4.4E-07)		
D(TE)	-0.021371	1.26E-05		
	(0.01179)	(1.1E-05)		

3 Cointegrating Equation(s): Log likelihood -319.0296

Normalized cointegrating coefficients (standard error in parentheses)

CPI	CE	ICP	PLR_PPP	TE
1.000000	0.000000	0.000000	625.9958	15.61447
			(283.784)	(5.96911)
0.000000	1.000000	0.000000	495265.5	-7663.810
			(164611.)	(3462.44)
0.000000	0.000000	1.000000	-33.62784	-0.058246
			(10.5100)	(0.22107)

Adjustment coefficients (standard error in parentheses)

D(CPI)	0.011366	1.10E-05	0.189915	
	(0.01399)	(1.4E-05)	(0.47413)	
D(CE)	-396.4024	-0.031393	-10274.88	
	(203.636)	(0.19999)	(6902.75)	
D(ICP)	0.004064	-1.43E-06	-0.296145	
	(0.01804)	(1.8E-05)	(0.61164)	
D(PLR_PPP)	-3.71E-05	1.16E-06	0.022153	
	(0.00049)	(4.8E-07)	(0.01668)	
D(TE)	-0.030256	2.75E-05	-0.519875	
	(0.01022)	(1.0E-05)	(0.34660)	

4 Cointegrating Equation(s): Log likelihood -314.3509

Normalized cointegrating coefficients (standard error in parentheses)

CPI	CE	ICP	PLR_PPP	TE
1.000000	0.000000	0.000000	0.000000	14.36223
				(4.00859)
0.000000	1.000000	0.000000	0.000000	-8654.536
				(2470.46)
0.000000	0.000000	1.000000	0.000000	0.009023
				(0.16154)
0.000000	0.000000	0.000000	1.000000	0.002000
				(0.00554)

Adjustment coefficients (standard error in parentheses)

D(CPI)	0.011436	1.07E-05	0.196581	6.346880
	(0.01401)	(1.4E-05)	(0.48028)	(5.35923)
D(CE)	-390.0608	-0.055644	-9675.326	96785.42
	(202.594)	(0.20369)	(6945.94)	(77506.7)
D(ICP)	0.003402	1.10E-06	-0.358656	10.23407
	(0.01790)	(1.8E-05)	(0.61384)	(6.84954)

D(PLR_PPP)	-9.18E-05	1.37E-06	0.016976	-0.324853
	(0.00045)	(4.5E-07)	(0.01536)	(0.17140)
D(TE)	-0.029791	2.57E-05	-0.475872	13.24312
	(0.01009)	(1.0E-05)	(0.34603)	(3.86123)

(Source: Author's computation)

Appendix III: VEC granger causality/block exogeneity Wald tests

Dependent variable: D(CPI)

Excluded	Chi-sq	df	Prob.
D(CE)	0.448952	1	0.5028
D(ICP)	3.492265	1	0.0617
D(PLR_PPP)	0.766169	1	0.3814
D(TE)	0.682633	1	0.4087
All	8.587283	4	0.0723

Dependent variable: D(CE)

Excluded	Chi-sq	df	Prob.
D(CPI)	1.449033	1	0.2287
D(ICP)	0.316479	1	0.5737
D(PLR_PPP)	0.528047	1	0.4674
D(TE)	3.047851	1	0.0808
All	4.633029	4	0.3271

Dependent variable: D(ICP)

Excluded	Chi-sq	df	Prob.
D(CPI)	11.46227	1	0.0007
D(CE)	1.166602	1	0.2801
D(PLR_PPP)	0.701079	1	0.4024
D(TE)	0.206107	1	0.6498
All	17.88539	4	0.0013

Dependent variable: D(PLR_PPP)

Excluded	Chi-sq	df	Prob.
D(CPI)	14.24378	1	0.0002
D(CE)	3.382245	1	0.0659
D(ICP)	3.227894	1	0.0724
D(TE)	1.230037	1	0.2674

All	16.23434	4	0.0027

Dependent variable: D(TE)

Excluded	Chi-sq	df	Prob.
D(CPI)	3.576138	1	0.0586
D(CE)	3.338022	1	0.0677
D(ICP)	0.147001	1	0.7014
D(PLR_PPP)	0.403272	1	0.5254
All	9.085507	4	0.0590

(Source: Author's computation)

Appendix IV: Granger Causality and Diagnostic Test Results

Table A1: Granger causality test

Null Hypothesis:	Obs	F-Statistic	Prob.	
CE does not Granger Cause CPI	28	0.1893	0.8288	No causality
CPI does not Granger Cause CE		0.2099	0.8122	No causality
ICP does not Granger Cause CPI	28	2.2293	0.1303	No causality
CPI does not Granger Cause ICP		2.2042	0.1331	No causality
PLR_PPP does not Granger Cause CPI	28	7.1486	0.0039	Uni-directional
CPI does not Granger Cause PLR_PPP		1.2702	0.2998	Uni-directional
TE does not Granger Cause CPI	28	1.5695	0.2296	No causality
CPI does not Granger Cause TE		0.1960	0.8234	No causality
ICP does not Granger Cause CE	28	0.4738	0.6286	No causality
CE does not Granger Cause ICP		1.3941	0.2682	No causality
PLR_PPP does not Granger Cause CE	28	0.6093	0.5523	No causality
CE does not Granger Cause PLR_PPP		1.0874	0.3538	No causality
TE does not Granger Cause CE	28	1.2052	0.3179	No causality
CE does not Granger Cause TE		3.1555	0.0615	No causality
PLR_PPP does not Granger Cause ICP	28	4.3277	0.0254	Uni-directional
ICP does not Granger Cause PLR_PPP		0.7552	0.4812	Uni-directional
TE does not Granger Cause ICP	28	1.0445	0.3680	No causality
ICP does not Granger Cause TE		0.7283	0.4936	No causality
TE does not Granger Cause PLR_PPP	28	0.1559	0.8565	No causality
PLR_PPP does not Granger Cause TE		1.3757	0.2727	No causality

(Source: Author's computation)

Table A2: Residual serial correlation LM tests

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	23.27958	25	0.5612	0.918380	(25, 46.1)	0.5811
2	17.06616	25	0.8794	0.635895	(25, 46.1)	0.8873

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	23.27958	25	0.5612	0.918380	(25, 46.1)	0.5811
2	42.30815	50	0.7719	0.734936	(50, 35.3)	0.8436

(Source: Author's computation)

Table A3: Residual normality tests

Component	Skewness	Chi-sq	df	Prob.*
1	0.699	2.281	1	0.1310
2	-0.121	0.068	1	0.7940
3	0.075	0.026	1	0.8721
4	0.432	0.870	1	0.3510
5	0.447	0.935	1	0.3337
Joint		4.179	5	0.5240

Component	Kurtosis	Chi-sq	df	Prob.
1	4.000	1.167	1	0.2799
2	3.732	0.625	1	0.4293
3	1.677	2.043	1	0.1529
4	2.772	0.060	1	0.8058
5	2.278	0.609	1	0.4352
Joint		4.504	5	0.4793

Component	Jarque-Bera	df	Prob.
1	3.448	2	0.1784
2	0.693	2	0.7072
3	2.069	2	0.3554
4	0.930	2	0.6281
5	1.543	2	0.4622

Joint	8.683	10	0.5624

*Approximate p-values do not account for coefficient estimation

(Source: Author's computation)

Table A4: Residual heteroskedasticity tests

Joint test:

Chi-sq	df	Prob.
199.8547	180	0.1480

Individual components:

Dependent	R-squared	F(12,15)	Prob.	Chi-sq(12)	Prob.
res1*res1	0.496395	1.232105	0.3462	13.89907	0.3072
res2*res2	0.336115	0.632857	0.7850	9.411226	0.6675
res3*res3	0.627124	2.102323	0.0877	17.55948	0.1297
res4*res4	0.743761	3.628261	0.0105	20.82531	0.0530
res5*res5	0.517253	1.339348	0.2925	14.48308	0.2709
res2*res1	0.477949	1.144400	0.3964	13.38256	0.3419
res3*res1	0.561818	1.602698	0.1923	15.73091	0.2039
res3*res2	0.468995	1.104027	0.4215	13.13186	0.3595
res4*res1	0.644849	2.269629	0.0679	18.05577	0.1140
res4*res2	0.634989	2.174550	0.0785	17.77968	0.1225
res4*res3	0.624023	2.074671	0.0915	17.47264	0.1327
res5*res1	0.522777	1.369318	0.2790	14.63774	0.2618
res5*res2	0.592377	1.816562	0.1369	16.58657	0.1658
res5*res3	0.565337	1.625793	0.1854	15.82944	0.1992
res5*res4	0.529355	1.405932	0.2632	14.82195	0.2513

(Source: Author's computation)

Appendix V: VEC Model Stability and Forecasting Diagnostics

Table A5: Inverse root of autocorrelation

Root	Modulus
1.000000	1.000000
1.000000	1.000000
1.000000	1.000000
1.000000	1.000000
0.906537	0.906537
0.288338 - 0.732665i	0.787361
0.288338 + 0.732665i	0.787361
-0.459391	0.459391

0.267160	0.267160
-0.055407	0.055407

VEC specification imposes 4-unit root(s).

(Source: Author's computation)

Table A6: Variance decomposition of CPI

Variance Decomposition of CPI: Period	S.E.	CPI	CE	ICP	PLR_PPP	TE
1	1.465007	100.0000	0.000000	0.000000	0.000000	0.000000
2	2.715567	97.13843	0.124483	0.665873	2.034710	0.036505
3	3.753210	88.76429	0.219389	1.650224	7.754481	1.611618
4	4.733754	79.59605	0.998753	2.108404	12.10672	5.190069
5	5.833884	73.91251	2.154138	2.009080	13.48346	8.440805

(Source: Author's computation)