UNIVERSITY OF MPUMALANGA

Creating Opportunities

Impact of climate change on agricultural production and food inflation in Southern Africa: a spatial panel data approach

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DEDICATION

As Proverbs 16:3 reminds us, “Commit to the Lord whatever you do, and He will establish your plans.”

This dissertation is wholeheartedly dedicated to God, the Author and Finisher of my faith, whose boundless grace has not only sustained me throughout this year of rigorous research but has enabled me to achieve what once seemed impossible. What was meant to be a two-year journey was condensed into one, not by my own strength or wisdom, but through His divine provision and favor. Through every moment of doubt, He was my reassurance. Through every challenge, He was my fortress. Therefore, this achievement is not my own, but a reflection of His faithfulness and His promises fulfilled in my life.

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ABSTRACT

The present study analyzes the impact of climate change on agricultural production and food inflation in Southern Africa by employing quantitative analysis of annual data from 1981 to 2020. Annual mean temperature and average rainfall are employed as proxies for climate change, the analysis focuses on the agricultural production and food inflation as the dependent variables. To assess the order of integration of both the regressands and regressors of interest, three panel unit root tests are employed; Levin, Lin and Chu (LLC); Im, Pesaran, and Shin (IPS); and Fisher Chi-square tests. Furthermore, the PMG/Panel ARDL approach for cointegration is employed to evaluate the long run relationship among the variables. The results indicate that temperature and rainfall patterns have a negative and significant impact on agricultural productivity as a 1°C increase in temperature leads to 16.63 units of decrease in agricultural output. It could therefore be contended that the agricultural sector in Southern Africa is particularly at risk from climate change due to the unique geology and farming systems of this region. On the other hand, only temperature has a positive and significant impact on food inflation, since temperature is a critical determinant of crop yields, warmer temperatures negatively affect the growth cycles of staple crops by causing heat stress and reducing water availability, hence increased food prices. To mitigate these challenges, this study recommends climate-resilient farming practices, input tariff reductions, enhancement of regional trade integration, and support for renewable energies so that productivity improves while food prices remain stable. Flexible monetary policies and increased social protection measures will thus be substantially instrumental in safeguarding livelihoods and food security for the population, fostering a strong agricultural economy against both structural and climatic challenges.

Keywords:

Climate Change, Agricultural Production, Food Inflation, PMG/Panel ARDL

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LIST OF ACRONYMS

ADF	Augmented Dickey Fuller
ARDL	Auto-Regressive Distributed Lag
FAO	Food and Agriculture Organization of the United States
FAOSTAT	Food and Agriculture Organization Statistics
FISP	Malawi’s Farm Input Subsidy Programme
GDP	Gross Domestic Product
GHG	Green House Gas
IPCC	Intergovernmental Portal of Climate Change
IPS	Im, Pesaran, and Shin
LLC	Levin, Lin, and Chu
NASA POWER	National Aeronautics and Space Administration, Prediction Of Worldwide Energy Resources
PMG	Pooled Mean Group
SAGIS	South African Grain Information Service
SARB	South African Reserve Bank
SDG	Sustainable Development Goal
STATSSA	Statistics South Africa
UNDRR	United Nations Office for Disaster Risk Reduction
WDI	World Development Index
Zimstat	Zimbabwe Statistics

CHAPTER ONE: INTRODUCTION

1.1. Background of the study

Intergovernmental Panel on Climate Change (IPCC) defined climate change as the assembly of weather in various temporal scales, spanning from several months to hundreds of thousands of years, and generally involves factors which include temperature, rainfall, and wind (Le Treut et al., 2007). In relation to that, IPCC has explained extreme climate events as extreme deviation from the normal statistical levels in a particular region (McPhillips et al., 2018).

Climate change has had a variety of consequences on global agriculture during the past several years as a result of changes in both temperature and rainfall patterns. High temperatures, for example, reduce crop yields by reducing the soil moisture content and increasing weed and pest infestations. On the other hand, high temperatures may speed up frost periods, thus promoting the possibility of cultivation in cooler but marginally cropped areas (Lesk et al., 2021). Precipitation variability further amplifies the probability of crop failure and extended production decline. This, in turn, affects rainfed agricultural systems with great variability, especially in the rainfall pattern, which restricts soil moisture and adds to vulnerability (Zaveri et al., 2020). While irrigation reduces some of the risk from climate variability, these systems depend on reliable water supplies in their own right and are thus subject to alterations in river flow quantity in both space and time.

For instance, the fourth assessment report by the IPCC discussed the future impacts of climatic changes on agriculture and foresees a general rise in average temperature, increase in desertification, heat waves, water stress, and intense rainfall events across nearly every part of the world (Bhattacharyya et al., 2020). Such extreme weather conditions significantly affect countries whose economies rely heavily on agriculture and whose GDP comprises a significant proportion of agricultural output. Anderson et al. (2020), projected that a temperature rise of not less than 2.5°C or even greater could lead to crop yields falling and substantial food price increases due to surging global demand beyond expanded capacity in food production. Climate change may increasingly be vulnerable to the rainfed agricultural systems of Africa. Furthermore, over 70% of Africa's population is located in the rural areas, and to a large extent rely on agriculture. Moreover, upwards of a quarter of all continental GDP emanates from agriculture (Moyo, 2016). Besides presenting uncertainties within agricultural productions, climate change decreases soil nutrient availability, hence impacting productive capacity. Due to this, agricultural output decreases ultimately causing food to become more costly. Rising food prices indicate demand and supply imbalances and increasing deficiencies of resources, which can be caused by supply factors inclusive of decreased productivity from climatic changes and decreased agricultural land resulting from the degradation of soil and transition into alternative uses, or demand factors consisting of population growth and income advancement (Odongo et al., 2022).

However, despite the vast body of literature on climate change and its impact on agricultural productivity, there remains a gap in understanding its implications for food inflation and economic stability in Southern Africa. Most of the studies that are presently published including that of Kilroy (2015), focus on the bio-physical impacts of climate change, such as changes in temperature and precipitation, while mainly neglecting the socio-economic impacts, such as inflation of food items and availability of food at the household level. Moreover, there are limited studies that explicitly examine the extent to which climate variability influences the production level in areas that heavily rely on agriculture for survival and economic development. This study aims to address this gap by examining the impacts of climate change on agricultural productivity and food price inflation in Southern Africa, thereby offering essential regional evidence that can guide policy formulation and adaptation strategies.

In order to carry out an in-depth analysis, this study focuses on Malawi, Lesotho, Zimbabwe, Botswana, Namibia, Mozambique, South Africa, and Zambia, due to their heavy dependence on agriculture, range of climatic variations, and most notably, availability of credible data. All these countries a combination of arid, semi-arid, and tropical climates, making them vulnerable to climatic variability and its impacts on food security and inflation. Malawi and Zimbabwe are heavily reliant on rain-fed maize production and therefore are susceptible to irregular rainfall and prolonged drought, which usually results in food shortage (Mapila et al., 2022). Lesotho is vulnerable to periodic cycles of drought and soil erosion, which threaten its smallholder agriculture and livestock production (Pryor et al., 2022). Botswana struggles to maintain its subsistence farming and cattle sector due to its semi-arid conditions and lack of cultivable land (Nhamo et al., 2019). Desertification and drought reduce farm output in Namibia, which is the region's driest country (Liu and Zou, 2021). On the other hand, Mozambique is experiencing regular food shortages as a result of the tropical cyclones and floods, which destroy crops and infrastructure (Okou et al., 2022).

South Africa, the largest producer in the region, is facing intensifying water stress and rising temperature variation destabilizing many practices of agriculture (Shikwamba et al., 2023). While Zambia, a country largely dependent on agriculture for employment and GDP is encountered with irregular rainfall patterns and prolonged dry periods, posing a threat to the country's farm production and economic sustainability (Phiri et al., 2020). There is no continent more familiar with climate change and its effects on agricultural productivity than Africa, where the majority of national economies still rely heavily on the agricultural and other climate-sensitive sectors.

1.2. Statement of the research problem

In any economy, maintaining stable prices is the essential objective of monetary policy. However, in developing nations where the impoverished utilize a significant amount of their disposable income on consumption of food, high food price inflation impacts not solely macroeconomic stability but also small farmers and impoverished consumers (Pawlak & Kołodziejczak, 2020).

Southern Africa is presently facing a decline in agricultural output and an increase in food costs due to long-lasting droughts, erratic rainfall, and higher temperatures (Nhemachena et al., 2020). Although extremely vulnerable to climate change, agriculture remains a key industry for economic stability considering that it employs more than 60% of the population and contributes significantly to GDP. However, efforts aimed at mitigating the impacts of climate change, including conservation agriculture and the cultivation of drought-resistant crops, have not entirely alleviated the adverse effects on agricultural output and food inflation (Mabhaudhi et al., 2019). Cereal production in the region is projected to decline by almost 50% by 2080, consequently intensifying food insecurity (Yerlikaya et al., 2020).

In Southern Africa, increasing temperatures and decreasing precipitation have resulted in diminished agricultural productivity, contributing to heightened volatility in food prices. For instance, in South Africa, the drought of 2015-2016 resulted in a 45% reduction in maize production, contributing to a food inflation rate of 12% by December 2016 (StatsSA, 2018). In 2022, Zimbabwe saw a 45% decrease in maize yields, while food inflation rose to 55.3% in March 2024 (Zimstat, 2024). In February 2024, maize prices in Mozambique increased by 12%, surpassing the five-year average by 20% (FAO, 2024). Meanwhile, Botswana experienced a peak in food inflation at 14.6% in 2023, which subsequently declined to 1.2% in 2024 as a result of decreasing global cereal prices (StatsBots, 2024). In Lesotho, ongoing crop failures compelled 41% of rural households to allocate more than half of their income to food (Sekaran et al., 2021). In Malawi, maize prices increased by 160% relative to the five-year average, resulting in a 32.3% inflation rate in April 2024 (IPC, 2024). The 2019 drought in Namibia caused a 2% increase in the price of food, which increased to 6% in 2021 when there was a global increase in gas prices (Liu & Zhou, 2021; Shikangalah, 2020). The inability to regulate agricultural productivity has dire economic repercussions as inflationary pressures in the agricultural sector accelerate poverty and cause macroeconomic uncertainty. Current climate adaptation and food security policies have been unable to effectively to address these concerns, rendering numerous countries susceptible to external shocks including global food price swings and catastrophic weather events (England et al., 2018).

This may be evidenced by the South African National Climate Change Adaptation Strategy (NCCAS), which presents a general structure for climate change adaptation across sectors, including agriculture. Its operation is greatly disabled by the lack of adequate enforcement measures and insufficiency of budgetary allocation (Khavhagali et al., 2024). Critics point out that despite a well-defined plan, it fails to convert objectives into concrete action, especially at local levels, where farm firms are particularly exposed (Matikinca et al., 2024). This current study explores the relationship between climate change and its impact on agricultural production and food inflation in Southern Africa, based on a panel ARDL econometric model.

1.3. Research questions

Understanding the impact of climate change on agricultural production and food inflation in Southern Africa is imperative. More specifically, this study seeks to address the following questions:

- How do climate change risk indicators impact agricultural output in Southern Africa?
- How does climate change impact food inflation in Southern Africa?
- What is the impact of climate change on the relationship between agricultural production and food inflation in this region?

1.4. Research objectives

1.4.1. Primary objective

The main objective of this study is to analyze the impact of climate change on agricultural production and food inflation in Southern Africa over the period of 1981 to 2020.

1.4.2. Secondary objectives

Theoretical objectives

In line with this study, the following theoretical objectives are formulated:

- To review and discuss the theories on agricultural production, food inflation and climate change.
- To conduct a literature review on the empirical studies that analyzed the relationship between agricultural production and food inflation.

1.4.3. Empirical objectives

In line with the research questions of the study, the following empirical objectives are formulated:

- To assess the impact of climate change on agricultural production in Southern Africa.
- To evaluate the impact of climate change on food inflation in Southern Africa.
- To analyze the relationship between agricultural production and food inflation in Southern Africa.

1.5. Hypothesis of the study

The study hypothesizes the following three sets of hypotheses:

Hypothesis 1

H_0: Climate change and related variables do not exhibit any significant relationship with agricultural output.

H_1: Climate change and related variables exhibit a significant relationship with agricultural output.

Hypothesis 2

H_0: Climate change and related variables do not exhibit any significant relationship with food inflation.

H_1: Climate change and related variables exhibit a significant relationship with food inflation.

Hypothesis 3

H_0: Agricultural output and food inflation do not exhibit any significant relationship.

H_1: Agricultural output and food inflation exhibit a significant relationship.

1.6. Significance of the study

Instead of addressing local adaptation measures, most studies dealing with the probable effects of climate change on world food supplies, including that by Fischer et al. (1994), tend to focus on the inherent vulnerabilities of agricultural systems. Moreover, most of the studies that are presently published focus on the bio-physical impacts of climate change, such as changes in temperature and precipitation, while mainly neglecting the socio-economic impacts, such as inflation of food items and availability of food at the household level. More holistic methods that consider both the biophysical and the socioeconomic aspects are required, as suggested by Mendelsohn et al. (2000). The cross-sectional analysis and simulation models commonly applied in previous studies do not precisely capture the dynamic and complex nature of the effects.

This research project will therefore inform on practical and region-specific initiatives that may offset the adverse effects of climate change on agriculture through research into local adaptation techniques and their efficacies. This study, therefore, tries to address the above-mentioned methodological deficiencies by integrating empirical data with econometric modeling tools for a comprehensive understanding of implications.

The present study will therefore help in informed decision-making by farmers and the government on how variable climatic conditions impact yields and water availability for crops, livestock management, and its related practices to enhance resilience and sustainability in agriculture. Food price variability may affect food accessibility and enhance poverty, affecting general economic stability and social wellbeing through inflation rates. This research therefore contributes further to the proactive measures that countries within Southern Africa and the respective central banks may wish to take in mitigating climate change-related impacts on agricultural output and eventually food inflation.

1.7. Methodology

To investigate the impact of climate change on agricultural production and food inflation Southern Africa, the study's empirical analysis employs quantitative secondary data that was obtained from FAOSTAT, NASA POWER, and WDI database. The study makes use of panel data spanning from 1981 to 2020. The first regressand of this study is agricultural production while regressors encompass the following agricultural aspects, livestock, land, labor, machinery, total fertilizer consumption and temperature and rainfall. The second dependent variable for this study is food inflation while independent variables include crop production, food exports, agricultural raw material imports, total fertilizer consumption, rainfall and temperature. Several diagnostic tests were carried out including the normality test and cross section dependence test in order to evaluate the model's validity.

The Panel ARDL cointegration approach is used in this study after considering the results of the panel unit root test. EViews 12 was further employed to conduct the previously suggested econometric analysis. Chapter 4 offers a further explanation on the methodology employed to ascertain the correlation between the variables.

1.8. Ethical Consideration

The current study employs secondary data derived from the FAOSTAT, NASA POWER, and WDI data sources. The obtained data involves yearly quantitative data pertaining the selected climate change, agricultural production and food inflation variables. The aforementioned database renders the data utilized in the study to be publicly available, and it believed that these data sources follow and comply with the fundamental principles of ethical use when gathering and disseminating data. The study acknowledges the data source and additional information sources presented in the study.

1.9.Outline of the study

The study encompasses the following chapters:

Chapter 1: Introduction and background of the study

This chapter covers the introductory framework and contextual background of the research, as well as stating the research problem statement together with the related objectives. It further highlights the hypothesis of the study. Finally, it explains the significance of the study, its methodology, ethical considerations, and gives an outline of the structure of the study.

Chapter 2: Dynamics of climate change in Southern Africa

This chapter explores the intricate relationship between climate change, extreme weather events and the socio-economic landscape of Southern Africa. Furthermore, it discusses the historical and projected trends of climate change and the potential effects these have on various sectors, including agriculture, water resources, and food prices in the selected countries.

Chapter 3: Literature Review

This chapter gives a detailed discussion of the literature. The literature review covers inflation theories, including the Keynesian theory of inflation through the lens of cost-push inflation. The chapter further employs a conceptual approach to theoretically examine the impact of climate change on agricultural output. Conclusively, this chapter discusses the empirical literature by drawing references from previous studies.

Chapter 4: Methodology

This chapter provides the methodology, including a brief review of data sources, specification of the model, and variable description. The chapter further addresses the various tests utilised in the study, including the diagnostic tests, unit root test, cointegration test, and Panel ARDL model.

Chapter 5: Results and discussion

Chapter 5 of this study presents the findings from the tests performed on EViews 12 software. The chapter also includes a detailed explanation of the results to provide valuable knowledge on the correlation between the variables in the Southern African context.

Chapter 6: Conclusion and Recommendation

This final chapter concludes the assessment of the impact of climate change on agricultural production and food inflation by summarising the study's findings. It further provides research recommendations and prospects for future studies.

CHAPTER 2: THE DYNAMICS OF CLIMATE CHANGE IN SOUTHERN AFRICA

2.1. Introduction

The Southern Africa region has been highlighted as a climate change hotspot, that is, a place where climate change impacts are unusually high within a global context. These changes in climate are largely driven by human activities, especially the global burning of fossil fuels and the conversion of natural vegetation into croplands, pastures, and human settlements. Thus, the current chapter is an attempt at analyzing socioeconomic vulnerability in light of climate change concerning South Africa, Zimbabwe, Zambia, Mozambique, Botswana, Lesotho, Malawi, and Namibia; for example, emphasizing potential impacts sector-by-sector with further discussions on historical trending's and possible future scenarios.

2.2. The case of South Africa

The country is situated in an area that is termed a 'drought belt' and is the fifth utmost water scarce nation across Sub-Saharan Africa. South Africa is extremely sensitive to climatic variability and change considering its strong dependency on rain-fed agriculture and natural resources, widespread levels of poverty, and a limited adaptive capacity (Shikwamba et al., 2023).

2.2.1. Implications of climate change on the main sectors

Hydrology sector

Due to its geology, South Africa has always received irregular precipitation, thus experiencing the uneven distribution of river and groundwater resources. The country has a high level of scarcity brought about by low and variable rainfall, high evaporation rates, and increasing demands from agriculture, industry, and urban areas (Mabhaudhi et al., 2021). Decreasing rainfall and higher evaporation rates, exacerbated by rising temperatures, are expected to reduce soil moisture, leading to diminished river runoff and groundwater recharge (Nkosi et al., 2021). In semi-arid areas such as South Africa if the rainfall decreases, for example by 1 litre (1 millimeter per square meter in a year), the amount of water available as a usable resource decrease by about 3 litres (Scholes and Engelbrecht, 2021). This non-linear response means even slight drops in that ratio might switch perennial rivers into the intermittent category. Make no mistake, the majority of South Africa's freshwater resources, especially in areas that may be barely adequate to begin with, are very vulnerable to climate change, and under future climate change projections, this could get worse under an even (further) warming world, but only if those impacts are not curtailed through aggressive mitigation (Mabhaudhi et al., 2021).

However, the problem goes beyond scarcity to include deteriorating water quality. At the moment, 40% of freshwater systems are in a critical state, while 80% have been degraded due to increased pollution levels (Du Plessis, 2017). The country is experiencing water shortage problems, with 98% of the available water already being allocated. Such that it is unable to meet rising demand for water-based power generation and agricultural production, the catalysts for employment and economic well-being (Seetal., 2021). Vulnerable agricultural communities are also stressed by climate variability and changing precipitation patterns. Hence, adaptation strategies must consider these dynamics to ensure agricultural productivity supported primarily by irrigation-based agriculture of vegetables, fruits, and wine. Only 1.5% of land is irrigated in the country, but it contributes to 30% of all the crops, proving the importance of irrigation in the South African sector (Christian et al., 2018).

Agricultural sector

According to Kwame et al. (2022), the agriculture sector in South Africa is one of the key sectors in the overall economy where over 860 000 workers have direct employment in the sector thereby contributing to the country`s food security. Agro-industrial commodity chains for wheat, sugar cane and rice make up a consumption of approximately 94% in the country while maize is the largest crop in this sector (Muroyiwa and Mushunje, 2017). Climate change's effects on agriculture cannot continue to be disregarded, as agricultural productivity depends greatly on the accessible supply of water. Furthermore, dry-land farmers who rely on rain-fed crops for their sustenance are extremely susceptible (Boonwichai et al., 2018). Climate change continues to adversely affect agriculture with severe reduction in crop yield contributing to increasing food insecurity worldwide (Olabanji et al., 2020). The reason is that most agricultural crops considered important for ensuring food security maize, wheat and rice, for example, have relatively high consumptive-use intensity in their production. For instance, the estimated amount of water necessary to produce one kilogram of all three of these crops is $1.5m^3$, $1.0m^3$, and $2.5m^3$, respectively (Thomas et al., 2022).

As a result, regions with low supply of water brought about by the impact of climatic changes suffer severe reductions in crop yields, jeopardizing long-term security of food. Agriculture accounts for only about 4% of the country's GDP (Nhemachena et al., 2020). However, regardless of this relatively insignificant contribution to the economy of the country, the agricultural sector contributes to almost 10% of the overall labor force in the country, and around one-third of the country's total produce of crops is exported with significant returns on investment (Olabanji et al., 2020).

In addition, climate change has currently more than tripled the risks of long-term droughts in the winter's low precipitation zone, a risk which will continue to escalate with increased global warming. For example, South Africa suffered one of the most severe multiyear droughts during 2015 to 2017, during which a Cape Town disastrous weather-related drought extended to agriculture, hydrological and socio-economic impacts (Naik and Abiodun, 2024). During this protracted drought period, the storage of water levels in the main reservoirs of the Western Cape decreased roughly 23% while the remaining 12% of the water from dams was not usable (Botai et al., 2017). The province became known as a catastrophic area, and the crisis led the local government to enforce strict controls of water on agricultural and industrial users while scrambling to find a way to prevent the taps from running totally dry. The drought has significantly affected agriculture, livelihoods and communities Naik and Abiodun (2024).

For example, the agricultural industry experienced losses of around R5.9 billion and a loss of at least 30 000 jobs (Oluwatayo and Braide, 2022). On the other hand, the projected decrease in rainfall in the Western Cape by 2050 could be about 30% compared to the level recorded in 2019, hence showing possible shifts in climate pattern (Steyn et al., 2019). Such rainfall declines could have a major effect on agriculture by affecting surface water budgets and dam levels (Naik and Abiodun, 2020). Therefore, drought and climate change may have major effects on long-term availability of water and agricultural productivity, in addition to increasing temperatures and evaporation.

2.2.2. Implications of climate change on the food inflation

Climate change and dire weather events are intensifying and disrupting South Africa's fragile food system (Johnston et al., 2024). The cascading effects of droughts, storms, flooding, rising sea levels and increased pests and disease all impact the country's ability to produce food, leading to food insecurity and increased food prices. South Africa is recuperating from one of its most severe droughts in the past decade (Baudoin et al., 2017). The period between 2015 to 2016 was disastrous, with 2015 being the most drought-prone year in history since rainfall measurements commenced in 1904 (StatsSA, 2018).

These weather conditions have immediately affected the food supply and prices in South Africa. According to the World Bank (2022), it is estimated that since 1961, climate change has prompted a 21% decrease in worldwide productivity of agriculture. General food price inflation during the 2015 and 2016 droughts jumped by more than 15%, as reported by Adam and Paice, (2017). According to data from South African Grain Information Service (SAGIS), commercial maize production in particular fell by 45% in 2015 to 2016 compared to previous years, as a result South Africa had to import significant volumes of maize to balance the supply with demand (StatsSA, 2018). The decrease in agriculture production contributed to the rise in food inflation in 2016, which reached a peak of 12% in December of that year (StatsSA, 2018). Throughout 2016, sugar prices rose by 34% and vegetable oil prices increased by 11.4% (FAO, 2017). The resulting food supply shocks have ever since driven double digit inflation in South Africa for essentials, such as grains, cereals, vegetables and cooking oils (StatsSA, 2022).

Further supply restrictions and increased input costs resulted in global food prices reaching an all-time high in 2022, stretching back to January 2009. South Africa's total inflation rate in October 2022 was 7.6%, while food inflation stood well above that, with food price increases of 12% from the previous year (SARB, 2022). Rising food prices, which are required expenditures, increase poverty and deprivation, food insecurity, and the economy (Mbajiorgu and Odeku, 2023). This disproportionately affects the low-income household, which spends a greater proportion of their income on food. In 2023, the annual average of food price inflation was 11%, slightly higher than 9.5% recorded in 2022; this stood at 6.5% in 2021 and 4.8% in 2020 (StatsSA, 2024).

Furthermore, wholesale prices of white maize grain have increased by 3.3% compared to May 2024 and a 38.7% increase compared to June 2023 (FAO, 2024). The prices in South Africa heavily influence prices in the import dependent countries of Botswana, Lesotho, Namibia and Eswatini. These inflationary pressures can be largely attributed to gradual climate-related impacts experienced in previous years. Therefore, climate change contributes to the country's weak food system and makes it more vulnerable to price shocks as it negatively impacts significant crops that make up nearly half of the world's food supply (Masipa, 2017).

2.2.3. Future Climate Projections

Increased rainfall variability and long-duration droughts

Higher rainfall irregularity along with increased temperatures are currently predicted to have severe consequences on South African agricultural output (Botai et al., 2016). For example, a study by Theron et al. (2020), forecast a decrease in precipitation in the Western Cape area, which would result in a decrease in water readily accessible to agriculture, with associated socioeconomic consequences for farmers in this area. This, therefore, means that the projected 1.2 °C in 2020, 2.4 °C in 2050, and 4.2 °C by the year 2080 rise in temperature and a projected decline in rainfall of about 5 to 10% over the next 50 years consequently poses a high risk to South Africa's availability of food and socio-economic stability (Olabanji et al., 2020).With global warming reaching 1.5°C or more, the more frequent high-pressure systems which reduce summer rainfall will also increase multi-year droughts in the summer rainfall zone (Engelbrecht et al., 2024). As global warming continues, regional droughts will be more frequent, longer in duration, and more intense, which presents a serious risk to agriculture and water delivery systems. Considering the socioeconomic significance of agriculture and food security, there is a pressing need to develop and continually assess viable adaptation strategies to manage climate change effectively (Kwame et al., 2022).

Decrease in yield and viability of most major agricultural products

Most of the major agricultural products are thus expected to show a steep decline in yield and viability. Each crop has optimum temperature at different stages of development. The daytime mean temperature for most crops' ranges between 27°C and 30°C. Cereals, for example, experience almost complete failure of pollination at temperatures above 40°C during the day and above 30°C at night, with 50% success reduction when daytime temperatures are above 36°C and nighttime temperatures are above 26°C (Scholes and Engelbrecht, 2021).

Furthermore, for crops to successfully complete their life cycles, the soil must be sufficiently moist for a minimum amount of time. In South Africa, crop yields tend to increase linearly with soil moisture duration during the growing season, within their tolerance ranges (Thornton and Herrero, 2015). However, the country is already too dry for optimal crop production over most of its extent. In the majority of areas, further dryness will result in lower crop yields. Reduced water resources and competition from other industries limit the potential to make up for this through improved irrigation. Additionally, the viability of the livestock is compromised under rising temperatures. Overall, agriculture in South Africa, including downstream value addition, is already under climate stress, which will intensify with global warming. Throughout South Africa's interior, temperatures are rising rapidly than expected, and drier soils are becoming more prevalent. In 2019, approximately 11% of South African's population was classified as food insecure (Ziga, and Karriem, 2022). The risk of food insecurity, and the challenge to national food sovereignty, will increase in South Africa with a global temperature rise of 1.5°C, and even more so with further warming (Satgar and Cherry, 2021).

2.3. The case of Zimbabwe

Zimbabwe, a landlocked country in Southern Africa, shares borders with Zambia, Mozambique, Botswana, and South Africa. The subsequent sections cover Zimbabwe's economic susceptibility to climate change, the effect of climate change on agriculture and food price increases, and ultimately the expected climate projections for 2050.

2.3.1. Socioeconomic vulnerability to climate change

Between 1980 and 1990, Zimbabwe experienced rapid economic growth; the average growth of the GDP is 5.5% with a high record compared to the average in Sub-Saharan Africa (Ncube, 2019). However, the quality of economic stability worsened between 2000 and 2008 due to governance issues, economic mismanagement, and decreased international support (Moyo and Tsakata, 2017). The introduction of Zimbabwe's Fast Track Land Reform Programme in 2000, which was set to redistribute commercial farms to the landless indigenous populations for historical land inequalities and promoting family farmers, further disrupted commercial agricultural production and led to an economic decline. According to Mkodzongi and Lawrence (2019), this program undermined investor confidence, and foreign direct investment was therefore reduced in Zimbabwe's agriculture. Uncertainty over property rights and land tenure further discouraged both local and international investors from investing in agricultural infrastructure and technology. As shown by Moyo and Tsakata (2017), such a decline in agricultural productivity was coupled with reduced export earnings from agriculture, adding to broader economic instability.

The GDP growth rate fell for Zimbabwe, and it negatively impacted the levels of poverty while increasing dependence on exploiting natural resources for survival. According to Matandare (2017), this was the period between 2000 to 2008, which also corresponded with environmental issues of rising temperatures, erratic rainfall, and frequent droughts. It most affected rural areas, as 62% of the population is located there, and agriculture comprises 15 to 18% of Zimbabwe's GDP while accounting for 60% of inputs and 40% of export earnings.

The heavy reliance on agriculture that is dependent on rainfall, along with high poverty levels, low human and physical capital, and inadequate infrastructure, contributes to the country's high vulnerability to climate change. Not having enough irrigation infrastructure that would dampen the consequences of droughts further worsens the effects on agriculture. The negative consequences of climate change have led to a decline in export earnings, a factor that has negatively contributed to GDP and increased unemployment rates. In the last twenty years, these effects have called for the need for climate change adaptation strategies as a sure way of securing economic stability (Mkodzongi and Lawrence, 2019).

2.3.2. Impact of climate change on the agricultural sector

Zimbabwe's agricultural production is diverse in comparison to numerous other tropical countries. Sugar, cotton, maize, tobacco and sugar dominate crop production, with groundnuts, wheat, sorghum, coffee, citrus, tea, and vegetables providing substantially less monetary contributions.

The economy and livelihoods of Zimbabwe's poor are especially vulnerable to climate change due to their reliance on rain-fed agriculture. In this country, variation in rainfall is directly related to economic growth, reflecting the agricultural sector's dominance and vulnerability to water stress. Drought poses a significant problem to agriculture, impacting both cattle and crops. In 2015, agricultural output declined by 5%, and in 2016, by a further 3.6% (World Bank, 2017). Both years were characterized by drought conditions, which peaked in the 2015-2016 El Nino-induced drought that caused 2.8 million individuals in the country to suffer from food insecurity (Matunhu et al., 2022). Pests and diseases affecting crops and livestock pose a big challenge, especially given the likelihood that climate change would shift their distribution and prevalence.

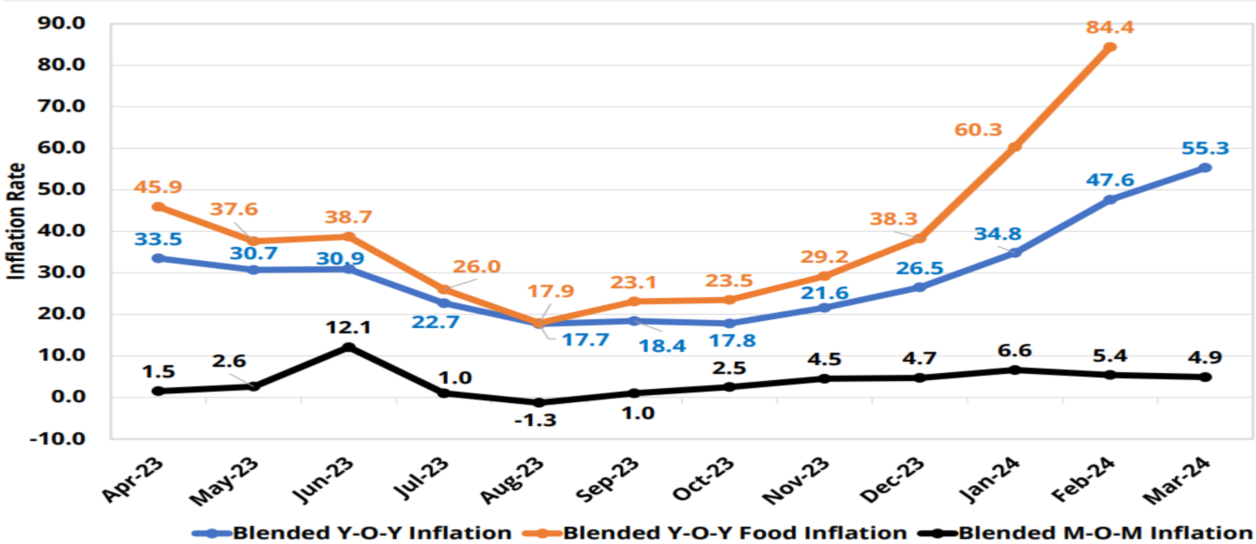
For instance, the fall armyworm emerged in 2016, a pest that had not been previously identified in the country and has the potential to result in maize crop losses of up to 70% if not effectively managed (Tambo et al., 2021).Therefore, climate change in semi-arid areas presents significant concerns to natural processes that promote food supply for cattle and moisture for rain-reliant crop cultivation (Descheemaeker et al., 2018). In particular, change in climate is predicted to result in the growth of marginal lands, which is currently occurring in Zimbabwe.

2.3.3. Food inflation dynamics as a result of climate change

Zimbabwe, located in the region's sensitive agricultural belt, has repeatedly encountered negative effects of El Niño from 1982 to current times (Mugiyo et al., 2023). Historically, El Niño events in Zimbabwe have been linked to disruptions of climatic patterns, including rainfall, resulting in both localized and widespread impacts on livelihoods and ecosystems. El Niño is climatic phenomena characterized by rising temperatures of the sea surface in the central and eastern equatorial parts of the Pacific Ocean (Mugiyo et al., 2023).

In the year 2022, the country was experiencing a protracted drought; this was the driest year in this region in 40 years. With maize yields 45% lower than in 2021, as a result an estimated 2.9 million people faced extreme food insecurity from January to March of 2022 (Mugiyo et al., 2023). Due to the continuous decrease in maize yields of the previous years, Zimbabwe is grappling with high inflation driven by food prices. The annual inflation rate in Zimbabwe continued to rise in March 2024, hitting an over one-year high of 55.3%, up from 47.6% in February, amid the sharp depreciation of the local currency (Zimstat, 2024). On a monthly basis, consumer prices rose by 4.9% in March, following a 5.4% surge in the previous month (Zimstat, 2024). In Zimbabwe, annual food inflation has trended upward since August 2023, Zimbabwe's annual blended inflation rate rose from 55.3% in March to 57.5% in April 2024 as illustrated in figure 2.1 (Zimstat, 2024).

Figure 2.1: Blended Inflation Rates



Source: ZimStats (2024)

Consumer prices were 2.9% higher month on month compared to 4.9% during the previous month. The continued increase in inflation is exerting pressure on all commodity prices and eroding household purchasing power across the country (Zimstat, 2024). Poor crop production has resulted in an atypically poor market supply of grains in the drought-affected areas of Zimbabwe. In Zimbabwe, staple grain prices are now higher than those recorded during the peak lean season in February and March 2024, and the alternative maize meal prices in July were 20% to 25% higher than normal (FAO, 2024). The lack of rain induced by the El Nino global weather pattern has also affected electricity production, as Zimbabwe relies on hydroelectric power (Dube and Nhamo, 2023).

2.3.4. Projected climate changes by 2050

Increase in temperature

Compared to historical average of 24.8 to 25.5°C, temperatures are projected to increase by at least 1.8°C in 2050, with increases of 2 to 2.7°C in the hottest months of October to December (Duube, 2023). A similar rise of 1.8 to 2.2°C is expected for all other months, including the cooler winter and high summer months (Tesfaye et al., 2015). Added to this, the forecast decrease in precipitation is likely to have a complex effect on Zimbabwe's agricultural sector. High-temperature increases, particularly for October to December reaching about 2 to 2.7°C, will increase crop water requirements and evapotranspiration losses from the soils of farming areas, concurrent with low rainfalls within these months (Hunter et al, 2020).

The combination exacerbates the risk of crop failure in crops such as maize, tomatoes, and peppers that are highly sensitive to climate stress during the establishment phase. In addition, increased average temperatures will likely include an increase in frequency or intensity of heat waves and unusually hot days, which further enhances the loss through evapotranspiration of water and crop stress. A combination of decreased rainfall and increasing temperature has a greater likelihood of reducing agricultural productivity, partly through decreased yield or outright crop failure, especially of those heat- and drought-sensitive agricultural produce, including wheat and maize (Hunter et al., 2020).

Reduction in rainfall

A consistent prediction for all ten provinces in Zimbabwe is a reduction in both mean monthly and total yearly rainfall from the baseline to 2050. Specifically, rainfall at the commencement of the rainy season in October and November is expected to decrease significantly, from 24.4 to 10.6mm per month and from 73.9 to 54mm per month, respectively, resulting in total reductions of 14mm and 20mm per season (Panagos et al., 2022). Further declines are expected in the peak of the rainy season between December and March, with monthly rainfall decreasing by 10 to 12mm per month (Panagos et al., 2022). These declines over the course of the rainy season will serve to lower the overall seasonal rainfall between October and March by 14%, from 572 to 494mm per season (Hunter et al, 2020).

An additional effect of these changes is the likely variation in the timing of rainfall onset at the start of the growing season, which will differ between provinces and agroecological zones. This could lead to insufficient precipitation necessary for successful cultivation during the traditional commencement of the growing season in some areas. As a result, changes in the climate could impede the expected start of rainfall in comparison to the traditional agricultural timeline. shifting the onset of key activities like field preparation and sowing. In general, the overall reduction in monthly rainfall and the probable delay in the onset of rainfall are expected to result in major shifts in local crop choices and agricultural practices, hence requiring far-reaching adjustments in farming strategies to suit the changing climatic conditions by 2050 (Mpala and Simatele, 2024).

2.4. The case of Zambia

2.4.1. Overview of the economy and agriculture in Zambia

Climate change in Zambia has presented itself in the form of a greater degree of extreme weather occurrences that seriously affect crop yields, particularly maize, which is the staple food for most Zambians. In excess of 98% of the smallholder households cultivate maize, occupying more than 54% of agricultural land (Phiri et al., 2020). The traditional schedule of farming is altered by this unpredictability of extreme weather conditions, thus resulting in poor harvests and low agricultural productivity. In addition to food security being at risk, this further lowers the standards of living for farmers, who constitute 65% of the labor force (Ngoma et al., 2021). Effects spiral across the economy, since a reduced agricultural output translates to higher food prices, increased poverty, and increasing vulnerability to other exogenous economic shocks. More than 57.5% of the population, as of 2015, lived below the poverty threshold, and the average unemployment rate from 2015 to 2018 was approximately 7.31% (Phiri et al., 2020). The inflation rates were 10.11% in 2015, 17.87% in 2016, 6.58% in 2017, and 7.49% in 2018, driven by currency depreciation, increased electricity tariffs, and lower food commodity supplies (Kamuhuza and Jianya, 2022).

Moreover, climate change exacerbates fiscal challenges in Zambia. Because of this, the government is forced to divert resources to address climate-related damages and support affected communities-straining already overburdened public finances with high debt levels. The debt-to-GDP ratio increased from 25% in 2012 to 61% in 2016, showing the fiscal pressure on the country (Tembo et al., 2020). This, in essence, reduces the government's scope to invest in other important sectors such as health, education, and building infrastructure. This therefore hampers the wheel of economic growth and development in the long run. Further consequences of climate change in the country include the dependence for a great part of its energy supply on hydropower which makes the economy of Zambia vulnerable to climatic occurrences such as droughts (Borowski, 2022). Reduced rainfall has led to energy deficits, decreasing productivity in the manufacturing industry by 60 to 70%, which accounted for an average of 7% of GDP from 2010 to 2017, thus introducing significant uncertainty to Zambia's overall economic growth (Tembo et al., 2020).

In Zambia, there exist policies, for instance, the National Agriculture Policy under the Ministry of Agriculture, formulated with an intention to foster development within the agricultural sector. This provides guidelines for agricultural development, utilization of sustainable resources, irrigation promotion, production of crops, agro-processing, livestock, and fishery development. Besides that, institutional and legislative frameworks are dealt with, cooperatives supported, and climate change issues addressed as stated by Bwalya and Deka, 2016. Despite of this policy, among others, the agricultural sector still suffers from low irrigation, low mechanization at smallholder level, low private sector participation, and low access to finance and credit. There is also a decline in investment in agricultural research, unsustainable natural resource utilization, and low resilience to climate change effects.

2.4.2. Implications of climate change on crop production in Zambia

The agricultural industry remains vital in Zambia, accounting for approximately 6% of national GDP (World Bank, 2019). The industry further generates approximately 22.3% of employment creation within the country, with 4.3% in the formal sector and 18% in the informal sector (Zamstats, 2019). The sector mainly comprises smallholder farmers, who mostly produce maize and rain dependent crops (Juliet et al., 2016). This production strategy has rendered the country, and especially rural smallholders, more prone to climate fluctuations and variations. Crop production is the main objective of small and medium-scale agriculture for two reasons: sustenance and earnings from marketed output (Ngoma et al., 2021). Climatic changes and variations have contributed to crop and livelihood losses, increasing food insecurity, and a decrease in agriculture's contribution to the country's GDP (Alfani et al., 2019). Rainfall is projected to get more unpredictable, and rainfall patterns are likely to fluctuate, rendering Zambian agriculture more susceptible to climate shocks. This is exacerbated by the fact that more than 90% of the crop grown by smallholders is reliant on rainfall (Ngoma et al., 2021).

Since the 1990s, extreme climate events have had a significant influence on crop output in the country; droughts are the most common climate shock that rural small-scale farmers in Zambia encounter, with 76% of small-scale farmers identified as prone to vulnerability. According to Alfani et al. (2019), households impacted by the El Niño drought from 2015 to 2016 endured a 20% decline in maize output and up to a 37% decrease in earnings, all other things being equal. Other repercussions include considerable fluctuations in maize and maize meal prices as a result of shortages in supply accompanied by poor irrigation; in certain years, maize yields have been barely 40% of the long-term average (Mulenga et al., 2019). Long dry spells within a season, as well as shorter rainfall seasons, have contributed significantly to the country's low yield over the last two decades. These factors impede progress towards food security and hunger eradication. Currently, cereals account for approximately 63% of Zambia's energy requirements, however cereals such as maize, the main grain, are prone to climate change (Mulenga et al., 2019).

However, since sorghum is a drought-tolerant crop, it is being promoted particularly in drought-prone areas to increase food security in places with frequent short rain periods. Climate change has posed a threat to sustainable agricultural practices, food security, and the country's GDP, necessitating a better understanding of the magnitudes of climate change's impacts on agriculture in order to support national adaptation strategy (von Grebmer et al., 2019).

2.4.3. Implications of climate change on food inflation in Zambia

In the past decade, Zambia experienced high inflationary episodes increasing from 7.9% in December 2014 to 21.1% in December 2015 prior to decreasing to 6.6% in 2017 (Chipili, 2022). The resumption of high inflationary pressures in this country in 2015 was caused by the steep increase in domestic fuel pump prices and the decreased availability of agricultural produce caused by drought, primarily maize, which is the primary staple (Chemura et al., 2022). High inflation was linked to the drought years of 1995, 1998, 2001, 2003, 2005, 2013, 2015, 2016, and 2018 (Chipili, 2022). Considering that agricultural production depends on rainfall, while food makes up a significant portion of the CPI basket, climate change had a huge impact on inflation (Tembo et al., 2020), consequently highlighting the impact of supply shocks on inflation

The country experienced a severe drought that started in mid-January 2024, affecting close to half of Zambia's population (Ngoma et al., 2024). In the country, a continued dry spell damaged about 43% of the planted grain, leading to a complete crop failure (Ngoma et al., 2024). This has raised the prices of food in all provinces in Zambia and reduced the level of access to affordable foodstuffs, hence aggravating food insecurity for millions of people across the country (World Bank, 2024). Besides, inflation reached 13.70% in April 2024, while the annual inflation rate in Zambia increased to 15.5% in August 2024, reaching its peak level since December 2021, from 15.4% in the previous month (Zamstats, 2024).This is primarily due to the increase in inflation caused by El Niño drought, which has resulted in increased food prices from 17.4% to 17.6% (Funyina et al., 2024).The horrific drought has resulted in poor crop yields, reduced hydropower, and increased import costs. In Zambia, annual food inflation in June 2024 was 16.8 percent, up from 16.2 percent the previous month, and is projected to increase further (Zamstats, 2024).

2.4.4. Projected Climate Trends

Severe impacts on the economy

According to Tembo et al. (2020), it is estimated that by 2045 to 2050, climate change could cause Zambia's GDP to decline by approximately 6%. It is further expected that the effect will increase gradually over time (Ngoma et al., 2021). A study by Arndt et al. (2019), projects that if worldwide carbon emissions are not regulated, Zambia's average level of GDP between 2046 and 2050 is most probable to be between -3% and -1%. According to a 2019 report published by the United Nations Office for Disaster Risk Reduction (UNDRR) and the Centre for International Media Assistance (CIMA), droughts have the potential to more than quadruple the impact on GDP in a high-emission scenario. The assessment takes into account the yearly average of possible GDP affected from 2016, with reduced production of hydropower playing an integral part in these losses.

Increase in temperature across Zambia

According to Hamududu and Ngoma (2019), temperatures will rise by 1.9°C and 2.3°C by 2050 and 2100, respectively, under a high emissions scenario. Similarly, a study conducted by Ngoma et al. (2021), predicts that temperatures will be roughly 1.8°C higher on average by 2046 to 2050 if global GHG emissions are not limited; the study also indicates that temperature rise in Zambia might reach 3.6°C. According to the study's estimate, increases in temperature from all Zambian areas will most certainly exceed the commonly used 1.5°C threshold. Another study by Mulungu et al. (2021), predicts that the average annual temperature will rise by 1.2 to 3.4°C in 2060, with warming occurring at a faster rate in the south and west. Based on the analysis, the regularity of warmer days and nights is expected to significantly increase. Similarly, a report by SADRI (2021), projects that hot days will increase by 15 to 29% by 2060, while warm nights will rise by 26 to 54% in the same period.

Decrease in rainfall in the Southern and Western regions

According to Hamududu and Ngoma (2019), rainfall will decline by roughly 3% by mid-century and by down to 0.6% by the end of the century across the country. However, the study finds significant geographic disparities, with the southern, eastern, and western regions predicted to be far severely impacted compared to the north. Ngoma et al. (2021), similarly forecast significant decrease in precipitation in the southern and western regions, averaging 3% to 4%. However, in the worst-case scenario, these regions might encounter a 20 to 30% decrease in rainfall, making them extremely susceptible to climate change.

2.5. The case of Mozambique

Situated along the Indian Ocean in southeast Africa, Mozambique is extremely sensitive to the changing climate and is shares borders South Africa, Malawi, Tanzania, Zambia, Eswatini, Zimbabwe.

2.5.1. Broader Key Macroeconomic Impacts and Vulnerabilities

Effects of climate change on food inflation and its implications for food security

Despite being a net importer of food, Mozambique's primary exports include sugar, tobacco, soybeans, legumes, seeds, and nuts, while its primary imports are wheat, palm oil, rice, sugar, and maize (FAO, 2021). Inflation reached a five-year high of 9.8% in 2022 and moderated to 7.1% in 2023 as global commodity prices subsided (World Bank, 2024). A study by Odongo et al. (2022), revealed that temperature fluctuations and rainfall greatly raise the country's food and total inflation rates. The results also showed that temperature fluctuations have an impact on Mozambique's ability to produce energy, which impacts the cost of food and other commodities in the consumer basket. According to a study by Baez et al. (2020), food markets near regions impacted by adverse weather conditions show more fluctuation in the price of maize in particular, which may additionally heighten the risks to food security for those in need in Mozambique.

A study conducted by Odongo et al. (2022), observed that in Mozambique, there is a significant spillover of foreign inflation by means of imported prices into domestic prices. Severe weather conditions having regional effects will exacerbate food inflation and, consequently, food security challenges as the country depends on the regional market for some of its essential food imports, including wheat. Given that climate change is also predicted to have a detrimental impact on maize output in the majority of neighboring countries, including Zambia and Malawi, Mozambique's lower maize yields may increase the country's dependency on imports, which are projected to become increasingly costly (Thomas et al., 2022). Overall, food inflation is expected to affect Mozambique's already susceptible population, as over 60% of the country's population suffers from abject poverty (World Bank, 2023). According to a study by Amosi and Anyah (2024), the impact of climate change on the recent agricultural season due to the recent Tropical Storm Filipo which led to strong winds, heavy rainfall, along with flooding and other cumulative effects of multiple and recurrent shocks over recent years due to Tropical Cyclone Freddy in the previous year have dire consequences of increased food insecurity. These climate change-related shocks have destroyed 31,000 hectares of various crops, food stocks and sources of income for numerous households (USAID, 2024). In February 2024, the average price of maize grain rose by 12%, this is usually the case during this time of the year (FAO, 2024). In February, the average price of maize grain increased by 20% from the previous five-year average and 24% from the previous year (FAO, 2024). The accumulated negative effects of challenges over the last five years constitute the root cause of this year's high costs. The prices of rice and maize meal remained generally stable between January and February. However, they were, on average, 7% higher than last year's prices and almost 20% higher than the five-year average (FEWS NET, 2024).

Headline inflation in the region is likely to continue rising due to lower production, increased import prices, and rising energy costs. Poor macroeconomic conditions, such as inflation and decreasing currency exchange rates, are likely to increase the consequences of regional shortages in production on the ability of households to meet their fundamental needs (Okou et al., 2022).

Limited fiscal space for climate adaptation actions in Mozambique

Government debt in Mozambique was at 102.6% in 2022, with interest payments accounting for 10.7% of total revenues that year (IMF, 2023). Mozambique is vulnerable to currency risk since 71.0% of its total debt is in foreign currency (IMF, 2023). Climate change may impact its trade balance in the future. While adaptability efforts may be less costly than frequent disaster support systems, they are projected to have a substantial impact on Mozambique's fiscal positions within the existing climate finance framework (Aligishiev et al., 2022). The Belgian government's recent offer of a €2.4 million "debt-for-climate swap" may be a significant start-up towards enhancing Mozambique's climate and economic resilience (IMF, 2023).

2.5.2. Overview of the agricultural sector in Mozambique

Agricultural land represents 52.7% of Mozambique's land area, with the remaining portion being covered by forests (World Bank, 2020). However, since the majority farming occurs in areas that are vulnerable to drought and flooding, only 7.2% of the land is arable, whereas less than 10% of the arable land is utilized (World Bank, 2020). Only a small portion of the land in the southern provinces is suitable for irrigation, despite their greatest need for it. While groundwater is used sparingly, mostly by smallholders, the majority of irrigation projects use surface water from rivers (FAO, 2016). Approximately 95% of agricultural production is produced by smallholder farmers, who are subject to climate variability because they primarily engage in rainfall-dependent agriculture (Armand et al., 2019). According to Manuel et al. (2020), maize is the main crop for nutrition and makes up 72% of all small and medium-sized farming units and is then followed by beans and cassava.

Climate change is projected to worsen the possibilities of flooding, thus affecting essential value chains such as sesame and pigeon pea, with negative consequences for local markets and farmers' income (Mulungu et al., 2021). For instance, a study by Baez et al. (2020), estimated that when cyclones, floods, or drought hit an economy, the consumption of food may decline up to 25 to 30%. Furthermore, rural communities are more vulnerable to the negative effects of severe weather conditions on agricultural output, in which 90% rely on agriculture as the primary source of livelihood Ayanlade et al., (2022). Pre-existing vulnerabilities in Mozambique's agricultural sector are expected to undermine the country's capacity to adjust to climate change concerns. These include lack of water infrastructure, interruptions in electricity supply, insufficient storage and logistics facilities, and underinvestment (ITA, 2022). The significant proportion of small-scale farmers is likely to give rise to shortcomings with implementation for adaption strategies and the wider adoption of climate-smart methods of cultivation. While irrigation may contribute to reducing the risks of climate change, water supply is expected to decrease and demands for irrigation in Mozambique are likely to be unmet (Mulungu et al., 2021).

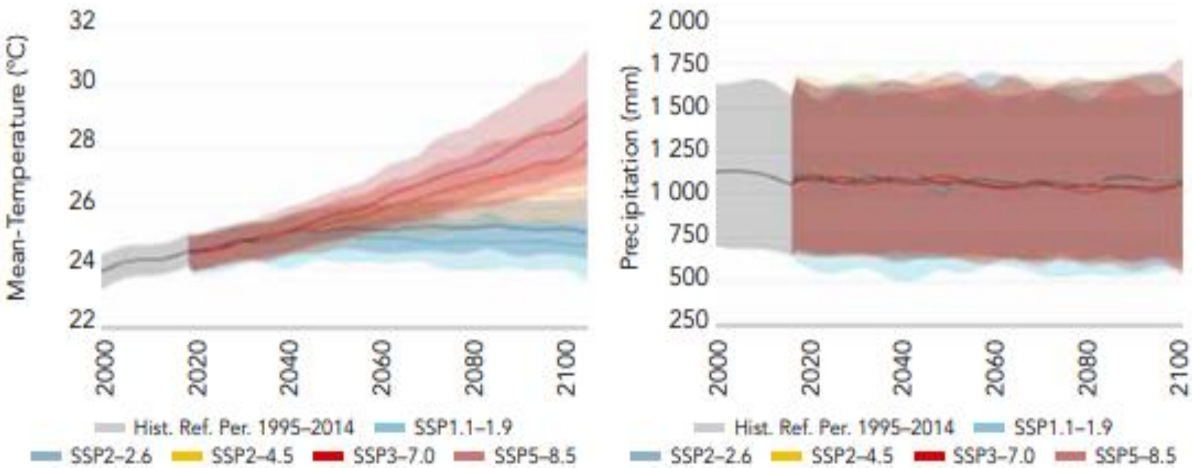
2.5.3. Projected Climate Trends

Low rainfall and increased temperature

Temperatures are projected to increase across the country, with rainfall becoming more erratic, particularly in Mozambique's south. Figure 2.2 depicts the expected changes in Mozambique's temperature and yearly rainfall. According to World Bank forecasts, temperature increases are predicted to continue until 2090, although yearly precipitation does not change considerably over time however is estimated to be more variable than previous averages.

Mozambique's Nationally Determined Contributions (NDCs) predict a rise in temperature throughout the country, accompanied by variety of warm days, and also increased fluctuations and intensity of precipitation (Mavume et al., 2021). Mozambique's National Climate Change Adaptation and Mitigation Strategy (NCCAMS) includes forecasts of a 2 to 9% decline in average precipitation by 2075. According to a report by Irish Aid (2017), temperatures along with the duration of hot days will rise on average, although precipitation is unlikely to change significantly, despite the sole exception of an increase in rainfall intensity.

Figure 2.2: Forecasted changes of weather conditions in Mozambique at the national level



Source: World Bank Climate Change Knowledge Portal (2023

2.6. The case of Botswana

2.6.1. Implications of climate change on agricultural productivity

In order to ensure its food security, Botswana imports 90% of its total food and is heavily reliant on the performance of neighbouring country's agricultural sectors (Bahta et al., 2017). Botswana's agriculture is primarily rain-fed, rendering the country particularly vulnerable to climatic unpredictability and change. Climate change trends are expected to jeopardize regional grain production in addition to the export and import of essential primary crops in Botswana and throughout Southern Africa (Nhamo et al., 2019). This alone affects import supply, food prices, and thus the availability of food, as crop production have already decreased in recent years.

For Botswana, the price of grains and market reliance are strategically linked, and the country depends on imports for sustaining the national demand for fundamental goods including sorghum and maize, which are primarily sourced from South Africa (Masipa, 2017). For instance, while South Africa's low rainfall in 2002 did not result in food shortages, this was regionally concerning considering that South Africa is the Botswana's primarily food exporter (Masipa, 2017). A healthy sorghum crop requires approximately 300mm of water in the root zone, which is already difficult to achieve in Botswana due to inadequate rainfall (Dietz et al., 2021). Due to high evapo-transpiration, the crop is water-stressed for the majority of the time and cannot produce optimal yields.

Over fifty percent of the populace resides in rural regions and relies primarily on sustenance agriculture and livestock husbandry. Domestic agriculture accounts for only a small portion of local food needs and contributes minimally to GDP; despite this, it still serves as a social and cultural benchmark. Botswana's crop output is further limited by conventional farming practices, frequent droughts, erosion, and infestations of pests. Livestock, which is dominated by cattle and is currently projected to be 2 to 3 million head, has been declining for several years (Urich et al., 2021). Given the forecast of rising temperatures and decreased precipitation, specifically in key agricultural zones in the country's east, sorghum and maize yields are projected to decrease by 10% to 35% by mid-century, posing serious challenges for livestock (Urich et al., 2021). An effective land use management approach will be necessary to restrict land usage and minimize pressure during periods of average to below-average rainfall (Atkinson et al., 2019).

2.6.2. Implications of climate change on food prices in Botswana

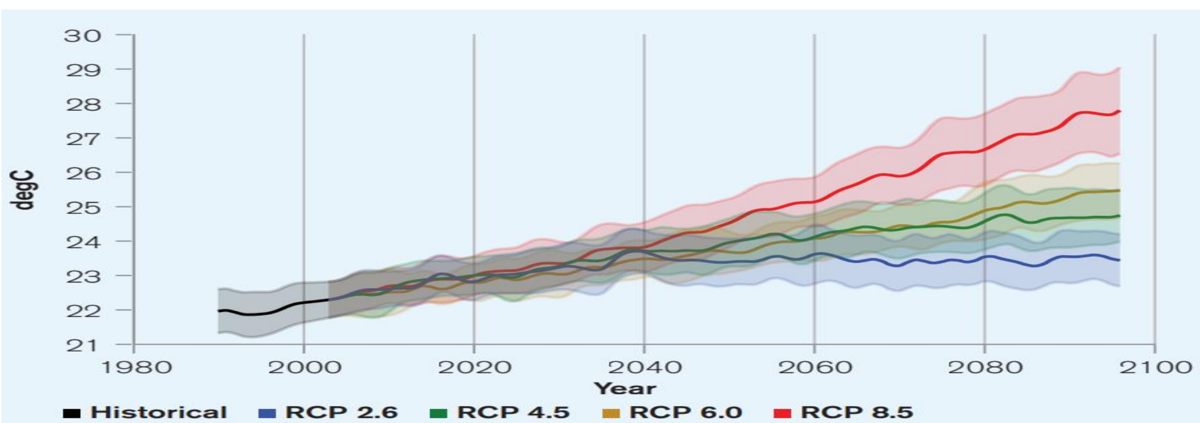
The overall production of cereal is forecasted at 73 000 tons in 2023, about 15% lower than the five-year average, reflecting the less-than-average rainfall amounts and uneven temporal distribution. High temperatures during the cropping season also worsened the risks of reduced rainfall on crop yields. However, the yearly food inflation rate decelerated during all of 2023 and was pegged to 9% in August 2023 from 13% a year earlier, in particular, because of an easing bread-and-cereals price (StatsBots, 2023). Given that the bulk of the country's national cereal requirements are imported, deceleration in price growth largely reflects a decline in commodity prices on the international market and a relatively stable exchange rate (FAO, 2023). Inflation-or a general rise in the level of prices for goods and services-has been easing this 2024, moving from 14.6% in August 2023 to 9.3% at the beginning of the year and down to 1.2% in August of the same year (Statsbots, 2024). However, such decline has largely been influenced by the slide in the prices of fuel earlier on this year and more or less stable price movements in other commodity groups other than the commodity grouping of food and non-food, non-alcoholic drinks.

2.6.3. Projected Climate Key Trends

Increased temperature

Temperature is estimated to rise in Southern Africa, particularly in Botswana, with average monthly temperature changes increasing by 2.5°C in the 2050s and 5.0°C by the end of the century under a high-emission scenario (Urich et al., 2021). According to Mulungu et al. (2021), under a high-emission circumstance, the frequency of days with high temperatures is predicted to rise by 138 days by the end of the century, with the largest significant spikes occurring between November and March. Higher temperature will also have the consequence of more frequent and intense heat waves, with higher evapotranspiration rates. These consequences will impact many aspects of local economic development, agricultural productivity, and beyond. As can be seen in Figure 2.3, during a high-emission circumstance (RCP 8.5), minimal temperatures are bound to rise at a rapid pace by the middle of the century. More records of heat and conditions of extreme heat will pose serious ramifications for both livestock and human health, ecosystems, agriculture, and the production of energy.

Figure 2.3: Historical and predicted average temperatures in Botswana from 1986 to 2099

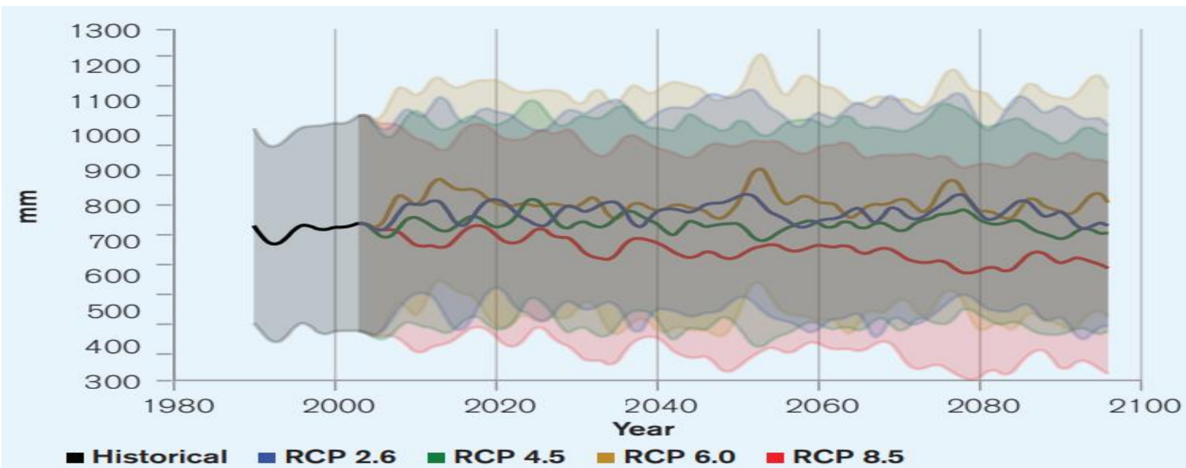


Source: WB Climate Change Knowledge Portal (CCKP, 2020)

Reduced precipitation

Given Botswana's enormous dimensions, arid environment, and diverse geography, the majority of the country is predicted to receive less precipitation; however, the northeast portions are expected to see more precipitation (Matenge et al., 2023). From April to September, conditions are expected to be slightly drier, increasing the frequency of droughts and dry spells. The graph below depicts changes in monthly precipitation, with the greatest decline projected in the course of the country's main rainy season from October to April (World Bank Group, 2021). Water supplies are likely to be more strained in regions with lower precipitation forecasts. In addition to rising temperatures, the country's evapotranspiration rate is predicted to rise further. With increasing severity and frequency of droughts, the Southern African region may face significant implications on the quality and supply of water, threatening the health of wetland ecosystems, agriculture, and cattle populations (World Bank Group, 2021). Under the RCP8.5 high emissions scenario, annual average precipitation is projected to decline partially by the end of the century.

Figure 2.4: Annual average precipitation in Botswana from 1986 to 2099



Source: WB Climate Change Knowledge Portal (CCKP, 2020)

2.7. The case of Lesotho

2.7.1. Implications of climate change on the economic sectors

Reduced water availability

Lesotho is known to have ample water resources, forming one of the major water catchment areas in Southern Africa, which supplies over 50% of the total catchment runoff (Pryor et al., 2022). The national economy highly relies on climatic conditions, where water serves as a major source of energy and one of the prominent exports to South Africa. The water supply is vital to promoting socioeconomic growth and the country's ecosystem sustainability, given that more than 95% of electricity consumed in Lesotho is from hydropower (MEMWA, 2013). While Lesotho has substantial levels of poverty and wealth inequality, water accounts for approximately 10% of the total GDP (World Bank Group, 2021). A significant amount of this benefit is derived from revenues related with the Lesotho Highlands Water Project, a multistage infrastructure project that permits water to be transferred from Lesotho's water-rich highlands to the African continent's economic engine in Gauteng while also contributing to the advancement of hydropower resources in Lesotho (Wendt, 2023). Despite its enormous water resources, Lesotho is highly susceptible to the effects of frequent and recurring floods and droughts.

The severe drought of 2015 to 2016 resulted in a 21% decline in wheat production and an urgent water scarcity as the country endured protracted dry spells characterized by low rainfall and high temperatures, causing large-scale agricultural damage (Dick-Sagoe et al., 2023). According to the Disaster Management Authority (2015), total national cereal production (maize, sorghum, and wheat) was estimated to be 89,000 tonnes to feed a population of around 350,948 tonnes. Small-scale farmers and households with agricultural livelihoods were particularly affected and faced disruptions as an immediate consequence of reduced production and rising costs, which increased the risk of food insecurity and malnutrition. These vulnerable populations also experienced temporary food insecurity from 2015 to 2017 (Dick-Sagoe et al., 2023). The country's biophysical features, particularly its significant amount of high-altitude rangeland and acutely erodible soils in the lowlands, make it more vulnerable to precipitation fluctuations and reduces water availability.

Declining crop production in Lesotho

Agriculture in Lesotho is primarily rainfed and is therefore extremely sensitive to the variation in precipitation, making attempts to increase food security extremely challenging. This sector is also vital in the creation of employment opportunities in the country since it creates about 60% to 70% of the labor income generated from farming. Major crops grown constitute maize, sorghum, and wheat, which form approximately 60%, 20%, and 10%, respectively, of the total area cropped (Verschuur et al., 2021). Lesotho's agricultural industry is characterised by low and diminishing production, which is which has recently been worsened by the implications of climate variation. As it stands, both the food and agricultural industries face significant risks not solely from historical yearly precipitation, but also from changes in climate (Nhemachena et al., 2020). Weather conditions account for 80% of the variability in agricultural productivity in Lesotho, particularly in rainfed systems. Rainfall variability affects not just the amount of land cultivated but also the consequent agricultural yields (Wendt, 2023).

Future climate projections regarding rainfall variability show that it would very likely lead to food inadequacy due to pressure from decreasing precipitation and increased temperatures. Effective adaptation measures notwithstanding, the trend of crop yields decline may continue nationwide. While Lesotho's geographic setting and location present numerous opportunities, the country's basic economic structure is extremely vulnerable to subsequent shifts in weather patterns. Ensuring a strong system for sustainable management and prospective growth of water resources will be crucial for achieving long-term improvements through economic development in the commercial, service, industrial, and agricultural sectors (Verschuur et al., 2021).

2.7.2. Implications of climate change on food prices

Lesotho experienced one of the worst droughts in 35 years, primarily caused by El Niño (World Food Program, 2015). The drought, combined with Lesotho's dependence on rain-fed agriculture, means that many households depended on food purchases for the most of 2016 and 2017. Throughout 2016, the general consumer price index increased, so did food inflation. Food prices rose by 15% per year in May 2016, and by 10% in September 2016, showing that food costs are rising faster than the entire basket (Lesotho Bureau of Statistics, 2016).

Maize meal prices increased during 2015, above both the previous year's average and the preceding five years' average, according to the Lesotho Disaster Management Authority (2015). Increases in prices fluctuated between 20% in Qacha's Nek to 32% in Butha Buthe during December 2014 and December 2015 (Disaster Management Authority, 2015). This continuous rise in food costs is projected to diminish consumer purchasing power and worsen Lesotho's food security situation (FAO, 2016). As a result, Lesotho faces a major food security crisis due to the impact of the El Niño-induced drought. The main factor contributing to local price increases in Lesotho and South Africa has been the tightening of maize supplies due the production failure caused by the El Niño-induced drought (Veschuur et al., 2021).

Persistent crop failures, dwindling food production, water shortages, and skyrocketing food prices have severely hit the country’s agricultural production with 41% of rural households now forced to spend more than half of their income just to put food on the table (Sekaran et al., 2021). The inflation rate was forecasted to reach 7.6% in 2022, decreasing to 5.9% in 2023, mainly due to a rise in the rate of food price inflation which fell to 8% in December from 8.10% in November 2022 (Central Bank of Lesotho, 2023). Headline inflation in April was 7.1%, surpassing 4.5% in July 2023. The highest level recorded so far this year was 8.2% in January 2024. Inflationary pressures may have been exacerbated by dryness conditions during important growing phases, which had an adverse effect on crops and fed into increased prices, causing households to purchase food earlier than usual (IMF, 2024).

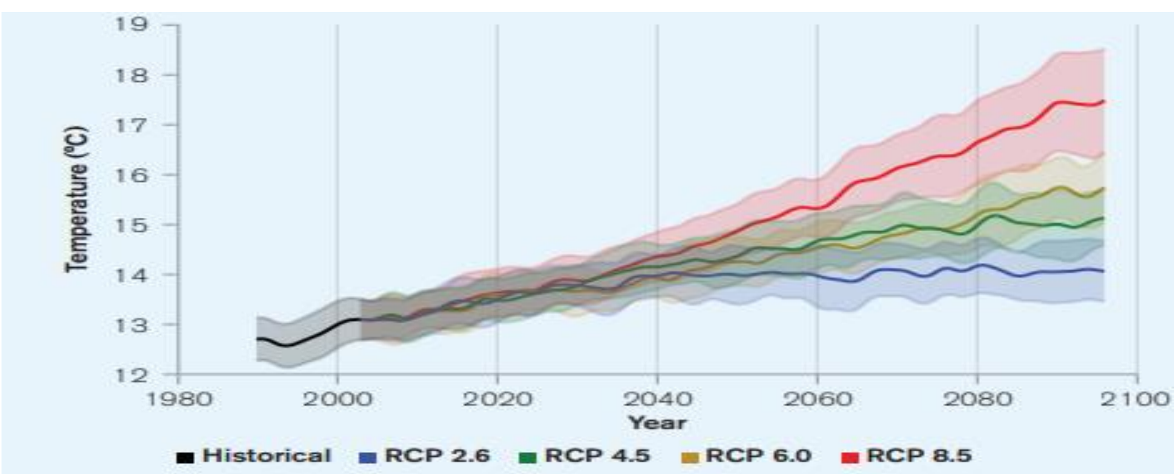
2.7.3. Projected Future Climate Trends

Increase in temperature

Temperatures are anticipated to rise in the region, with mean monthly temperature variations increasing by more than 2.0°C in the 2050s and 4.4°C by the end of the century under a high-emission scenario (Climate Change Knowledge Porta, 2021). Heat waves are projected to occur more frequently, as are increasing rates of evapotranspiration, which will have an impact on many areas of local economic development and agricultural output. Across all emission scenarios (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5), temperatures in Lesotho are expected to rise over the century.

As demonstrated in Figure 2.5, under a high-emission scenario, average temperatures are predicted to rise substantially over the next century. Temperature is projected to rise throughout the year due to the seasonal cycle. Increased and intense heat waves will have adverse effects on human and animal health, agriculture, and ecosystems. Predicted rises in temperatures could widen up new agricultural areas, enabling cultivation in formerly unproductive areas; yet persistent challenges with shallow soils on steep slopes may raise the risk of soil erosion (Climate Change Knowledge Portal, 2021).

Figure 2.5: Projected Average Temperature for Lesotho



Source: WBG Climate Change Knowledge Portal (CCKP, 2021)

Decrease in precipitation

Higher temperatures are projected to increase the rate of evapotranspiration in Lesotho and Southern Africa, putting pressure on water resources. As droughts become more regular and severe, the region's water supply and agriculture are likely to suffer. A concomitant increase in flooding episodes poses major water pollution concerns to wetland habitats, agriculture, and animal groups. Precipitation in Lesotho is widely diverse; northern portions of the country are projected to experience less than average rainfall through mid-century, with moderately more than normal precipitation until the end of the century (Climate Change Knowledge Portal, 2021).

According to the World Bank Group (2021), southern Lesotho is anticipated to experience below-average rainfall of 50 to 100mm annually till the end of the century. Lesotho's projected precipitation regime will only minimally deviate from documented historical patterns under the highest emissions scenario. However, variations in rainfall patterns in Lesotho are expected to result in a rise in severe rainfall events, along with the likelihood of long dry intervals between storms. These changes may intensify the country's drought zones, and decreased precipitation could result in a significant decline in crop yield (Wendt, 2023).

2.8. The case of Malawi

Malawi is an attenuated, landlocked country in southeast of the continent, shares borders with Tanzania, Zambia, and Mozambique. The country is prone to a range of climatic variabilities, including heavy precipitation and hurricanes, periodic conditions of drought, and unpredictable cyclones.

2.8.1. Socio-Economic Vulnerabilities

Malawian economy in the face of climate change

Climate-sensitive industries characterize Malawi's economy, where fishing, forestry, and agriculture comprised 22.7% of the GDP and 62% of the total labor force as of 2021. This is according to data obtained from the World Bank for 2023. It was tobacco, however, that continued to remain the significant cash crop for Malawi and accounted for nearly 50% of revenue earned through exports. Other major agricultural exports include tea, sugar, and cotton from Malawi, which accounts for at least 85% of its total exports. Furthermore, most of the facilities such as roads, energy, and water supply remain poorly developed; therefore, any deterioration due to climate change is more likely to have a worse effect on other sectors. Malawi's most recent Nationally Determined Contribution (NDC) projects that climate change will cost the country at least 5% of its GDP each year (Chirambo, 2020).

According to Arndt et al. (2014), the effects of changes in climate on the economy of Malawi are anticipated to worsen over time, as a result of decreased crop productivity and increased impairment to transportation infrastructure as the prevalence and magnitude of severe weather events increases. A World Bank Group report (2022), analyses five potential climatic scenarios and concludes that changes in climate could lower Malawi's GDP by amounts greater than those forecasted by the NDC should the ongoing trajectory of low-growth development persists. Corresponding to Arndt et al. (2014), the report concludes that impairment of bridges and roads is projected to be the primary channel of the impact of variations in climate on Malawi's economy, notably in a rainy scenario, due to the country's roadway vulnerability to flooding. The second most important channel is expected to be a decrease in the productivity of labor, specifically in extreme temperature scenarios. This is followed by reductions in crop production as a result of temperature and precipitation fluctuations in a dry scenario.

Malawi’s unsustainable fiscal position

As of July 2022, the International Monetary Fund (IMF) determined that Malawi's external and total public debt was in distress (IMF, 2022). In 2022, the government debt increased to 76.6% of GDP, resulting in a fiscal deficit of 8.8% of GDP. It worsened because of the rising commodity prices resulting from the conflict between Russia and Ukraine, which raised food costs, caused a severe lack of foreign exchange, and caused inflation to skyrocket to 26.7% as of October 2022 (World Bank, 2023). Continuous climate-related shocks continue to make Malawi economically vulnerable and distressed by debt, causing frequent and severe weather events disrupting agriculture, reducing economic growth, increasing government spending on disaster response, creating foreign exchange shortages, and driving inflation. The government tried to achieve fiscal consolidation to reduce the deficit through the reduction of non-priority spending and enhancing revenue collection. Despite these developments, Malawi till date has enormous fiscal ultimatums that lie ahead in its efforts toward poverty and inequality reduction, considering the increasing investment required in infrastructure, social services, and response to climate change (Raga, 2023).

2.8.2. Overview of the Malawian agricultural sector

The agriculture sector accounts for a large percentage of the economy of Malawi and employs a great deal of the workforce. In Malawi, just a minimal amount of agricultural land is irrigated, and commercial estates manage the majority of it. Despite the fact that irrigation is becoming more popular, with 61 977 hectares expected by 2019, it comes at a high expense (Mapila et al., 2022). Consequently, crop yield in Malawi continues to be heavily dependent on precipitation. Large-scale farmers focus solely on exporting sugar, tea, tobacco, and macadamia. Small-scale producers are primarily subsistence farmers that grow legumes, maize, cassava, rice, and sweet potatoes. Ultimately, 80% of Malawi's populace lives in communities that rely on rain-dependent harvesting agriculture (World Bank, 2018). Many essential crops have demonstrated diminishing agricultural yield. Investment in agriculture is required to improve productivity and provide greater resilience to unfavorable climate events. Potential economic shocks are made more severe by the increased likelihood of minimal yield seasons in agriculture. In the case of high emissions, these effects are likely to be substantially greater. Climate warming may double the frequency of low-yield occurrences for maize (Stevens and Mandani, 2016).

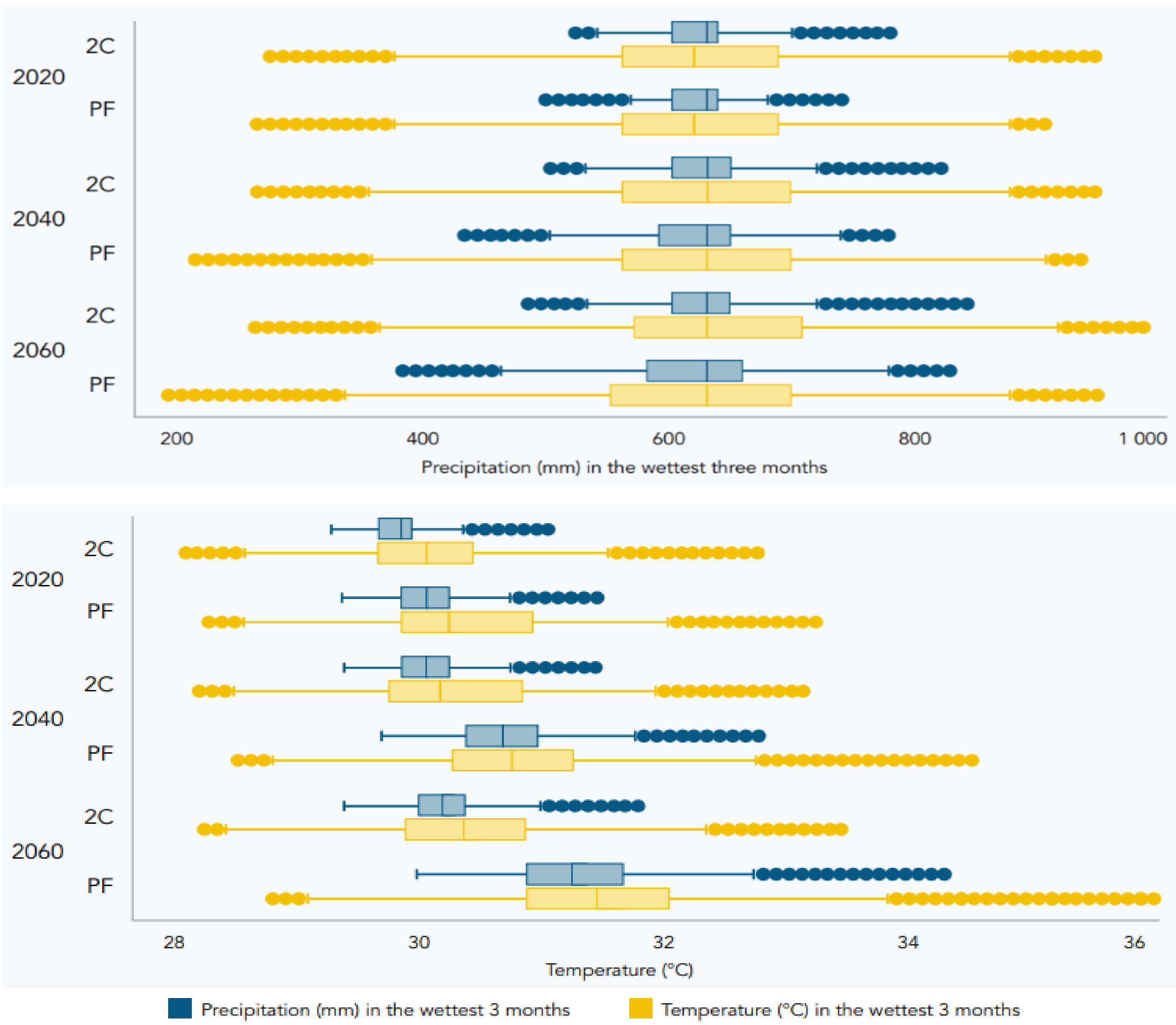
2.8.3. Implications of climate change on food inflation

Inflation increased from 20.8% in 2022 to 28% in 2023. Malawi continues to experience high levels of inflation, with a year-on-year inflation rate of 32.3% for April 2024, and elevated food prices, with maize prices averaging 160% above the five-year average (IPC, 2024). The high cost of agricultural inputs in 2023 has further exacerbated the situation for the poorest and most vulnerable households (FAO, 2023). Increased costs of transporting imported foods and agricultural inputs, due to devaluation and depreciation of the Malawi currency, are thus elevating transportation costs for such food and agricultural inputs during the lean season of November 2024 to April 2025 (FAO, 2023). Recurrent climate shocks have left a considerable number of Malawian families needing emergency food assistance. Forecasted La Niña conditions are projected to result in above-average rainfall with floods predicted in many of the drought affected districts toward the last quarter of 2024 to the first quarter of 2025 rainy season (IPCC, 2022).

2.8.4. Future climate trends

The average temperature is projected to rise further during the 2020s and 2060s, maybe much higher if global emissions reduction efforts fail. Thomas et al. (2022), employed a broad ensemble of climate estimates from 2000 to 2069 to generate frequency ranges for temperature and rainfall, displayed in Figure 2.6. The figures show the average daily maximum temperature for the warmest month during the most humid three months of the year for each pixel, in addition to the total amount of rainfall for the most humid three months of the year for each pixel for the specified decade. The scenario with lower emissions is shown in the figure as 2C, and the scenario with greater emission levels is shown as PF. Under the less emission scenario, the variation in the daily peak temperature during the warmest months of the year is minimal, whereas, under the higher emissions scenario, it is enormous.

Figure 2.6: Projected changes in rainfall and average daily peak temperatures for the wettest three-month and the hottest month period from 2020s to 2060s



Source: Thomas et al. (2022)

The combined fluctuation and unpredictability of precipitation throughout Malawi's wettest months, especially under a heightened emissions scenario, escalates the risk of drought, particularly in the south. Although the average rainfall of the wettest three months is expected to change minimal at the country level, for the most extreme emission forecast (that is, the ‘reference' forecast, which is moderately greater than the PF forecast); a slight decrease in average rainfall and moderately greater variation in rainfall indicate an approximate double of drought frequency in the south and a potential increase of 50% for the majority of the country. This potential variability is due to rainfall patterns and greater vulnerability (Thomas et al., 2022). World Bank (2018) also reported an increasing risk of reduced precipitation, notably in Malawi's southern regions accompanied by additional days of prolonged dryness each year. A corresponding study by IFAD (2020), predicts a total drop in Malawi's yearly and seasonal rainfall by mid-century, with a 10.5% decrease in seasonal precipitation from October to April.

2.9. The case of Namibia

The nation is experiencing water stress, which is mostly manifested by extremely high evaporation rates of 83% and low and highly unpredictable average annual rainfall. Natural disasters are common in Namibia, the country therefore struggles with drought and flooding (Shikangalah, 2020).

2.9.1. Implications of climate change on the hydrology sector

Drought impacts on the hydrology sector

Water is essential in many economic areas, including agriculture, cattle, fishing, mining, and industry. Despite its small contribution to GDP, agriculture consumes up to 75% of total water output in Namibia (Liu and Zou, 2021). However, agriculture's water productivity is far lower than normal. Droughts are now a regular occurrence in most parts of the country; in recent decades, droughts occurred from 2012 to 2013 and in 2019. The drought in 2012 to 2013 was expected to be the most severe of the decade, with almost 42% of the overall populace experiencing food insufficiency (Shikangalah, 2020). The El Niño Southern Oscillation (ENSO) had a substantial impact on Namibia's rainfall and temperature, resulting in lesser than average rainfall which was received during the ENSO (Shikangalah, 2020).

According to Mupambwa et al. (2021), the average yearly precipitation for nearly two-thirds of the country is 250mm during normal rainy seasons and less during ENSO. With such little average rainfall, the country is primarily reliant on groundwater systems for supply. It is believed that only 2% of Namibia's precipitation ends up as surface run-off, with only 1% accessible to recharge groundwater. The remaining 97% is lost through direct evaporation (83%) and evapotranspiration (14%). Rainfall frequently evaporates before reaching the ground, and a 1% change in rainfall has an effect of 1.2 to 1.6% on carrying capacity. A slight decline in the amount of precipitation as a result of changes in climate will exacerbate water scarcity, reduce livestock, decrease agricultural productivity in Namibia (Liu and Zou, 2021).

Projected climate trends in the hydrology sector

Changes in precipitation across Angola and Zambia of 10 to 20% by 2050 would have a 20 to 30% impact on discharge and drainage of perennial rivers in northern Namibia (Thorn et al., 2023). Furthermore, the majority of the country's irrigation projects are situated along the perennial northern rivers that form its borders. As a result, diminishing flow from these rivers may jeopardize irrigation development for greater food production, as envisaged by Namibia's government. As temperatures rise over 3°C, evaporation also rises by 5% to 15%, making even less water accessible for discharge and storage (Spear et al., 2018). Daily peak temperature is expected to rise by 5 to 6°C by the end of the century. Namibia's groundwater often serves as a drought buffer in many areas; however, persistent future droughts are projected to lead to descending groundwater tables and declining flows of surface water (Thorn et al., 2023).

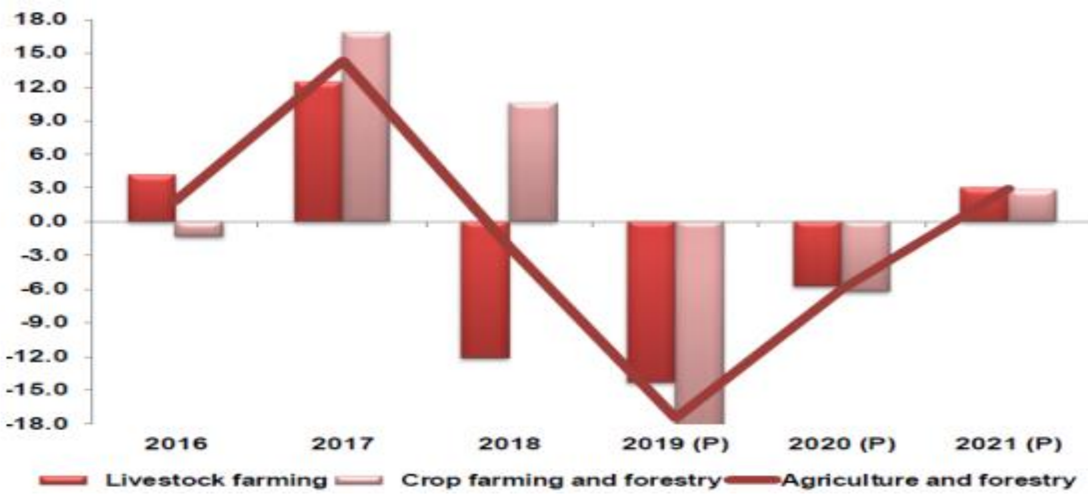
2.9.2. Implications of climate change on the agricultural sector

Drought impacts on the agricultural sector

The agricultural industry is essential to Namibia's economy and food security, accounting for 7% to 10% of the country's GDP (World Bank, 2018). Seventy percent of Namibia's population is reliant on rain-fed agricultural output, with about 48% of rural households relying on subsistence farming. Agricultural exports, particularly livestock, beef, and grapes, are a significant element of the country's trade portfolio. However, with the recent and ongoing climate shocks in the country, there has been a sharp decrease in agricultural output, thus disrupting economic stability (Simaku and Sheefeni, 2017).

For instance, during the 2019 drought, Namibia and Botswana's annual agricultural output was predicted to be less than 50% of the 5-year average (FAO, 2019). Furthermore, production in the sector decreased by 17.5%, with crop growth being the most severely hit. Figure 2.7 shows that as the cultivated area decreased in 2019, output fell from a significant 10% in 2018 to a negative 18%. Furthermore, livestock production was already negative in 2018, and it fell even worse in 2019. As total production of crop decreased during 2019, the production of cereal was predicted to be 53% less than in 2018 and 42% lesser than the 20-year average. In Figure 7, "P" represents projection.

Figure 2.7: Annual percentage (%) changes of farming activities



Source: Shikangalah (2020)

The agricultural sector's sensitivity to climate, in addition to its dependence on rainfall and water supplies, have significant repercussions for Namibian farmers and the economy as a whole.

Projected climate trends in the agricultural sector

Agriculture in Namibia (crop production, livestock husbandry, and fishing) is extremely vulnerable to weather conditions. Temperatures across the country are expected to rise by an average of 3.8°C to 5.1°C. Together, these conditions and future extreme climates will have an enormous impact on crop productivity and livestock (Spear et al., 2018). Climate change could have significant implications for agriculture, and thus GDP. Even heat-tolerant crops inclusive of millet are expected to suffer due to climate change in Namibia's drought-prone regions. Cereal crop yields are expected to decrease by up to 20% in the northeastern region and 50% in the northcentral region under rainfed circumstances (Karunaratne et al., 2015). Heat and water stress on livestock are likely to reduce feed intake, milk output, and reproductive rates. Climate change is expected to reduce livestock carrying capacity across the country by 10% in the northeastern region, 15% to 30% in the northcentral region, and 35% in the central region (Nhamo et al., 2019). These changes will put more pressure on grazing lands and animal management systems. Cattle numbers are expected to fall to around 51% of current levels by 2080 as carrying capacity declines (Spear et al., 2018).

2.9.3. Implications of climate change on food inflation

In 2019, Namibia experienced a nationwide drought, and most of its provinces are still recovering from the disaster (Shikangalah, 2020). The impact of the drought affected both crop and livestock production. During this period, food and nonfood prices increased twice by 2 to 6% until 2021. This price increment was further triggered by the increased global fuel prices, as a result, people's purchasing power reduced (Liu and Zhou, 2021).

In addition, poor rainfalls in the northern crop-producing area during the 2022-2023 farming season and localized flooding in the northeast in January 2023 led to poor crop productions (USAID, 2024). This has been the cause of the increases in the prices of foods and non-foods that started in March 2022 and are expected to last throughout 2023, partly supported by high import costs for fuel, food, and fertilizers. High and erratic global commodity prices negatively affected the purchasing power of the poor. In 2023 to 2024, poor communities experienced a prolonged lean season due to inadequate food supply. On the other hand, food prices peaked at 14.6% during the peak lean season for households dependent on food markets but has been consistently decreasing since then. This coincides with Namibia's most significant trading partner, South Africa, where it stabilized in December 2023 at 7.4% (Namibian Statistics Agency, 2023).

Prolonged dry spells and erratic rainfall, exacerbated by El Niño, in the 2023 to 2024 rainfall season have had a negative impact on crop and livestock production in 2024 (IPC, 2023). The Namibia Metrological Service Climate Bulletin report for March 2024 indicated that the rainfall performance over Namibia has been minimal with the bulk of the country having received below-normal rainfall for the period of October 2023 to April 2024 (IPC, 2024). According to the Namibian Statistics Agency (2023), the average annual inflation rate for May 2024 stood at 5.2%, this also exacerbates the existing food security challenges and demanding increased humanitarian support, livelihoods recovery, and resilience building.

2.10. Conclusion

Based on this review, it is undisputed that climate change poses substantial risks to key economic sectors and has far-reaching consequences for achieving developmental goals such as alleviation of poverty and development sustainability. Southern Africa faces a multifaceted challenge, mostly affecting the water and agricultural sectors due to decreased rainfall and rising temperatures. These changes jeopardise water availability and agricultural systems' ability to supply rising food demand from a growing population while also contributing to sustainable development. As a result, comprehending how change in climate and its unpredictability affect water supplies and agricultural systems is critical in developing response strategies to establish resilient systems. Most African countries, including those discussed in this research, have limited fiscal flexibility and large public debt. As a result, macro-level climate change mitigation policies that require huge financial easing may be unfeasible in the short to medium term.

CHAPTER 3: LITERATURE REVIEW

3.1. Introduction

This section reviews the literature by looking at the theories that inform the relationship between climate change, agricultural production and food inflation. To address the objective of this literature, a comprehensive and critical discussion of relevant academic articles, reports and empirical studies focusing on the economic impacts of climate change on agricultural output and food inflation will be analyzed. This section will further highlight literature gaps that the study intends to address.

3.2. Theoretical Framework

It is commonly accepted in both theory and practice that determining the factors that contribute to inflation is crucial to pursuing an anti-inflationary policy that effectively aims to achieve price stability. This theoretical literature framework attempts to investigate the theoretical perspectives of inflation through the lenses of cost-push inflation under the Keynesian Theory in order meet the study's theoretical objectives. The review will employ a conceptual framework to better explore how climate change affects agricultural output.

3.2.1. Keynesian Theory of Inflation

Since both policymakers and society are directly and indirectly impacted by the results of inflation, it is still a crucial macroeconomic issue that they continue to regularly monitor. Additionally, the detrimental effects of climate change on agriculture cause crop yields and productivity to fluctuate, which in turn causes changes in the availability of food and fuels food inflation (Paudel et al., 2023). Understanding what inflation is, how it is calculated, and why it matters (the cost, challenges. and repercussions) are essential to comprehending the factors that influence inflation.

Inflation is defined as a long-term increase in the general cost of goods and services within an economy (Salim, 2019). When prices increase across the board, each unit of currency may buy fewer goods and services. Accordingly, inflation also indicates a decline in the purchasing power of money as well as a decline in the actual value of the economy's internal medium of exchange and unit of account (Bonab, 2017).

In the Monetarist view, increases in money supply are controlled by slowdowns in the velocity of circulation of money, meaning that the extra money is likely not spent on goods or services but on investments in capital assets, which would stimulate economic growth and therefore increase the output rather than price (Ball, 2017). Even though monetarists contend that inflation is strictly a monetary process that can only occur when the money supply expands more rapidly than output capacity, the Keynesian theory of inflation takes a distinct approach to what defines inflation. Madito and Odhiambo (2017), argue that monetarist economists disagree with the non-monetary causes of inflation posited by Keynesian theory, such as changes in government fiscal policies, cost-push factors, and scarcity of food and fuel. They argue that inflation can only emerge from excessive increase in the supply of money. However, Keynesians contend that imbalances in aggregate demand and supply are the root causes of inflation.

The Keynesian theory provides insight into inflation in the complexity real world of government policy, supply disruption, and cost of production. However, this theory underestimates the importance of monetary determinants and long-run inflation expectations which are central aspects of the operation of contemporary central banks (Wei & Xie, 2020). While the Keynesian theory is relevant for short-term inflationary shocks, its assertion that cost-push inflation may persist without monetary expansion faces significant criticism (Fornaro and Wolf, 2023). In the modern global economy, where trade, financial markets, and technology increasingly shape dynamics, it is essential to integrate these factors into inflation models to appropriately represent price stability.

In a broader context, the impact of climate change on agricultural productivity and food inflation in Southern Africa can be analyzed through the lens of Keynesian theories of inflation. While Keynesian theories of inflation are primarily concerned with macroeconomic factors, they provide insights into the possible implications of climate change on the variables in question. According to the Keynesian theory, only two types of inflation arise, either based on the demand side factors which result in demand-pull inflation or based on the supply side factors, resulting in cost-push inflation (Kahn, 2022). Based on the two determinants of inflation, the current study is informed by cost-push inflation.

3.2.2. Cost-push inflation

Cost-push inflation occurs when the aggregate supply of goods and services which can be produced in the economy falls (Shaik et al., 2022). A rise in production costs is frequently the reason for this decline in total supply. Consequently, consumers pay more for the final products as a result of the increased production expenses (Charles et al., 2022).

In contrast to the demand-pull hypothesis, which claims that inflation arises as a direct or indirect result of both expansionary monetary and fiscal policies, the cost-push theory proposes that prices rise as a result of factor prices that accelerate faster than factor productivity. One of the effects of cost-push inflation is that high production costs frequently lead to a decrease in employment rates as firms strive to offset higher production costs, especially in a labor-intensive work environment. This frequently leads to a decrease in productivity, which then results to a reduction in output. Monetarists argue that a tight fiscal policy without a decrease in the rate of monetary expansion cannot decrease inflation (Palley, 2015). The cost push theory proposes that inflation occurs as a result of a reduction in aggregate supply. However, the cost-push inflation theory upholds that wage increases prompt prices of goods and services to rise (hence the term "cost-push inflation"), which is frequently perpetuated by trade unions or due to pricing policies imposed by monopolistic and oligopolistic firms in the economy. Alternatively, this process can be understood through wage and salary increases, in addition to an increase in the cost of raw materials utilized as inputs in firms' manufacturing processes. Cost-push inflation is further explained by rising import raw material prices (also known as imported inflation) and the decreasing value of the local currency (Machlup, 2020).

The underlying assumption is that wage earners and profit recipients desire incomes that exceed the total value of their production when the economy is at full employment. Consequently, at any given time, one or both groups will be dissatisfied (Brown & Johnson, 2017). If wage earners are dissatisfied, they demand higher wages, which employers may partially concede during negotiations, initially impacting profits. Subsequently, employers raise prices to compensate for increased costs, although this restores profits, it simultaneously diminishes the real incomes of wage earners, thereby laying the groundwork for another iteration of demand for increased wages (Blanchard & Johnson, 2013). If the money supply remained constant, this process would lead to growing monetary tightness, making it more challenging to finance wage increases and acquisition of goods with recently raised prices. It would also hinder overall production and distribution, although in some cases, the velocity of circulation can rise significantly, enabling the limited supply of money to be more effectively utilized. In practice, the money supply adjusts according to demand, partially because monetary authorities aim to avoid the disruption of capital markets that would arise from severe monetary tightness and substantial increases in interest rates.

Overall, the interplay between wage earners, profit recipients, price adjustments, and the money supply demonstrates the complex dynamics and considerations involved in balancing incomes, prices, and monetary conditions in an economy (Moore, 2023). This kind of inflation is possible under the Imperfectly Competitive Market and is driven by the following causes among many (Park & Shin, 2019):

(I) Increased cost of key inputs

A surge in the cost of domestic or imported inputs including oil and raw materials raises manufacturing costs in a range of industries (Shaik et al., 2022). Faced with rising production costs, firms may respond by limiting output and raising pricing for their goods and services (Machlup, 2020). This price hike could have a knock-on impact, raising the cost of goods and services across the economy. For instance, an increase in oil prices, which is a primary input for many sectors of the economy, can result in higher petrol costs (Su et al., 2021). When petrol prices rise, it becomes more costly to transport goods. Given that many products must be shipped from one location to another, the additional cost of transportation is frequently passed on to consumers. As a result, the prices of numerous commodities may rise, even if they are unrelated to petrol (Dua and Goel, 2021).

(II) Supply Shocks

Supply shocks are also the source of cost-push inflation. A supply shock is an abrupt shift in the price of a commodity or service (Ascari et al., 2024). Adverse supply shocks are often events that increase the cost of production. A negative supply shock can lead to stagflation when prices rise and output falls (Fornaro and Wolf, 2023). The most typical source of supply shocks is oil prices. The Organization of Petroleum Exporting Countries (OPEC) drastically raised oil prices twice: once in 1973-1974, when prices quadrupled and then redoubled, and again in 1979-1980, when prices more than doubled again (Aronson and Cowhey, 2019). Domestic economies cannot remain insulated from such external price shocks, as they must accept the increased foreign prices. These shocks are worsened when the prices of imported goods used in domestic production are calculated in local currency. If the price shock coincides with local currency devaluation or higher tariffs, it further raises the cost of domestic goods due to the increased production expenses (Krugman, 2017).

(III) Climate-Driven Inflation

Climate change, as well as the mitigation efforts that accompany it, have nonlinear and long-term consequences on the economy's supply and demand. As climate change accelerates, central banks confront two new obstacles to their price stability targets (Boneva et al., 2022). The first is climateflation, which refers to the inflationary effects of a warming planet. The second is greenflation, which refers to inflationary pressures caused by the implementation of climate mitigation policies in order to achieve a low-carbon economy (Oman et al., 2024). Greenflation, on the other hand, refers to the inflationary pressure that comes with transitioning to a carbon-neutral economy. The first occurrence is comparable to an adverse supply shock, whereas the second is a combination of both supply and demand disruptions (Guerrieri et al., 2022). Thus, due to climateflation and greenflation, central banks must strike a strong balance between ensuring stability of prices and promoting a resilient economy. Each of these occurs on different timescales and with varying degrees of impact, with fossil fuel fundamentals being the most immediate and visible, climate risks being the most disruptive and emerging, and green transition inflation being transitory and still largely hypothetical (Sahuc et al., 2023). The following section discusses how climateflation exacerbates supply chain disruptions and the long-term repercussions on economic viability.

Impact of climateflation on supply disruption

Climateflation refers to larger inflationary effects caused by climatic phenomena such as extreme weather, natural catastrophes, and supply chain disruptions. As the frequency of natural disasters and severe weather occurrences increases, so does their impact on economic activity and pricing (Panwar and Sen, 2019). For instance, the extraordinary droughts in many parts of the world have contributed to the recent steep increase in food costs, which is putting a strain on a society that is already struggling.

Climate change serves as a negative productivity shock, increasing the marginal cost of production and causing inflationary pressures in the economy (Kabundi et al., 2022). Similarly, catastrophic weather events that decrease the availability of inputs cause inflation and supply shocks, disrupting the supply chain. Kanike (2023), defines supply chain disruption as an interruption in the flow of manufacturing, sales, and distribution of certain commodities or services. Cost-push inflation can also occur due to supply shocks in specific industries, such as natural disasters or extreme weather (Ciccarelli and Marotta, 2024). Periodically, severe cyclones and hurricanes occur frequently around the world, destroying vast amounts of agricultural output and causing significant increases in the price of processed food, leading in temporary periods of greater inflation (Kumar et al., 2022).

A recent study by Patel et al. (2022), incorporates theories of inflation to examine the relationship between climate change, price pass-through mechanisms, and inflation persistence. The authors discuss the New Keynesian framework, which highlights the role of price stickiness and cost-push factors in shaping inflation dynamics. They argue that climate change-induced supply shocks can disrupt price pass-through mechanisms, leading to changes in the degree and duration of price adjustments in the economy and influencing inflation persistence. The study emphasizes the importance of understanding the underlying mechanisms through which climate change impacts price dynamics to design effective inflation targeting policies in the context of a changing climate.

Fossilflation as a cost-push factor

Many emerging and industrialized countries are facing worsening inflation at a faster rate than at any point in the previous decade (Ahmed et al., 2021). This has been fueled in part by rising energy prices, either as a direct component of the consumer price index (CPI) basket or as an underlying input cost in the manufacturing and transportation of other goods. The direct inflationary impacts of a greater price of carbon energy are referred to as fossilflation, a form of inflation caused by an increase in the price of fossil fuels and hence linked directly to an economy's reliance on such fuels (Jackson, 2024).

Carbon pricing and environmental restrictions, for instance, might increase firms' production costs as they promote the transition to a net-zero economy. Increased operational costs for facilities that remain integrated in a fossil-fuel-based energy system may have an impact on prices, with these costs passed on to consumers (Davis et al, 2020). The exposure of many countries to recent energy shocks has prompted deeper reflection on the supply insecurities inherent in global energy markets, the continued reliance on fossil fuel-based energy, the price volatility it causes, and the role of the energy transition in easing these tensions (Davis et al, 2020). Fossilflation is anticipated to be a transient phenomenon that will fade as emissions decline. However, the transition period is expected to last far beyond the short term, and so will have a significant impact on central banks' monetary policy (Jackson, 2024). Greenflation may result from firms shifting away from carbon energy and towards non-carbon energy, often known as greenflation (Simmens, 2023).

Greenflation

Another climate-related element that contributes to cost-push inflation is greenflation, which is associated with the costs of transitioning to a carbon-neutral economy. As sectors and industries embrace greener technologies and comply with stronger environmental rules, production costs may rise (Olivsson and Vestin, 2023). Shifting from fossil fuels to renewable energy sources may necessitate large upfront investment in new technology and infrastructure (Kabel and Bassim, 2020). Higher costs of production can be passed on to the consumer in the form of increased prices, resulting in cost-push inflation. Furthermore, as demand for green technologies and products expands, supply may struggle to keep up, causing costs to increase further (Kabel and Bassim, 2020).

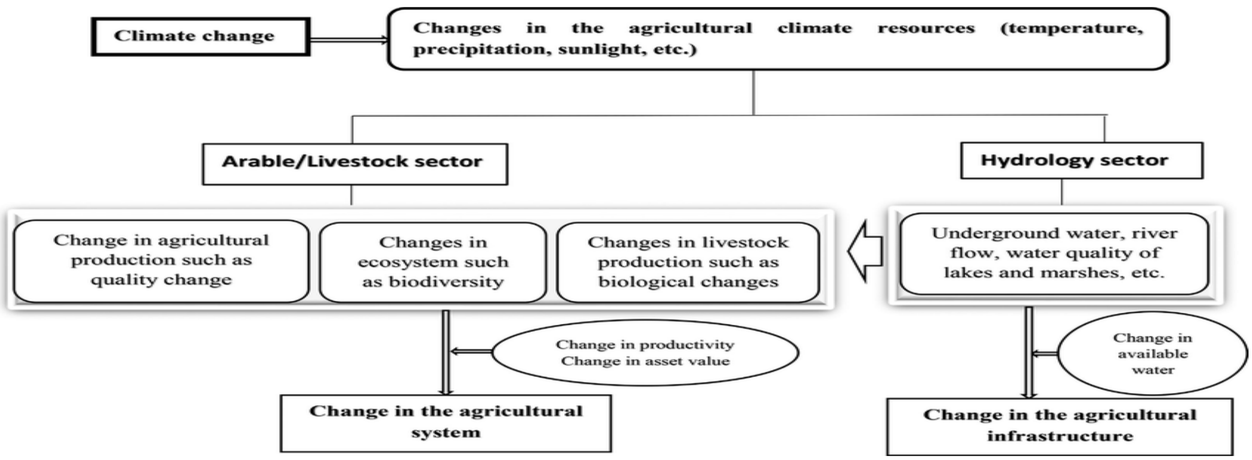
3.2.3. Conceptual approach

Impact of climate change on agricultural output

Climate change presents enormous challenges to agricultural systems worldwide. This conceptual framework analyses the complex effects of climate change on agricultural output, with an emphasis on the arable farming and livestock industries. Understanding these effects is critical for creating adaptive solutions that assure food security and sustainable farming practices.

Agricultural production is carried out through identifying crops that are appropriate for the climate of a particular region and using adequate farming techniques. Thus, agriculture is a climatic sensitive bio-industry with distinct geographical characteristics. Regional characteristics refer to ecological features that are determined by the region's climate. Climate change disrupts the agriculture ecosystem, altering agricultural climatic variables such as temperature, precipitation, and sunlight while also effecting the arable, livestock, and hydrological sectors (Kim, 2012). According to Kumari et al. (2020), the effects of climate change on the arable and livestock sectors can be seen in biological changes such as variations in flowering and harvesting seasons, quality alterations, and shifts in cultivated areas. Figure 3.1 below illustrates the progression of climate change's effects on the agriculture industry.

Figure 3.1: Flow of climate change impact on the agricultural sector



Source: Kim (2012:9).

Climate change causes biological changes in the livestock sector, such as fertilization and breeding, which in turn alters pasture growth patterns (Henry et al., 2018). Higher temperatures may speed crop development cycles, limiting the amount of time available for grain filling and resulting in below average yields. For crops like wheat and maize, extreme heat during critical growth stages, such as flowering and grain filling, drastically reduces productivity. Additionally, increased temperatures reduce not only livestock fertility, but alter breeding cycles, and negatively affect the health of newborn animals. Livestock under heat stress result in less milk production, less weight gain, and low productivity altogether. Rojas-Downing et al. (2017), attested that water supply for irrigation is directly impacted by alterations in precipitation patterns. Changed precipitation patterns affect soil moisture, which is crucial for crop development. Excessive rainfall leads to the problems of waterlogging, soil erosion, and loss of nutrients, while drought condition degrades the soil, hence lowering agricultural productivity. Agricultural productivity may remain low during the time and resources needed to recover from these occurrences (Eekhout et al., 2018).

According to Shrestha (2019), changes in climate disrupts the agricultural ecology, giving rise to blights and pests, spurring population movement, and reducing biodiversity. Warmer temperatures and changing precipitation patterns bring about advantageous conditions for pests and diseases, affecting sustainability and the yield of crops. This necessitates increased pesticide use, which can have further environmental and economic implications. Changes in climate further alter species composition and distribution within agricultural ecosystems. On the other hand, biodiversity loss compromises ecosystem resilience, reducing the natural services that support productive agriculture, such as pollination and pest control.

Climate change also has an impact on hydrology, including subsurface water level, water temperature, flow of rivers, and the quality of water in lakes and marshes, through rainfall, evaporation, and moist soil content (Oliazadeh et al., 2022). in particular, climate change increases precipitation, which increases outflow, whereas rising temperatures increase evaporation, which reduces outflow. When climatic changes, such as higher temperatures occur, the boundary and suitable areas for cultivation shift north, and thereby the primary fields for cultivation alter resulting in the expansion of arable land in some regions and a reduction in others (Kim, 2012). Farmers may need to adapt by changing crop varieties or farming practices to suit new climatic conditions. The effects of climate change on agriculture are mixed, with good impacts offering opportunities and negative consequences resulting in costs. As a result, it is a mandate to develop adaptation techniques that can maximize opportunities while minimizing costs to ensure sustainable agriculture development.

3.3. Empirical literature

The empirical research on how climate change affects food prices, specifically in developing nations, is examined. Several studies have found that climate change has the potential to impair agricultural output, resulting in a rise in food prices.

3.3.1. Climate change as a driver of food and overall inflation

The risks of climate change influencing key economic variables are divided into physical and transitional impacts (Anderson et al., 2020). This section will explore the macroeconomic effects of both the physical and transitional impacts associated with climate change by drawing evidence from various countries.

(I) Physical Impacts of climate change

According to Walsh et al. (2020), the physical effects of climate change are caused by an upward trend in both the severity and frequency of acute weather conditions such as flooding, high temperatures, and windstorms, in addition to gradual or chronic climate changes such as rising temperatures and sea levels.

A study by Fajri et al. (2019), evaluated the implications of climate change on food prices in Indonesian districts impacted by the El Nino and La Nina phenomenon. According to the study, the key factor driving climate change in Indonesia is the El Nino Southern Oscillation (ENSO), which is segmented into three phases: El Nino, La Nina, and Normal. The study additionally noted that ENSO has an essential role in climate variability and precipitation severity, which can have an impact on the agricultural sector, particularly the food crops sub-sector, which is exceptionally prone to climate change. The findings revealed that El Nino has a significant impact on the increase of soybean and rice prices, in addition to the decline in maize prices. While La Nina greatly impacts the rise in rice prices, El Nino has an even bigger impact on food prices than La Nina. Based on the findings, the study indicated that rice is the most vulnerable commodity to changing climates considering that both the El Nino and La Nina phases might induce a surge in rice prices. These findings are consistent with economic theories that emphasize inflation, specifically in alignment with the agricultural price transmission theory, thereby strengthening theoretical expectations of price changes created by climate changes. Fajri et al. (2019) used local correlation analysis to evaluate the relationship of climate, however, the present study expands the analysis by exploring a range of additional climate variables using the ARDL approach to provide a more comprehensive understanding of both short and long-run relationships between climate variables and food prices across the Southern African region.

Heinen et al. (2019), investigated the implications of severe weather on consumer prices in countries that are developing by creating a monthly dataset of prospective hurricane and flood destruction indices and relating it to inflation data for 15 Caribbean islands. The study follows hurricanes based on a wind speed index. This is considering that stronger winds are very destructive to infrastructure, houses, and even crops. The index reflects the localized impact of wind speed, which indirectly captures storm surges and heavy rainfall contributing to extensive economic damage in the region. Floods are detected based on excessive rainfall data. This aspect of the study proxies the extent of destruction from extreme precipitation, which can lead to water overflow and erosion, damaging agricultural land and disrupting local economies. The econometric model employed in the study reveals that extreme weather occurrences can have a significant impact on prices. To demonstrate potential welfare losses from such pricing impacts, the study paired its estimations for Jamaica using event probability and pricing elasticities derived from a demand system. The findings revealed that projected monthly losses are minor, however uncommon events can cause significant drops in monthly wellbeing due to price rises. While physical consequences of climate change have been proven to temporarily increase inflation, particularly food prices, these effects have tended to fade in the longer term. The study also contended that the consequences of such disasters may be worse in the future should extreme weather conditions become more common and severe.

Beirne et al. (2022), investigated the impact of catastrophic events (droughts, earthquakes, storms, floods, heat and volcanic eruptions) on eurozone inflation. Estimating panel and customized structural vector autoregression models by integrating estimated disaster impairment with monthly Harmonized Index of Consumer Prices data for all eurozone nations from 1996 to 2021. Aside from evaluating the influence on total headline inflation, the study looked at effects on its 12 main sub-indices and additional sub-categories of food price inflation. The findings indicated that natural catastrophes have a considerable positive influence on total headline inflation, with divergent results at the sub-index level, resulting in diverse inflation effects among countries. Italy, France, Germany, and Spain were shown to have had the most natural disasters of any of the sample countries. Most of the disasters were caused by floods and storms, with earthquakes, extreme temperature events, wildfires, and droughts occurring less frequently. Therefore, the study indicates that natural disasters cause inflationary pressure disruption to supply chains, infrastructure damage, and loss of agricultural productivity-especially in the food sector. The study therefore denotes that these risks can increase with climate change since it is linked with dire weather conditions that are likely to be more frequent or intense, making it quite very difficult to maintain price stability by central banks such as the European Central Bank.

The Central Bank of Seychelles (2022) conducted a study on the challenge of climate change and its implications for inflation in the SADC region. Carbon emissions were used as one of the variables to measure the intensity of climate change, and it was noted that higher magnitudes of CO2 imply increased severity in climate events. These are associated with disruptions in supply chains, which in turn may cause inflationary pressures. The results indicate that for every 1% increase in carbon emissions, there was a corresponding 0.38% increase in the year-on-year inflation rate, significant at the 10% level. On the other hand, natural disasters-cum-climate change have contributed to the spiraling inflation due to breakdowns in the supply chain, particularly food. In some cases, the rate of food inflation has increased greatly owing to the disruption in its availability. On the other hand, whilst prices of some sub-categories of the CPI may increase during the aftermath of a disaster, prices of other sub-categories may fall due to depressed economic activity, thus resulting in no overall rise in headline CPI. Thus, this is indicative that the effect of disasters on inflation is ambiguous and is dependent on the aftermath of the crisis (Parker, 2018). Nevertheless, the result of the estimation indicates inflationary effects of rising carbon emissions in the SADC region based on the data sampled between 2015 and 2019. This relationship is primarily due to supply-side factors, such as drought-induced crop failures, which increase inflationary pressures.

Cevik and Jalles (2023), employed a local forecasting technique to empirically evaluate whether climate shocks, defined as climate-induced natural disasters (storms, droughts, and temperature), affect inflation and economic development in a broad panel of nations from 1970 to 2020. According to the findings, both inflation and real GDP growth respond substantially and differently in terms of direction and magnitude to various types of climate-related disasters. The study discovered that while high temperatures lower inflation, droughts and storms raise inflation. In the event of a temperature shock, headline inflation falls significantly below its original level in the first year and over time. This decline hits a bottom about four years after the shock, when headline inflation is 3.5 percentage points lower than it would have been if the temperature shock had not occurred. A drought shock, on the other hand, generates a quick increase in headline inflation above its previous level, which lasts for some time and amounts to approximately 1.5% greater than if the shock did not occur. Storms, on the other hand, have an identifiable impact pattern that distinguishes them from other forms of weather disasters. The study found that headline inflation rises by about 0.2% in the first year following the storm shock, though it then falls by 1% in the long term if the shock did not occur.

A study by Cunpu et al. (2023), used the mean temperature serves as an alternative indication for climatic shocks. The authors employed panel data from 1995 to 2021 for the 26 selected countries: America includes 4 countries, Asia includes 8 countries, Oceania includes 1 country, and Europe includes 13 countries. They investigated the impact of temperature variations on levels of consumer prices. The results showed that temperature variation and high prices are positively related in the selected countries, which is consistent even after taking the analysis through various robustness tests. Furthermore, accounting for heterogeneity reveals that the extent of inflation's response to variations in temperatures varies by country. In terms of underlying mechanisms, this study highlighted the importance of energy demand as an essential channel influencing inflationary pressures at the country level, as changes in temperatures affect agricultural output and energy demand, which ultimately impacts global price levels when demand exceeds supply.

(II) Transition impacts of climate change

As the economy transitions to a low-carbon and eventually net-zero economy, a number of transitional effects on the macroeconomy emerge from the process of modifying policies, preferences, and technology (Hallegatte et al., 2024). These impacts can be orderly, leading to a smooth transition, whereas a disruptive transition may induce amplified effects on the economy through the various channels.

A study by Mairate (2023), aimed at investigating the macroeconomic implications of the green transition using scenarios, asserted that the transition to a carbon-neutral economy is currently disrupting the supply side of many industries, especially those reliant on fossil fuels. According to the same study, as carbon pricing and more stringent environmental regulations are implemented, energy costs increase for industries that have not fully transitioned to renewable energy sources. These increased costs trickle down to goods and services, causing cost-push inflation. This makes the agricultural sector very vulnerable to increases in the costs of fossil fuels, as it is highly dependent on these for fertilizers, transportation, and energy (Wang et al., 2024). Higher costs for these inputs, aside from the impact of climatic changes on crop yields, result in increased food prices and add to food inflation.

In addition, financial stability is exposed to both physical and transition risks. Many central banks worldwide have recognized the need to consider the rising financial risks of climate change (Network for Greening Financial System, 2021). These include potential loan losses for banks as a result of business disruptions and bankruptcy caused by hurricanes, wildfires, droughts, and other extreme occurrences. Transition risks linked with the shift to a carbon-neutral economy include unanticipated reductions in the value of assets or firms that rely on fossil fuels (Semieniuk et al., 2021). Even long-term threats can have an immediate impact when investors revalue assets for a low-carbon future. Financial firms with low carbon emissions may yet be extremely sensitive to climate-related credit risk through loans to affected businesses or mortgages on coastal real estate. If such exposures were broadly comparable across regions or industries, the associated climate-related risk could negatively impact the financial system's overall stability (Semieniuk et al., 2021).

Such structural changes required by the energy transition also create inflationary pressure. The transition from carbon-intensive industries towards renewable energy sectors, requires considerable reallocation of inputs and financial investments which tends to cause input bottlenecks (Zakeri et al. 2022). This includes shortages of pivotal resources in renewable energy systems that may result in price increases. It also creates implications for the economy in lower economic growth influenced by the reallocation of resources from carbon-emitting sectors to cleaner options, thus causing temporary disequilibrium (While and Eadson, 2022). Even renewable energy, though it may cut costs over the long term, creates significant risks in inflation within a transition period.

3.3.2. Climate change as a contributing factor to lower agricultural output

Climate change, through physical and transitional risks, has had negative impacts on agricultural output. Physical risks here include increasing temperatures, changed rainfall patterns, and rising frequencies of extreme weather conditions, disrupting the optimal climate conditions that were once required for crop yield and livestock productivity. This often coincides with increasing scale of soil fertility deterioration and pest and disease pressures. Conventional agricultural systems as both a significant source of emissions and a potential part of the solution to climate change, may face transitional risks. These risks could be subjected to new regulation, market changes or changing consumer preferences in the face of climate impacts (e.g., Belmin et al., 2023).

(I) Physical impacts of climate change on agricultural output

In the study of Alboghdady and El-Hendawy (2016), the production function model was employed using FER analysis on the impacts of climate change and variability upon agricultural production in the MENA region. The panel data utilized in the study are pooled from 20 countries across the MENA region spanning from 1961 to 2009. The results indicated that with a 1% increase in temperature during winter, agricultural production decreased by 1.12%. In addition, it was found that with a 1% increase in the variability of temperature during winter and spring, agricultural production decreased by 0.09% and 0.14%, respectively. Results further indicated that increased precipitation during the winter and fall seasons, along with changes in rainfall during the winter and summer seasons, had a negative impact. The computed parameters for squared temperature and precipitation show that the changing climate has a strong quadratic impact on agricultural output in the MENA region.

A study by Agba et al. (2017), studied the impact of both climate change and non-climate change variables on crop production in Nigeria. The study adopted an empirical research approach using secondary sources of time series annual data from reputable sources for the period 1980 to 2013 and employed the Error Correction Mechanism for the analysis. Results showed that in the short run, only rainfall has a significantly positive relationship with crop production. However, in the long run, the study found that CO_2 emissions, rainfall, temperature, and carbon emissions will significantly influence crop production. Additionally, carbon dioxide and carbon emissions from manufacturing and industrial activities negatively impact crop production. Furthermore, non-climate change characteristics such as economically active population, gross capital formation, and irrigation-ready land area all had a considerable beneficial impact on agricultural output. To limit the consequences of climate change on crop output, the study proposed that policymakers develop policies that assist farmers in adopting climate-resilient farming practices. Furthermore, governments and other relevant agencies should develop programmes to encourage people to get more involved in agricultural production.

Another study by Haile et al. (2017), which intended to evaluate the effect of changing climates, extreme weather events, and price risk on the global supply of food by analyzing the factors influencing global production for maize, wheat, rice, and soybeans between 1961 and 2013. Using seasonal production data, changes in prices and volatility statistics at the country level, and future climate data from 32 global circulation models, the study forecasted that climate change could lower world agricultural production by 9% in the 2030s and 23% in the 2050s. Furthermore, climate change could result in 1 to 3% larger yearly fluctuations in global food production during the next four decades. The study discovered a strong, positive, and statistically significant supply response to changing prices for all four crops. However, output fluctuations in prices, which signals risk to farmers, limits the supply of these important global agricultural staple crops, particularly wheat and maize. The study discovered that climate change has a considerable negative impact on the production of the world's important staple crops. Weather extremes, namely shocks in temperature and precipitation during crop growing months, have a negative impact on the production of the aforementioned food crops. Extremes of weather also increase the yearly oscillations of food supply and therefore may further increase volatility with its adverse effects on production and poor consumers. Mitigating and adapting to climate change in a combination approach, a key component for the fulfillment of global production and the quest for food security is hereby addressed.

Sibanda and Ndlela (2019), investigated the link between carbon emissions, agricultural production, and industrial output in South Africa. This study employed data from 1960 to 2017 at an annual frequency, resulting in 58 yearly observations. The Autoregressive Distributed Lag approach was used to estimate the model on a bivariate basis. The results showed that agriculture and industrial output have little influence on carbon emissions. In contrast, carbon emissions and industrial output both have an impact on agricultural output. The findings imply that climate change caused by carbon emissions has resulted in lower agricultural output due to the harmful impact that carbon emissions have on plants and the environment, hence jeopardizing food security. The study concluded that there is a considerable correlation among industrial and agricultural output, implying that a properly functioning industrial sector will result in an increase in agriculture output.

According to Letta et al. (2022), the empirical literature on the impact of weather shocks on agricultural prices often focusses on post-harvest price dynamics rather than pre-harvest ones. The study uses the intra-annual competitive storage theory to experimentally analyze the role of weather shocks in traders' expectations of pre-harvest price swings in India's local marketplaces. Using a panel of district-level monthly wholesale food prices from 2004 to 2017, the study uses the time gap between a weather anomaly and the associated supply shock to isolate price reactions caused by changes in forecasts. According to the study, drought conditions significantly increase food expenditures during the growing season, even before harvest failure occurs. These findings suggest that markets respond swiftly to expected supply shortages by updating their views and responding accordingly, and that the expectation channel accounts for a sizable percentage of supply-side food price movements. When compared directly to the effects of the same weather anomalies on pricing in the first harvest month, expectations predict more than 80% of the total price impact.

Another study by Otim et al. (2023), examines the effect relationship and the direction of causality between CO_2 emission and Agricultural Production Index, with the intervention of renewable energy consumption, arable land and governance. The authors cover a time period between 1996 and 2019. The study has a transversal approach covering 6 countries within the East African Community regional block. These include Kenya, Rwanda, Uganda, Burundi, Tanzania, and the Democratic Republic of Congo. The study has utilized pooled mean group/autoregressive distributed lag and fixed effect approaches and has performed the Dumitrescu and Hurlin Granger non-causality test on the causality of the considered variables. The long-run model indicated that CO2 emissions, renewable energy consumption, labor force and arable land size all have positive effects on the crop production index. Apart from this, consumption of renewable energy, arable land size and good governance have a positive relationship with the livestock production index. The CO2 emissions both ways are not the Granger cause of crop production index, whereas the significant effects of good governance and the size of arable land showed inconclusive results on agricultural production.

(II) Transition impacts of climate change on agricultural output

A study by Lehtonen et al (2022), which attempted to analyse the transition of agriculture to low carbon avenues with regional distributive implications, maintained the following: This study, based on agricultural sector modelling, demonstrates how changes in food consumption and land use strategies might reduce GHG emissions from Finnish agriculture, while considering the effects on regional levels of agricultural production, GHG emissions, land use, and farm revenue. The findings suggest that it is difficult to achieve a significant reduction in GHG emissions from agriculture by simply changing diet as agricultural emissions are closely linked with essential activities inclusive of livestock farming and crop production, which are fundamental for food security. Changing food consumption patterns, such as reducing livestock product intake, can lower emissions, but it also disproportionately impacts regions reliant on livestock farming. Regions such as Finland may face income losses and economic disruption, making the transition socially and economically difficult. The most effective way to reduce GHG emissions from agriculture is to combine changes in food and land use; yet relatively disadvantaged regions with substantial shares of livestock production and peatlands may face significant agricultural and land use restructuring. Furthermore, the sectoral disruptions caused by a disorderly transition to a low-carbon economy can be significant, posing serious financial risks. The study, therefore, provides more incentive for government officials and financial institutions to promote and prepare for an early and orderly transition.

3.4 Assessment of literature

A complete social welfare analysis is needed to quantify the extent of total economic losses from climate change. This covers everything from direct losses of income and production, the value of resources, goods, and services that are no longer available or the reduced quality, damage to productive capital and infrastructure, decreases in ecosystem services, impact on morbidity and mortality as well as loss of subjective well-being from more intangible advantages such as the extinction of species or deterioration of ecosystems (Piontek et al., 2021). Existing literature such as that from the study of Kilroy (2015), and that of Sintayehu (2018), is more focused on biophysical impacts such as change in crop yields, soil health, and water availability. Less attention is given to the socioeconomic factors that arise due to climate change, particularly food and overall inflation.

Therefore, there remains a major gap in understanding the impact of climate change on food prices, and economic resilience, including the effectiveness of adaptation strategies and policy interventions to stabilize food prices and increases in agricultural productivity. Solely a few studies considered both sides of this imbalance, indicating a neglect of the need for more integrated research that combines biophysical and socio-economic dimensions, particularly on the relationship of climate change, agricultural production, and inflation with food prices (Piontek et al., 2021).

3.5. Chapter Summary

This section addressed the numerous theoretical and empirical approaches used to unravel and diagnose the relationship between climate change, agricultural production, and food inflation.

Amongst other theories that determine inflation, this section included the Keynesian theory by focusing on the cost-push inflation which occurs when overall price increases due to increased costs of wages and raw material. This section also used the conceptual approach to describe the impact of climate change on the agricultural sector. From a very critical analysis of the available empirical literature, it is observable that climate change presents a big challenge since the results indicate that the relationship between climate patterns, agricultural productivity, and economic stability is complex and multidimensional. The reviewed studies consistently show that disruption due to climate change, manifested in extreme weather events, altering rainfall patterns, or even rising temperatures, has its reflections in agricultural production and, further, in food security and supply chains, bringing inflationary pressures on foods.

CHAPTER 4: RESEARCH METHODOLOGY

4.1. Introduction

This chapter presents the research design to be adopted for the study, which gives a systematic approach in analyzing the impact of climate change on agricultural production and food inflation in Southern Africa. It starts with the research design, which describes the overall strategy and framework that guide the study. The section on data sources and sampling describes the methods of data collection and sampling techniques used to ensure reliability. In that respect, the model specification and description of variables detail the analytical models with which the variables are defined, and their respective roles. Ultimately, the estimation methods section would focus on the statistical techniques necessary for data analysis to ensure findings are robust and valid.

4.2. Research design

The study employs a correlational research design using secondary data to determine the impact of independent variables on dependent variables (Seeram, 2019). The study uses two models and in the first model, agricultural production serves as the dependent variable, while independent variables encompass labor, livestock, machinery, fertilizer, agricultural land, as well as rainfall and temperature. In the second model, food inflation is the dependent variable, with independent variables comprising crop production index, food exports, oil prices index, agricultural raw material imports, rainfall, and temperature. This study aims to determine the impact of climate change on agricultural production and food inflation in Southern Africa.

4.3. Model 1: Agricultural Production

4.3.1. Data Sources and sampling

This study employs a production function method and an inflation model to investigate the effects of climate change on agricultural production and food inflation in Southern Africa. The empirical analysis is based on panel data from 8 Southern African countries for the time period between 1981 and 2020, thus equivalent to 320 observations.

This sample size is selected based on the fact that it will be representative of the long-term trend and cyclical variations, capturing the slow effects of climate change while also being recent enough to reflect the current climatic conditions. The countries are selected based on their heavy reliance on agriculture, diverse climatic conditions, and most importantly, based on the availability of reliable data that can enable the study to make meaningful conclusions applicable to the broader region. The countries to be studied are Malawi, Lesotho, Zimbabwe, Botswana, Namibia, Mozambique, South Africa, and Zambia. Temperature and precipitation data will be obtained from the NASA Prediction Of Worldwide Energy Resources. The study uses country-level climate data for mean annual temperature in °C, and average annual rainfall in mm, since these are the most commonly used meteorological variables in these studies.

For economic variables such as agricultural production index, livestock production index, economically active population in agriculture, agricultural land, agricultural machinery, and fertilizers consumption, data in the model will be obtained from the Food and Agriculture Organization of United Nations Statistics Division (FAOSTAT) and World Development Indicators (WDI). The NASA Prediction of Worldwide Energy Resources (POWER) is reliable because the high-resolution, scientifically developed data by experts are accurate and reliable. On the other hand, Food and Agriculture Organization of the United Nations Statistics Division-FAOSTAT and World Development Indicators (WDI) are reliable sources because they provide comprehensive, standardized, and globally recognized statistics on agriculture. Data from the two mentioned sources ensures credibility and reliability of the study due to their wide usage in research and policymaking.

4.3.2. Model Specification and Discussion of Variables

To examine the impact of climate change on agricultural production in Southern African countries, the study specifies a production function where the agricultural production index is a function of a number of economic inputs and climate factors: AGRP=f(LAB, LIV, AMAC, TFC, AGRL, RAIN, TEMP). AGRP represents the agricultural production index; LAB, LIV, AMAC, TFC, and AGRL are agricultural labor, livestock, agricultural machinery, total fertilizer consumption, and agricultural land, respectively. The proxy of capital stock is agricultural machinery that represents the number of tractors. Climatic factors that may impact agricultural production are represented by rainfall (RAIN) and temperature (TEMP). This specification of the production function is adapted from a study by Belloumi (2014), in which the contribution of climate change to changes in agricultural production in countries from Eastern and Southern Africa was examined. The major advantage of using the production function framework is that it explicitly controls for other inputs

(Ochieng et al., 2016). The agricultural production model used in the present study comprises the subsequent specification form:

$$AGRP_{it} = \beta 0 * LIV_{it}^{\beta 1} * AGRL_{it}^{\beta 2} * LAB_{it}^{\beta 3} * AMAC_{it}^{\beta 4} * TFC_{it}^{\beta 5} * e^{\varepsilon it} * e^{\beta 6 RAINit + \beta 7 RAINit^2 + \beta 8 TEMPit + \beta 9 TEMPit^2} \quad (4.1)$$

According to the FAO (2020), each commodity's production volumes are determined by the 2014-2016 global commodity price averages and averaged for the year. The unit of production is international dollars, not production quantity or local currency. LIV represents the livestock production index (2004-2006 = 100). AGRL is for agricultural land (in hectares), and it refers to the percentage of land area that is arable, under crop rotation, or under permanent grazing. LAB stands for the total number of economically active individuals in agriculture, AMAC for the number of wheel and crawler tractors in operation, and TFC for the total amount of agricultural fertilizer consumed in kilograms per hectare of arable land. Climate variables include rainfall and temperature. Climate variables are rainfall (mm per year) and temperature (°C per year).

Considering that the study takes into account several countries over many years, the analysis incorporates a mechanism to capture regional and temporal scale differences. After taking the log on both sides of the model given by equation (4.1), the panel data model is given by equation (4.2) for any country i at time t:

$$lnAGRP_{it} = \beta_0 + \beta_1 lnLIV_{it} + \beta_2 lnAGRL_{it} + \beta_3 lnLAB_{it} + \beta_4 lnAMAC_{it} + \beta_5 lnTFC_{it} + \beta_6 RAIN_{it} + \beta_7 RAIN_{it}^2 + \beta_8 TEMP_{it} + \beta_9 TEMP_{it}^2 + \varepsilon_{it} \quad (4.2)$$

where lnAGRP, lnLIV, lnAGRL, lnLAB, lnAMAC, and lnTFC are the logarithms for agricultural production index, livestock production index, agricultural land, agricultural labor, agricultural machinery, and total fertilizer consumption, respectively. To account for the nonlinear relationship between agricultural production and climate factors, the model estimates both linear and quadratic terms for climate variables. The error term is represented by ε_{it}. The coefficients to be estimated are βs.

Table 4.1: Variable Description

Variable	Abbreviation	Description	Measurable Indicator	Expected sign
Agriculture Production Index (2004-2006 = 100)	AGRP	The FAO agricultural output indices show the corresponding percentage of aggregate agricultural output for each year as compared to the base year 2004-2006.	Index	Dependent Variable
Livestock Production Index (2004-2006 = 100)	LIV	The livestock production index includes meat and milk from all sources, dairy products such as cheese and eggs, wool, honey, raw silk, and hides and skins.	Index	(+)
Agricultural Land (hectares)	AGRL	Agricultural land is defined as the area of land that is cultivable, under crop rotation, or under permanent grazing.	Hectares	(+)
Labor in agriculture	LAB	Agricultural labor refers to the number of people who work in the agricultural sector or are economically involved in agriculture.	% of total labor force	(+)
Total Fertilizers Consumption (tons)	TFC	Total fertilizer consumption in agriculture in kilograms per hectare of arable land.	Kg/ha	(+)
Agricultural machinery, tractors	AMAC	Agricultural machinery refers to the total number of wheel and crawler tractors (excluding garden tractors) employed in agriculture.	Tractors per 100km^2 of arable land	(+)

Average rainfall (mm per year)	RAIN	The mean rainfall is the country's long-term average of yearly rainfall volume	mm per year	(+)
Mean annual temperature	TEMP	Mean annual temperature	°C per year	(-)

4.4. Model 2: Food Inflation

4.4.1. Data and Methods

The study includes annual panel data from eight Southern African countries: Malawi, Lesotho, Zimbabwe, Botswana, Namibia, Mozambique, South Africa, and Zambia. The study contains 320 observations from 1981 to 2020. The estimation sample was chosen based on the availability of data on the primary variables of interest, as well as the availability of high frequency annual data. Food pricing indices are acquired from the relevant country databases, whereas the food consumer price index, crop production index, agriculture raw material imports, and food exports are obtained from the FAOSTAT database. Rainfall and temperature data are collected from NASA POWER.

4.4.2. Model specification and Discussion of variables

Consistent with past studies, such as Nahoussé's (2019), which investigated the drivers of inflation in West Africa, this study specifies a food inflation model that includes climate change proxies in the form of yearly mean rainfall and yearly average temperatures. Equation (4.3) specifies the general equation for estimation.

$$\boldsymbol{\pi_{it} = \alpha_i + \beta X_{it} + \pi_{it-1} + \varepsilon_{it}} \qquad \textbf{(4.3)}$$

where π_{it} is the food price index for country i in time t, X_{it} represents exogenous forces driving inflation, πit-1 is the lagged regressand, αi represents country-specific effects, and ε_{it} is the error term. Equation (4.4) specifies the model to be estimated.

$$\mathbf{FCPI_{it} = \alpha_i + \beta_1 CROP_{it} + \beta_2 FEX_{it} + \beta_3 ARMI_{it} + \beta_4 OILPRI_{it} + \beta_5 FPRI_{it} + \beta_6 RAIN_{it} + \beta_7 TEMP_{it} + \beta_8 FPI_{it-1} + \varepsilon_{it}} \qquad \textbf{(4.4)}$$

Where the FCPI captures the Food Consumer Price Index, and it is the dependent variable in this model for this study. CROP is the crop production index, FEX is the food exports (% of merchandise exports), ARMI is the agricultural raw materials imports (% of merchandise imports), OILPR is the oil price index, FPRI is the fertilizer price index and climate refers to the two proxies of climate change risk indicators, namely: annual average rainfall amounts (R) and annual mean in temperature (T).

The study employs average rainfall and mean temperature data to highlight the unpredictability in food availability that contributes to high food costs. Improved rainfall is expected to lower food inflation as supply expands, resulting in greater agricultural productivity. However, significant variations in rainfall and temperature are expected to induce inflation. Temperature fluctuations have a distinct impact on inflation than average monthly rainfall since high temperatures are associated with drought, which causes inflation. Temperature fluctuations cause inadequate rainfall thus resulting in drought, lowering hydropower generation capacity both directly and indirectly by means of electricity price connections to other consumer basket commodities including food and non-food non-fuel products. Price changes in the global oil market affect local fuel costs in all of the countries under consideration, which are predominantly fuel importers. A surge in international oil prices would thus bring about a rise in prices of domestic fuel, which would then lead to a rise in the prices of food resulting from higher transportation costs.

Table 4.2 shows a definition of the key variables used in the study, along with their definitions, measurement indicators, and hypothesized impact on food inflation. The study considers a group of agricultural, climatic, and economic variables to analyze their impact on food prices. All of the variables are selected based on empirical and theoretical significance, with hypothesized signs that determine whether each variable is likely to increase or decrease food inflation.

Table 4.2: Variable Discussion

Variables	**Abbreviation**	**Discussion**	**Measurable Indicator**	**Expected Sign**
Food Consumer Price Index	FCPI	The food price index tracks the changes in the prices of a basket of food items overtime. Higher food prices can directly contribute to food inflation as it becomes more expensive for consumers to purchase essential food items.	Index	Dependent Variable
Crop production index (2014–2016 = 100)	CROP	Measures the overall productivity of agricultural crops. Less crop production can result in reduced food supply, potentially leading to increased food prices and higher inflationary pressure.	Index	(-)
Food exports (% of merchandise exports)	FEX	If a significant proportion of the country's food production is exported to other regions, it can reduce domestic food supply and increase domestic food prices, thus contributing to food inflation.	% of merchandise exports	(+)
Oil Price Index	OILPR	Changes in the worldwide oil market affect domestic prices for fuel, resulting in higher prices of food for countries hat mostly import fuel.	Index	(+)

Agricultural raw material imports (% of merchandise exports)	ARMI	Higher import costs for agricultural materials lead to increased production costs which result in increased food prices and ultimately inflation.	% of merchandise exports	(+)
Fertilizer price index	FPRI	Changes in fertilizer prices impact the Farmers' input costs, affecting their decisions on crop production and ultimately influencing food prices.	Index	(+)
Average rainfall	RAIN	The mean rainfall is the country's long-term average of yearly rainfall volume	mm per year	(-)
Mean in temperature.	TEMP	Mean annual temperature	°C per year	(+)

4.5. Estimation techniques and procedures

4.5.1. Descriptive Statistics test

Calculating descriptive statistics represents a vital first step when conducting research and should always occur before making inferential statistical comparisons (Kaur et al., 2018). Descriptive statistics are methods used to effectively summarize and describe the main features of a dataset in an organized manner by providing an overview of the relationship and patterns between variables in a sample (Mishra et al., 2019). That is, it would comprise central tendency measures, like mean, median, and mode, describing the average for a set of data; there would be measures of variability such as range, variance, and standard deviation that give a description of spread or dispersion of the data. There are also descriptive statistics portraying data through graphical means; thus comes the histogram, the box-and-whisker plots, and scatter plots to pictorially show the data represented (Cooksey and Cooksey, 2020). Therefore, the descriptive statistics to be undertaken in this study will help in the identification of outliers and analysis of data, which also informs the selection of appropriate statistical methods for further analysis.

4.5.2. Correlation Analysis

To test for possible relationships among the studied variables, the correlation analysis which tests the association between two or more quantitative variables is utilised. This approach is primarily predicated on the assumption of a linear relationship among the quantitative variables. Similar to the measures of association for binary variables, correlation analysis quantifies both the intensity and direction of the relationship between the variables (Schober et al., 2018). The outcome of a correlation analysis is a correlation coefficient that ranges from negative one to positive one. A correlation coefficient of positive one signifies a perfect positive linear relationship between two variables, a coefficient of negative one signifies a perfect negative linear relationship, while a coefficient of zero indicates the absence of a linear relationship between the two variables under examination (Gogtay and Thatte, 2017).

4.5.3. Panel Unit Root test

Unit root tests are one of the statistical tests applied to determine whether a time-series variable is stationary or possesses a unit root, implying that it is non-stationary (Khraief et al., 2020). The unit root tests are important in determining the stochastic properties of the variables under investigation. Furthermore, unit root tests assist in examining the presence of a spurious relationship which occurs when two non-stationary variables appear to be correlated purely due to chance, without any genuine underlying relationship (Herranz, 2017).

The order of integration of the variables of interest will be determined using three panel unit root tests: Levin, Lin, and Chu (LLC) and Im, Pesaran, and Shin (IPS), as well as Fisher Chi-square tests. These tests presume cross-sectional dependence between units. The LLC test presupposes that the residuals are unbiased and equally dispersed with a mean of zero and a constant variance, and that the autoregressive parameter is the same across all panels (Lau et al., 2019). While the LLC test allows for differences in intercepts across panels, the IPS test allows for differences in both intercepts and slopes, accommodating more heterogeneity among the cross-sectional units. Im et al. (2003), developed the IPS panel unit root test, which is less restrictive and more powerful than other tests such as (LLC), established by Levin et al. (2002). IPS's proposed test addresses Levin and Lin's serial correlation problem by assuming heterogeneity across units in a dynamic panel framework (Mburamatare et al., 2022). These tests have a non-stationarity null hypothesis, and comparing the results from multiple approaches is an effective way to assess the veracity of the conclusions (Lau et al., 2019). The rejection criteria for both the Levin Lin Chu (LLC) and Im Pesaran Shin (IPS) panel unit root tests stipulate that the test statistic must be sufficiently negative, leading to the rejection of the null hypothesis of a unit root if the p-value is below 0.05.

The Fisher-type test has been proposed as a remedy by Maddala and Wu (1999) and Choi (2001), for several defects in LLC and IPS frameworks. These authors have proposed the use of non-parametric Fisher-type test based on the combination of p-values of unit root test statistics, for example, the ADF test, computed for each cross-sectional unit. While the LLC test restricts the alternative to maintaining the same parameter ρ in both the null and under-alternative conditions, for the Fisher test it becomes more general; thereby allowing flexibility. The null is presented as all panels have unit root meaning that a panel is nonstationary where the alternative hypothesis to test is that at least a single panel is stationary. Similarly to the LLC and IPS test, the Fisher Chi-square test rejects the null hypothesis when the aggregated p-value is less than 0.05, indicating that at least one panel is stationary (Maddala & Wu, 1999; Choi, 2001).

4.5.4. Lag Length Selection

Selecting the most suitable lag length is a critical step before running the panel cointegration test. The process is quite crucial since the incorrect lag length will result in model misspecification, which will ultimately make the results invalid and unreliable (Han et al., 2017). To ensure the selection of an appropriate lag length, standard information criteria is employed, namely, the Akaike Information Criterion (AIC) and Schwarz Criterion (SC). The lag length selection is based on values for which either Akaike Information Criterion (AIC) or Schwarz Criterion (SC) are minimized. The best criterion that best fits the model is the one with the lowest figure.

4.5.5. Panel Cointegration Test

After determining whether or not the variables have a unit root, a panel cointegration test is performed. This is to determine whether there is a long-term relationship between the variables. Panel cointegration tests are divided into three types: Pedroni residual cointegration tests, Kao residual cointegration tests, and the Johansen fisher panel cointegration test (Kalymbetova et al., 2021). The Pedroni cointegration test is the most commonly used in panel data regression analysis as it accounts for cross-sectional dependence, particularly when countries have similar outlooks (economic, social, political, etc.) while allowing for significant heterogeneity (Dankumo, 2021). However, for robustness, both Kao and Pedroni cointegration panel tests are employed in this study to determine whether there is a long-term correlation between independent and dependent variables. These tests involve a null hypothesis of no cointegration. Rejecting the null hypothesis implies that the variables are cointegrated across all panels.

According to Dincer and Yuksel (2023), the Pedroni cointegration test permits variation in the dynamics of the cointegrating vectors across multiple cross-sectional units, allowing for greater flexibility than the Kao test. Pedroni (1995), offered seven distinct statistics for evaluating panel data co-integration. The first four are based on pooling, known as the within dimension, while the last three are based on the between dimension. Both types of testing are based on the null hypothesis of no cointegration. To reject the null hypothesis that there is no co-integration, the calculated test statistics must be less than the tabulated critical value.

Similar to the Pedroni cointegration, the Kao cointegration test acknowledges the heterogeneity between cointegrating vectors both in the short-run and long-run (Heriqbaldi & Mufidah, 2023). As much as the Kao cointegration test uses the same basic approach as the Pedroni test (the residual-based approach), the test also considers cross-section specific intercepts and homogeneous coefficients during the first-stage regressors (Cetin & Ecevit, 2015). The null hypothesis for Kao cointegration test is that there exists no cointegration between the cross-sectional variables while the alternative hypothesis assumes the presence of a long-run relationship between variables. If the p-value falls below 0.05, the null hypothesis is rejected.

4.5.6. Pooled Mean Group (PMG)/Panel Autoregressive Distributed Lag (ARDL)

If no cointegration is discovered after performing the panel unit root tests and cointegration tests, the panel ARDL model is employed. To estimate long-term associations using the autoregressive distributed lag model, a non-stationary series is required. A series is deemed non-stationary if its mean, variance, and covariance change with time (Brooks, 2019). The ARDL framework restricts variables to being either integrated of order I(0) or I(1).

The panel ARDL model is used in this study to investigate the relationship between climate change, agricultural production, and food inflation in southern Africa. Pooled Mean Group (PMG) estimation, often known as the panel ARDL model, offers the advantage of identifying dynamic long and short run correlations (Mensah et al., 2019). This estimate permits the short-run coefficients, including intercepts, the rate of adjustment to long-run equilibrium values, and error variances, to vary by nation, yet the long-run slope coefficients are consistent across countries. This is especially relevant when there are grounds to believe that the long-run equilibrium relationship between the variables is consistent across countries, or at least a subset of them (Mensah et al., 2019).

This approach is appropriate since it is more efficient and compatible with the presence of long-term relationships. According to this framework concept, the long-run equilibrium relationship between variables is consistent across countries (Pesaran et al,1999). The PMG estimator is based on the assumptions below. First, the error terms are not serially correlated. Second, there is a long-term association between the dependent and independent variables, and the long-term characteristics are consistent across nations (Lee et al, 2015). Failure to meet these parameters will result in inconsistent PMG estimation. Compared to other existing estimators, the pooled mean group (PMG)-ARDL econometric technique fits into this research paradigm since the study assumes a short- and long-term relationship between the variables under consideration. This econometric estimation technique also gives consistent coefficient estimates in the presence of potential endogeneity and serial correlation challenges given that it covers both lagged dependent and independent variables (Pesaran et al, 1999).

4.5.7. Panel Data Analytic Models

The study uses two panel data analytic models to generate its results. These models contain both fixed-effects and random-effects models. The primary contrast between fixed and random effects is whether the unobserved individual effect contains parts that are correlated with the model's regressors, rather than whether these effects are stochastic or not (Hill et al., 2020). The Hausman test determines the best fitting model for data analysis.

Fixed Effects Model

When examining the impact of variables that change over time, the fixed effects model is applied (Kelejian & Piras, 2017). Every entity (country, organization, or individual) has unique traits known as time invariant variables, which may alter the quantitative relationship between the regressed and regressors (Hill et al., 2020). The basic premise is that certain qualities, such as culture or gender, remain constant across time. To compensate for unobservable variables that can bias parameter estimates, a study by Hsiao (2022), suggests treating them as fixed parameters during model estimation. Given that each element will have unique properties, it is predicted that the error terms and constants will be uncorrelated. If these conditions are satisfied, the fixed effects model can be used in model estimate to account for unobserved heterogeneity (Bell et al., 2019). In this case, should the error terms be associated, the fixed effects model will not be applicable. The following equation describes the fixed effects model, which controls for both entities and time:

$$\mathbf{Y_{it} = \alpha_i + \beta X_{it} + u_{it}} \qquad \textbf{(1)}$$

Where:

Y_{it} is the regressing, and αi (i=1…. n) is the intercept for the ith entity/unknown intercept for each entity.

β is a k x 1 vector of parameters to estimate/coefficient for the regressors, while X_{it} is a 1 x k vector of explanatory variables/independent variable.

u_{it} is the remaining disturbance, which is the error term minus the effect of the time invariant variables (Marandu, 2018).

Random Effects Model

The random effects model assumes that change between entities is random and unrelated to the model's regressors (Bell et al., 2019). Furthermore, the model must incorporate all feasible variables, including the invariant temporal fixed features; otherwise, the model will be skewed by missing data. In essence, if variations across the entities have a significant impact on the model output values for the regressed, use the random effects model (Wooldridge, 2019). As a result, the study can incorporate time-invariant variables into the model; however, one significant drawback is that data for such variables may not be available. However, the random effects model has the advantage of providing results that are applicable outside of the sample (Dettori et al., 2022). The random effects model has an additional advantage over the fixed effects model in that it has fewer parameters and avoids losing degrees of freedom since the error component is considered random (Bell and Jones, 2015).

The model below represents a random effects panel data regression model:

$$\mathbf{Y_{it} = \alpha + \beta X_{it} + U_{it} + \varepsilon_{it}} \qquad \textbf{(2)}$$

Where:

Torres-Marandu (2018), defines ε_{it} as the within-entity error for the ith independent variable at time t, and U_{it} as the between-entity error for the same variable at time t.

Hausman Test

When analyzing panel data with a time-varying covariate, a preliminary Hausman test is usually performed to identify whether subsequent inference should be made using the random effects model or the fixed effects model. The Hausman test is based on the null hypothesis that the random-effects model is the best fit, with the alternative hypothesis that the fixed-effects model is better (Baltagi, 2024). Fundamentally, the assessments strive to evaluate whether there is a relationship between the unique errors and the model's regressors. The null hypothesis states that there is no relationship between the two; however, if the p-value is below 0.05, the null hypothesis must be rejected. If the Hausman test rejects the null hypothesis that there is no association between random effects and time-varying covariates, the fixed effects model is applied for further inference; otherwise, the random effects model is preferred (Mainzer, 2018). This promptly model selection technique is frequently used in econometrics and has been integrated into major computer programs such as SAS, Stata, and EViews (Baltagi, 2024). The Hausman test is employed in this study to find the best-fitting model.

4.6. Diagnostic tests

Since the study uses panel ARDL, the diagnostic tests that are employed are the normality test and the cross-section dependence test to further validate the findings and guarantee that they are statistically significant. Results from the model can be used for analysis if it produces results that are satisfactory and do not contain any biases.

4.6.1. Normality Test

The Jarque-Bera normality test, which is based on OLS residuals, will be used in this study. The Jarque-Bera normality test assesses whether sample data residuals are regularly distributed (Nosakhare and Bright, 2017). This test is necessary as unreliable test results will occur if the residuals lack normality. The Jarque-Bera (JB) test primarily estimates the skewness and kurtosis measures of the OLS residuals, with the null hypothesis that the residuals have a normal distribution (Adenomon and Ojo, 2020). The null hypothesis is accepted when the residuals are regularly distributed. The probability must be greater than 0.05 to accept the null hypothesis (Khatun, 2021). If the JB statistic differs sufficiently from zero, the hypothesis that the residuals have a normal distribution can be rejected. Alternatively, if the p-value is large enough (i.e., the JB statistic is near zero), the null hypothesis of residual normality cannot be rejected (Khatun, 2021).

4.6.2. Cross-section Dependence Test

A cross-sectional dependence diagnostic test is used in economic and statistical analysis to identify cross-sectional dependence (or correlation) in panel data models (Pesaran, 2021). This dependence arises when observations from multiple cross-sectional units, such as countries, firms, or individuals, are not independent of one another, which is frequently caused by common shocks or interactions among the units. Avoiding cross-sectional dependence might result in biassed and inconsistent parameter estimations, inaccurate statistical inferences, and reduced model efficiency (Xie and Pesaran, 2022).

The Breusch-Pagan LM test, which is used for large panels by calculating the correlation between residuals of each pair of cross-sectional units, and Pesaran's Cross Dependence (CD) test, which is appropriate for both small and large panels and looks for average pairwise correlations of the residuals, are two common cross-sectional dependence tests, according to Akgun et al. (2021). Pesaran's test computes the correlation coefficient to identify cross-sectional dependence, whereas Friedman's test is a non-parametric technique that ranks data across cross-sections to evaluate independence (Baltagi et al., 2016). The alternative hypothesis contends that cross-sectional dependence exists, whereas the null hypothesis maintains that there is none. The presence of cross-sectional dependency is indicated by the rejection of the null hypothesis if the test statistic differs significantly from zero (Pesaran, 2021). The following discussion of these tests argues for the importance of their application in this study:

Pesaran CD Test

According to Baltagi et al. (2016), the Pesaran CD test for cross-sectional dependency is used under the null hypothesis of cross-section independence and can be applied even in cases when the dataset's sample size is very small. Additionally, as each cross-sectional unit parameter is calculated using that unit's time series observation alone, the Pesaran CD test is unaffected by the presence of individual specific effects (potentially correlated with the regressors) (Juodis and Reese, 2022). However, the CD test is useful for a high number of cross-sectional units (N) observed across (T) time periods, in contrast to the conventional Breusch Pagan LM test (Khalid and Shafiullah, 2021). Since the time periods (T) exceed the number of cross-sectional units (N), this test is therefore inappropriate for the purpose of this study.

Breusch-Pagan LM test

The Breusch and Pagan (1980) cross-sectional dependence test, according to Pala (2020), is a technique that examines the null hypothesis of dependence among panel members and is applicable to a variety of panel data with a long time period (T) and few cross-sections (N). Arshad, Roba, and Botelho (2020)**,** also point out that panels with N<T, that is, panels whose cross-sectional dimensions are smaller than their time dimensions perform better when using the Breusch-Pagan Langrage Multiplier (Yalçın and Ünlükaplan, 2024). The study's cross-sectional dimensions amount to eight, but its time dimensions amount to forty-two, indicating that T>N. Consequently, the Breusch-Pagan LM test is suitable for the present study.

4.7. Chapter Summary

This chapter presented the research methodology employed to investigate the impact of climate change on agricultural production and food inflation in Southern Africa. It began by outlining the research design, detailed data sources and sampling methods, followed by the model specification and description of variables. Lastly, estimation methods were discussed in the ways in which statistical techniques are considered to ensure the findings of the study are robust and valid. Climate change has been a critical issue across the world with its impacts extending from the environmental perspective into different economic aspects. Overall, this is a very good methodology from which the results of the study can be derived.

CHAPTER 5: EMPIRICAL ANALYSIS AND RESULTS

5.1. Introduction

In this chapter, a series of tests have been employed to investigate the impact of climate change on agricultural production and food inflation in Southern Africa. The first section of this chapter analyzes the agricultural production model, while the last section focuses on the food inflation model. For both models, trends or descriptive statistics of the data are presented. These are followed by panel unit root test results to detect and assess the stability of the variables using the Levin, Lin, and Chu (LLC), Im, Pesaran, and Shin (IPS), and Augmented Dickey Fuller tests. The long-run estimation equation is then conducted based on the panel cointegration test, followed by empirical results from the estimation model using the Pooled Mean Group estimator of the panel ARDL method. Finally, the diagnostic test results are highlighted to assess whether there are omissions in the residuals that could lead to a biassed or ineffective model.

Model 1: Agricultural Production

5.2. Descriptive Statistics Test

Table 5.1: Individual Sample: Descriptive Statistics of Variables from 1981-2020

	Observations	Mean	Std. Dev.	Min	Max
AGRP	320	80.55	38.88	19.07	178.33
LIV	320	75.86	34.97	13.97	183.69
LNAGRL	320	14.41	1.26	12.11	16.44
LAB	320	36.92	29.32	0.00	85.06
TFC	320	25.99	24.06	0.00	99.88
AMAC	320	10820.62	34588.60	0.00	175557.0
RAIN	320	63.10	61.29	0.88	276.67
TEMP	320	32.16	4.19	20.45	39.81

Source: Author's computation using EViews

The descriptive statistics demonstrate that the variables in Table 5.1 display high variation. Agricultural production (AGRP) has a mean of 80.55, a standard deviation of 38.88 with minimum and maximum ranging from 19.07 to 178.33, highlighting significant variability in output levels for the region. Livestock (LIV) displays comparable variability around its mean, indicating an irregular distribution of livestock. While agricultural land (LNAGRL) has a limited range of 12.11 to 16.44 with a minimal standard deviation, signifying more equitable agricultural land access. Agricultural labour has a considerable range of 0 to 85.06, while TFC demonstrates extensive variation of 0 to 99.88, reflecting disparities in farming practices and availability to resources. The abnormally increased maximum value of agricultural machinery (AMAC), paired with its substantial standard deviation, indicates considerable disparity in mechanisation levels. Rainfall exhibits significant variability throughout the region, evidenced by its extensive range and standard deviation, whereas temperature remains comparatively stable, with minimal fluctuation around the mean. The summary statistics for regressors clearly demonstrate greater dispersion between the mean and standard deviation.

5.3. Correlation Analysis

Table 5.2: Correlation Analysis Results

Variable	AGRP	LIV	AGRL	LAB	TFC	AMAC	RAIN	TEMP
AGRP	1.0000	0.4960	-0.0322	0.1494	0.2826	-0.0481	-0.4698	-0.2190
LIV	0.4960	1.0000	-0.3756	0.0346	-0.0971	-0.2015	-0.4734	-0.0941
LNAGRL	-0.0322	-0.3756	1.0000	0.2532	0.5300	0.4215	0.1013	0.3657
LAB	0.1494	0.0346	0.2532	1.0000	-0.1092	-0.2686	0.2072	0.1102
TFC	0.2826	-0.0971	0.5300	-0.1092	1.0000	0.4746	-0.1524	0.0325
AMAC	-0.0481	-0.2015	0.4215	-0.2686	0.4746	1.0000	-0.1722	0.0346
RAIN	-0.4698	-0.4734	0.1013	0.2072	-0.1524	-0.1722	1.0000	-0.0572
TEMP	-0.2190	-0.0941	0.3657	0.1102	0.0325	0.0346	-0.0572	1.0000

Source: Author's computation using EViews

Through correlation analysis, it can be determined whether agricultural output and its potential determinants are significantly correlated. Livestock (LIV) and agricultural production (AGRP) have the strongest relationship with a correlation of about 0.496, indicating that livestock contributes to the significantly and positively to agriculture production. A moderate positive relationship of 0.283 exists with total fertiliser consumption (TFC) which means that there is a tendency for more fertiliser use to correspond with higher agricultural output. Although the relationship between LAB and AGRP is positive, there is low correlation. The relationship between agricultural productivity and the two climatic variables is however negative, indicating that Southern African agricultural productivity is negatively impacted by climatic factors. Rather surprisingly, very low, though negative, correlations exist between AGRP and agricultural land in its natural lag period (LNAL) and agricultural machinery use (AMAC), both correlation coefficients of -0.048 and -0.032, respectively. This entails that both LNAL and AMAC have a slight contribution towards increasing agricultural production.

5.4. Unit Root Test

To assess the stationarity properties of model variables, the unit-root test results are presented in Table 5.3. Before determining whether agricultural output and climate variables are cointegrated, the study examined into the order of integration for each series. Three separate unit root tests were used to evaluate the integration order of the series: (i) Levin, Lin and Chu (LLC); (ii) Im-Pesaran-Shin (IPS) and (iii) Augmented Dickey-Fuller (ADF) test. The probabilities of the three-unit root tests are significant at 1% level of significance for all the variables in question, thus indicating stationarity of the variables. Based on the depicted unit root results, the null hypothesis which states that there is unit root among the variables is rejected.

Table 5.3: Panel Unit-Root Test Results

H0: all variables have unit root (non-stationary)						
Variables		**LLC P-value**	**IPS P-value**	**ADF P-value**	**Order of Integration**	**Acceptance Region P < 0.05**
AGRP	*1st Difference: Intercept*	P = 0.0000***	P =0.0000***	P = 0.0000***	I(1)	Reject H_0
LIV	*1st Difference: Intercept*	P = 0.0000***	P =0.0000***	P = 0.0000***	I(1)	Reject H_0
LNAGRL	*1st Difference: Intercept*	P = 0.0000***	P =0.0000***	P = 0.0000***	I(1)	Reject H_0
LAB	*1st Difference: Intercept*	P = 0.0000***	P =0.0000***	P = 0.0000***	I(1)	Reject H_0
TFC	*1st Difference: Intercept*	P = 0.0000***	P =0.0000***	P = 0.0000***	I(1)	Reject H_0
AMAC	*1st Difference: Intercept*	P = 0.0000***	P =0.0000***	P = 0.0000***	I(1)	Reject H_0
RAIN	*Level: Intercept*	P = 0.0000***	P =0.0000***	P = 0.0000***	I(0)	Reject H_0
TEMP	*Level: None*	P = 0.0000***	P =0.0000***	P = 0.0000***	I(0)	Reject H_0
		NB: (***) Denotes significance at 1% level of significance				

Source: Author's computation using EViews

As indicated in Table 5.3, the study employed the unit root test at the level and first difference forms, with an order of integration that combines I(0) and I(1). In this case, the findings show that rainfall and temperature are stationary at the level, whereas agricultural production and associated regressors are stationary at the first difference. Due to the existence of mixed levels of integration among the variables, the study proceeds to apply the Panel Pooled Mean Group ARDL approach. However, before that, a panel cointegration test is employed.

5.5. Panel PMG/ARDL Results

5.5.1. Optimal Lag Selection

Generally, the lag length selected is based on values for which either Akaike Information Criterion (AIC) or Schwarz Criterion (SC) are minimized, indicated by the asterisks in Table 5.4. From the table, the best criterion that best fits the model is the Akaike Information Criterion with the lowest figure of 41.82 in contrast to that of the Schwarz Criterion which is 43.293. It is therefore concluded that the lag length selection is made based on the AIC value because the lower the AIC value, the better the model. According to the results below as shown by the asterisk sign of AIC, the optimal lag length to use for the model is 3.

Table 5.4: Optimal Lag Length Results

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-6809.4	NA	5.36e+15	53.245	53.329	53.279
1	-5425.1	2693.0	1.43e+11	42.711	43.293*	42.945
2	-5329.1	182.2	8.94e+10	42.243	43.323	42.677
3	-5239.0	166.7	5.87e+10*	41.821*	43.399	42.455*

Source: Author's computation using EViews

5.6. Panel Cointegration Test

After determining the order of integration of the different variables, ARDL is estimated based on the cointegration to analyze the long-term correlation between the variables.

5.6.1. Pedroni test

Table 5.5: Pedroni Residual Co-integration Test Results

H_0: No cointegration		
Panel cointegration statistics(within-dimension)		
	Statistic	Probabilities
Panel v-statistic	1.780535	0.0375**
Panel rho-statistic	-2.516770	0.0059***
Panel PP-statistic	-6.862833	0.0000***
Panel ADF-Statistic	-7.031124	0.0000***
Group mean cointegration statistics (between-dimension)		
Group rho-statistic	-0.990628	0.1609
Group PP-statistic	-8.069380	0.0000***
Group ADF-statistic	-7.049184	0.0000***
NB: (***) and (**) indicate rejection of the null hypothesis of no co-integration at 1% and 5% significance level.		

Source: Author's computation using EViews

The Pedroni Cointegration test was conducted with eight cross-sections over a sample period of 1981 to 2020, totaling 320 observations. The null hypothesis of no cointegration was tested under both the within-dimension and between-dimension of the Pedroni test. For the within-dimension statistics, all the four statistics in the panel co-integration statistics are found to be significant at both 1 and 5% level of significance, thus, strongly supporting the rejection of the null hypothesis of no cointegration.

Within the interdimensional analysis, the Group rho-Statistic would have a probability of 0.16, which is not sufficient to reject the null hypothesis. On the other hand, both the Group PP-Statistic and Group ADF-Statistic come out highly significant with a probability of 0.00, which gives strong evidence in support of cointegration among the variables. Taking these results as a whole, in six out of the seven Pedroni statistic tests, there is sufficient evidence to reject the null hypothesis of no cointegration, which implies that the variables under study share a long-run equilibrium relationship.

5.5.2. Kao Test

Table 5.6: Kao Cointegration Test Results

H_0: No cointegration		
	t-Statistics	**Prob.**
ADF	-2.188623	0.0143**
(**) indicates rejection of the null hypothesis of no co-integration at 5% significance level.		

Source: Author's computation using EViews

In line with the Pedroni test, the Kao cointegration test results also demonstrate a rejection of the null hypothesis of no cointegration at the 5% significance level, as indicated by the ADF t-statistic of -2.188623 and the corresponding p-value of 0.0143. This implies that the variables selected for the study have a long-term, statistically significant relationship.

5.6.2. Long run panel ARDL empirical results

The panel Autoregressive Distributed Lag (ARDL) is employed to analyze the long term as well as the short-term effects of a host of variables, including climate variables on agricultural output in Southern Africa for the period from 1981 to 2020. In the model, agricultural production (AGRP) is used as the dependent variable, presumably representing the first difference of agricultural output, and the independent variables are livestock (LIV), labor (LAB), rainfall (RAIN), temperature (TEMP), and total agricultural fertilizer (TFC). Agricultural land with its natural log (LNAGRL) and agricultural machinery (AMAC) variables are excluded from the Panel ARDL model due to their contribution to a positive and statistically insignificant error correction term, which undermines the model's capacity to capture short-run equilibrium relationships effectively.

Table 5.7: Long-run panel ARDL estimates

Long Run: Dependent Variable: D(AGRP)				
Variable	**Coefficient**	**Std. Error**	**t-statistics**	**Prob***
LIV	0.3392	0.0869	3.9024	0.0001***
LAB	0.2348	0.0661	3.5543	0.0005***
TFC	1.3659	0.1390	9.8238	0.0000***
RAIN	-0.1110	0.2744	-4.0494	0.0001***
TEMP	-16.6312	5.7640	-4.4185	0.0000***
NB: (***) Denotes significance at 1% level of significance				

Source: Author's computation using EViews

In the long run, total fertilizer consumption, with a large and statistically significant coefficient, emerges as a critical factor affecting agricultural productivity and thus highlighting the importance of input-intensive approaches to increase crop yields under environmental and soil fertility stresses. Labor represents the region's dependence on labor-intensive agricultural practices, while temperature is a strong negative element, underlining the crucial importance of climate adjustment measures to safeguard productivity; the variable-specific findings are presented in detail below:

Livestock Production (Index)

A 1 unit increase in the livestock production index (LIV) leads to 0.34 units increase in the agricultural production index (AGRP), indicating that livestock production plays a complementary role in supporting agricultural systems in Southern Africa. Livestock production benefits agriculture by contributing manure, which enriches soil fertility and structure, and by providing draft power, especially on mixed farms where crop-livestock integration is common. In many parts of Southern Africa, smallholder agricultural practices rely on livestock as an additional source of income, which allows the farmer to invest in inputs for agriculture, thereby increasing crop production. For example, studies by Dhehibi et al. (2023) emphasize the very relevant synergy obtained between mixed crop-livestock systems. Resources such as manure coming from animals increase crop production and bring about issues of sustainability in developing economies where chemical fertilizers are not easy to access.

The positive interrelationship between livestock and crop production in this regard highlights the importance of policy interventions that promote integrated farming practices. In the regions where farmers strike a balance between livestock and crop production, improving the health and productivity of livestock can, therefore, increase crop production, thus helping to alleviate the food insecurity exacerbated by climate change. However, this relationship requires careful management since excessive livestock can stress the limited resources, as noted by World Bank highlighting the urgency of fair agriculture policies (Thornton and Herrero, 2010). Similarly, related current studies also caution against overdependence on livestock in resource-constrained ecosystems due to competition between livestock and its needs regarding the available water and feed. This can further result in the degradation of resources used to grow crops hence weakening general agricultural production as evidenced by the research done by Mabhaudhi et al. (2023).

Agricultural Labor (% of total labor force)

The coefficient of labor is positive and statistically significant at the 1% level, as expected. As a result, increasing the labor force in agriculture by 1% raises agricultural output by 0.23 units; this, therefore, explains the roles of manual labor in regions where there is no wide application of mechanized devices. Many studies are consistent in the emphasizing that labor-intensive techniques in agriculture are fundamental in regions such as Southern Africa, where technological resources may be inaccessible. A recent study by Murray et al. (2016), found that manual labor, particularly for smallholder farmers, is heavily involved in planting and harvesting, directly affecting crop yields and enhancing food security at a household level.

Results are in agreement with those identified by Amare et al. (2017), in a study that assessed the impact of agricultural productivity on improved welfare of farm households, using nationally representative panel data from the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) in Nigeria. The results showed a positive association between agricultural productivity and labor and farm inputs. This would suggest that agricultural productivity increases are related to a larger input of labor into agricultural production, measured in person-days, together with fertilizer and herbicide use. This may further imply that the introduction of inputs and the use of farming technologies contribute positively to increased agricultural productivity. The study also found that climatic risks and biophysical factors also contribute largely to agricultural productivity.

Total Fertilizer Consumption (kilograms per hectare of arable land (kg/ha)

Total Fertilizer Consumption has the expected sign and is statistically significant at the 1% level. This means that a 1 kg/ha increase in the use of fertilizer is associated with an increase of 1.37 units in agricultural production in the long run. The positive and statistically significant relationship indicates the importance of fertilizers in improving soil fertility, which remains crucial for crop yields in the Southern African region. Most regions face challenges such as soil degradation, nutrient depletion, and reduction in natural soil fertility, which reduce agricultural output (Gomiero, 2016). Thus, fertilizers provide essential nutrients that renovate the soil and enhance its fertility, hence allowing for better yields of crops. In the face of the soil degradation malaises faced in Southern Africa, a judiciously tailored expansion in fertilizer use is apt to bring in decisive improvements in both maintenance and improvement of agricultural productivity. For a sector that occupies the prime status in the economies of most countries, it implies that the positive contribution that fertilizers can make to agricultural production underlines their importance for food security.

Fertilizer-driven agricultural productivity growth can be expected to enhance local food availability, reduce reliance on imports, and therefore contribute to price stability. However, in addition to these benefits, the need to use fertilizers more sustainably must be recognized. This approach will contribute to avoiding over-application, which can cause environmental problems like soil acidification, water pollution, and greenhouse gas emissions (Shanmugavel et al., 2023). Long-term productivity in agriculture in Southern Africa calls for efficient and environmentally compatible fertilizer use, given the prevalence of small-scale farming.

The findings further support those of a study by (Huang and Jiang, 2019), which analyzed the efficiency in the use of fertilizers in Chinese arable agricultural production from 2011 to 2015. The average annual index of overuse of fertilizer varies between 0.008 and 3.139, with an average value of 0.685, signifying that the fertilizers have contributed positively and significantly to the output of the Chinese arable agricultural sector. Similarly, other scholars such as Amare et al. (2017), also found evidence from their study that fertilizer use, and the application of herbicides have highly significant positive effects on agricultural productivity. This evidence tends to imply that the use of other farm management practices can also promote significant improvements in agricultural productivity.

Rainfall (mm per year)

Rainfall is statistically significant at 1%, but the estimated coefficient is negative against the expected direction. This implies that each additional mm per year makes agricultural output lower by 0.11 units. Probably its negative coefficient could mean that whereas its optimum or average level is favorable, too much is deterring to crops due to erosion, waterlogging, and even making them more vulnerable to certain crop diseases. Rain-fed farming is mainly practiced in Southern Africa, where farming relies on seasonal rainfall. With the changing weather, the rainfall pattern becomes erratic, and most places are prone to either drought or heavy rains; thus, this increases the risk of crop failures (Godde et al., 2021).

This finding points out the urgent need for better systems of water management across Southern Africa. Investment in irrigation infrastructure and drainage systems will help farmers to manage water resources so as not to destroy crops with heavy floods after receiving scanty rain. Programs for developing climate-resilient crops that could stand erratic rainfall might mitigate some of the negative impacts of such findings. Policies promoting water conservation and the use of such techniques as contour farming and terracing would further enable farmers to maintain production in spite of erratic rainfall (Matchaya et al., 2019).

These findings agree with those obtained from the study designed and undertaken by Amare et al. (2018), to explore the effect of rainfall shocks on agricultural productivity and hence on rural household consumption. It then revealed that a negative rainfall disruption reduces agricultural production by about 38%. According to the present study, the plausible reason may be that rainfall being a source of risk to crop production enhanced the adoption of farm technology risk and, as such, reduced productivity in a rainfed, liquidity-constrained, and imperfect market environment. The findings presented herein are in consistency with earlier research, such as Borgomeo et al. (2018), that shows how the variability in precipitation triggers farmers to make decisions on the adoption of external input factors, which increase productivity but raise the risk of crop failure, hence affecting agricultural productivity.

Temperature (°C per year)

As expected, the temperature variable carries a negative sign and is significant at 1% in the long-run estimation of the model. In essence, this means that for every increase in mean annual temperature by 1°C, the agricultural output is reduced by approximately 16.63 units. From this very negative coefficient in the long run, the increase in temperature has significantly negatively affected agriculture in Southern Africa. Warmer temperatures increase plant respiration rates that make crops metabolize their food more rapidly, thus reducing growth and yields, especially in the case of the more temperature-sensitive staple crops like maize and wheat. On the other hand, increasing temperatures raise evapotranspiration, which reduces available soil moisture (Moore et al., 2021). High temperatures also favor infestation and diseases that thrive under high temperatures, thus further aggravating the pressure that such pests exert on agricultural crops and leading to even greater losses in yields. The yield losses that accrue from this also means increased food prices, preventing households from accessing adequate foodstuffs and increasing their vulnerability to hunger and malnutrition in the process accordingly (Mutengwa et al., 2023).

Given that agriculture contributes much to the GDP in most Southern African countries, such declines in productivity also weaken the economy because they reduce export volumes, shrink incomes for farming households, and increase food import needs, therefore straining national budgets (Jayne et al., 2021). Adaptation measures required on the ground with immediate effect, henceforth, to prevail over these challenges, involve drought-resistant types, better irrigation, and ways of soil conservation to enhance crops' resilience against temperature fluctuation so as to ensure a future that is sustainable for agriculture in Southern Africa.

The obtained results are consistent with those found in the study of Mbingui (2022), which sought to analyze the impact of climate change on agricultural production in the Republic of Congo using the ARDL methodology. In this study, agricultural yield was modeled as the dependent variable, while the independent variables were GDP, temperature, and rainfall. The results from the study indicate that, in the short run, there is a negative and statistically significant effect of temperature and gross domestic product on agricultural yield and a positive and statistically significant relationship between rainfall and agricultural yield. Thus, ceteris paribus, a 1°C increase in temperature, GDP, and rainfall all lead to a significant reduction of 4.70 and 0.30 (at 1% level of significance), respectively, and to a substantial rise of 0.02 at the 1% level of significance in agricultural yields.

5.6.3. Short run panel ARDL empirical results

Table 5.8: Short run results of panel ARDL

Short Run: Dependent Variable: D(AGRP)				
Variables	**Coefficient**	**Std. Error**	**t-statistic**	**Prob**
CointEq(-1)	-0.2602	0.1321	-1.9700	0.0505*
D(AGRP(-1))	-0.2707	0.1076	-2.5161	0.0128**
D(AGRP(-2))	-0.2002	0.0719	-2.7821	0.0060***
D(LAB(-1))	-0.8518	0.3194	-2.6668	0.0084***
D(TFC(-2))	0.2797	0.1450	1.9283	0.0556*
C	144.6408	69.9305	2.0684	0.0402**
NB: (***), (**) and (*) indicate rejection of the null hypothesis of no co-integration at 1%, 5% and 10% significance level.				

Source: Author's computation using EViews

Some of the variables that were in the long-run model, inclusive of livestock, rainfall, and temperature, are not significant in the short-run and therefore have been eliminated from the above table. The error correction term, CointEq(-1) falls within the benchmark range since it is negative and between -1 and 0. This suggests that about 26percent of any disequilibrium in the previous period is corrected in the current period. This adjustment speed is statistically significant at 10% level, indicating a slow meaningful pace toward re-establishing equilibrium after short-run shocks.

The short-run current production is driven by the agricultural production of the previous periods. With the coefficients of D(AGRP(-1)) and D(AGRP(-2)) being -0.27 and -0.20, respectively, it is evident that increases in production of the previous 2 years reduces current output. This pattern is highly significant at 5% and 1%, respectively, suggesting that agricultural production may experience natural cycles or adjustments over time. The lagged labor input, LAB, also enters negatively and significantly at the 1% level of significance, suggesting that the input of labor in the previous periods may lower the current period's production, probably due to diminishing marginal returns or adjustment in the use of labor. The coefficient of the second lag TFC is positive and statistically significant at 10% level of significance; this means that the shock of fertilizer consumption is gradual because its impact is apparently present after 2 years. The constant term is significant and explains the minimum level of output in agriculture when all variables are held constant.

5.7. Hausman Test

The null hypothesis of the Hausman test is that Random Effect Model (REM) is the appropriate estimator meaning that the error terms are not correlated with regressors, however, the alternative hypothesis states that Fixed Effect Model (FEM) is the appropriate estimator. If the null hypothesis is rejected, it can be concluded that the REM is not the appropriate estimator because random effects are probably correlated with the dependent variable.

Table 5.7 displays the regression results of random and fixed effect panel analyses for the four versions of the model outlined in equation 4.1 in the research methodology chapter. The initial version of the model includes precipitation and temperature as climate variables. In the second version, the study includes rainfall, its quadratic term, and temperature as climate variables. The third version replaces the quadratic term of rainfall with the quadratic term of temperature. The final version considers temperature, rainfall, and their quadratic terms. The Hausman test indeed surprisingly suggests REM for the first version, as a result of its simpler specification, with only precipitation and temperature, which may not be sufficient to capture the individual-specific effects across countries. Therefore, the random effects model appears to be appropriate, as it assumes that the individual effects are uncorrelated with the regressors. However, in the second, third, and fourth specifications of the model, where squared climatic terms are added to account for nonlinearities, the Hausman test prefers the FEM. These quadratic climate variables are likely to add to the correlation of individual effects and the regressors, thereby indicating that the estimation method should be FEM, to capture unobserved heterogeneity and time-invariant factors impacting the nexus between climate and agricultural production across selected countries.

Table 5.9: Hausman test results

Models	**Model 1**		**Model 2**		**Model 3**		**Model 4**	
Variables	**Coeff**	**Prob**	**Coeff**	**Prob**	**Coeff**	**Prob**	**Coeff**	**Prob**
LIV	0.350	0.0000***	0.348	0.0000***	0.349	0.0000***	0.349	0.0000***
LAB	0.205	0.0000***	0.208	0.0000***	0.206	0.0000***	0.206	0.0000***
TFC	0.686	0.0000***	0.700	0.0000***	0.699	0.0000***	0.699	0.0000***
RAIN	-0.114	0.0003***	-0.118	0.4613	-0.118	0.0036***	-0.115	0.4748
TEMP	-3.276	0.0009***	-3.930	0.0049***	-8.500	0.2846	-8.489	0.2871
$RAIN^2$	-	-	-2.92e-06	0.9954	-	-	-1.04e-05	0.9837
$TEMP^2$	-	-	-	-	0.071	0.5609	0.071	0.5613
C	141.129	0.0000***	162.1334	0.0009***	233.632	0.0702*	233.107	0.0769*
Obs	320	-	320	-	320	-	320	-
R-squared	0.499	-	0.683	-	0.683	-	0.683	-
F-stat	62.618	0.0000***	50.769	0.0000***	50.851	0.0000***	47.065	0.0000***
Chi-square	3.754	0.5853	156.082	0.0000***	114.423	0.0000***	103.85	0.0000***
NB: (***) and (*) indicate rejection of the null hypothesis of no co-integration at 1% and 10% significance level.								

Source: Author's computation using EViews

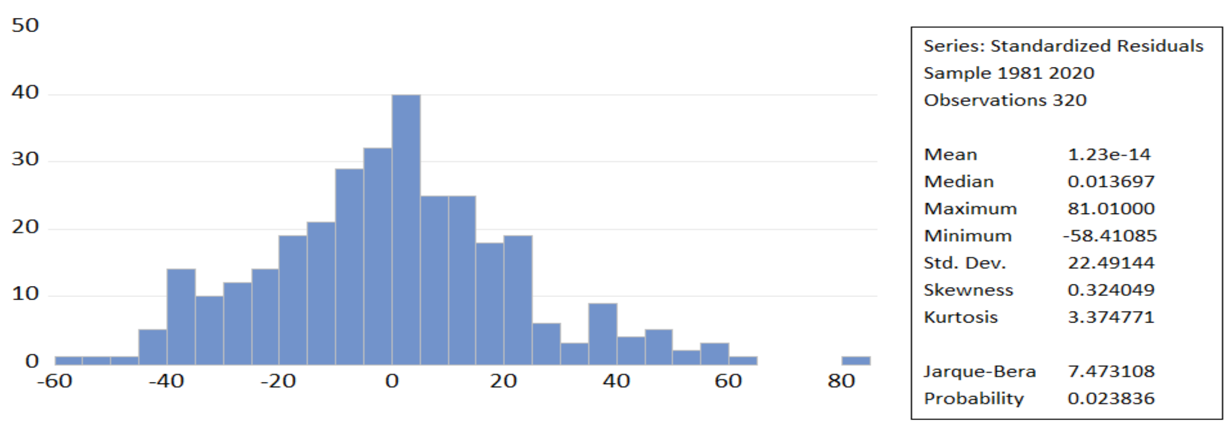
Given that the model includes a quadratic component for each climate variable to describe the non-linear relationship with agricultural productivity, the sign of a linear and quadratic term is always contrary. The regression findings indicate that the rainfall coefficients are unexpectedly negative in all four models and statistically significant in models 1 and 3 at the 1% level. Temperature has the predicted negative sign in all four model versions, although it is only significant in models 1 and 2. As predicted, the coefficients of the quadratic rainfall term are negative but insignificant in models 2 and 4. The squared term of temperature bears the expected positive sign in models 3 and 4 but insignificant in the two models. The insignificance of the squared terms for both precipitation and temperature suggests that the quadratic effects might not strongly influence agricultural production in this dataset and that their impact is not robust enough to reach statistical significance. Additionally, while rainfall's linear coefficient is significant in some models, the negative sign may indicate that excessive rainfall adversely impacts agricultural output, yet the nonlinear (squared) effect is not strong enough to show a significant additional impact. These results are in alignment with those obtained from a study by Belloumi (2014), which aimed at examining investigating the impact of climate change on agricultural production in Eastern and Southern Africa.

5.8. Diagnostic Tests

The diagnostic tests namely, normality and cross section dependence test are employed to verify the variable evaluation of the outcomes obtained by the model. Diagnostic tests aid in identifying errors within the estimated model's residuals, consequently preventing a biassed and inefficient model. The normality test employs the Jarque-Bera test to determine whether the residuals have a normal distribution, and the Cross Section Dependence test to determine whether the residual variance is constant (Oganesyan, 2017).

5.8.1. Normality Test

Figure 5.1. Normality Test



Source: EViews Computation

The histogram of the normality test suggests that there is no normal distribution among the residuals. The Jarque-Bera statistic of 7.47 and 0.02 p-values mean that the residuals are not normally distributed at a statistically significant value as the p-value is below the benchmark acceptance of 5% level of significance. These findings suggest that the climate variables of temperature, rainfall, and other agricultural production factors have nonlinear or asymmetric effects on the residuals. According to Frain (2007), massive samples do not necessarily indicate a "stable" distribution. Therefore, the null hypothesis of normally distributed residuals can be rejected in large samples. This addresses the problem that some regressions are not stable across time, despite the normality test being sensitive at large sample sizes (Kundu et al., 2011). This can lead to the null hypothesis test for normality being rejected more often than expected (Chen & Kuan, 2003).

5.8.2. Cross Section Independence Test

Table 5.10: Cross Section dependence results

H0: No cross section dependence			
Test	**Statistics**	**Degrees of freedom**	**Probability**
Breusch-Pagan LM	199.8589	28	0.4588
Pesaran Scaled LM	22.96561		0.9887
Pesaran CD	10.68899		0.4740

Source: Author's computation using EViews

The CSD test consists of three types of statistical tests: the Breusch-Pagan LM (Lagrange Multiplier) Test, the Pesaran Scaled LM Test, and the Pesaran CD (Cross-Dependence) Test. Since the p-value is above the 5% level of significance, the null hypothesis of no cross-sectional dependence cannot be rejected for all three tests. The absence of cross-section dependence in this study indicates the independence of agricultural productivity measures through different countries. The agricultural outputs of every country are determined individually and separately by the respective climate conditions and agricultural inputs. This independence is therefore helpful in making the model structure simple and thus allows for examining specific impacts of climate change on agriculture, without having to consider the correlated effects between the selected countries. This finding increases the validity of the outcomes concerning the specific impact that climate and agricultural inputs might have in each of these countries within the region.

Model 2: Food Inflation

5.9. Descriptive statistics

Table 5.11: Individual Sample: Descriptive Statistics of Variables from 1981-2020

	Observations	**Mean**	**Std. Dev.**	**Min**	**Max**
FCPI	320	69.747	585.139	-15.080	7375.300
CROP	320	80.553	31.881	19.070	178.330
FEX	320	19.807	27.730	0.000	96.023
ARMI	320	0.851	0.8881	0.000	4.153
FCON	320	25.991	24.055	0.000	99.877
RAIN	320	63.101	61.292	0.878	276.674
TEMP	320	32.158	4.190	20.449	39.819

Source: Author's computation using EViews

Descriptive statistics highlight the magnitude of variation in the variables. FCPI has the highest coefficient of variation, indicating high variability in food prices, characterized by a standard deviation of 585.1 and a wide range, from -15.1 to 7375.3, which suggests extreme variability. RAIN with a mean of 63.1 and standard deviation of 61.3 shows extensive variation in rainfall, further evidenced by its range of 0.9 to 276.7, indicating enormous fluctuations in the precipitation levels. CROP with a mean of 80.6 and standard deviation of 31.9 has moderate variation in crop yield, with a range of 19.1 to 178.3, indicating fluctuations, however, on a narrower scale compared to rainfall. TEMP, with a mean of 32.2 and low standard deviation of 4.2, indicates stable temperature conditions over the period, as corroborated by its narrow range of 20.4 to 39.8, suggesting low variation. FEX and ARMI show high variation, with standard deviations of 27.7 and 0.9, respectively. FEX's range of 0 to 96.0 and ARMI's range of 0 to 4.2 further suggest changing agricultural export values and raw material imports. While rainfall and food prices exhibit the greatest variability, agricultural production and temperature experience more limited variation across the period under consideration.

5.10. Correlation Analysis

Table 5.12: Correlation Analysis Results

Variable	FCPI	CROP	FEX	ARMI	FCON	RAIN	TEMP
FCPI	1.0000	0.0749	0.0019	0.1325	0.0937	-0.0901	0.0185
CROP	0.0749	1.0000	-0.0972	0.2533	-0.0649	-0.4697	-0.2190
FEX	0.0019	-0.0972	1.0000	0.3732	0.0169	0.5504	0.0720
ARMI	0.1325	0.2533	0.3732	1.0000	0.1558	-0.0113	-0.0902
FCON	0.0937	-0.0649	0.0169	0.1558	1.0000	-0.1022	0.0284-
RAIN	-0.0901	-0.4697	0.5504	-0.0113	-0.1022	1.0000	0.0573
TEMP	0.0185	-0.2190	0.0720	-0.0902	0.0284	-0.0573	1.0000

Source: Author's computation using EViews

The results from the correlation analysis illustrate that food inflation, indicated by the Food Consumer Price Index (FCPI), has weak linear relationships with the regressors. The crop production index (CROP) shows a minor positive correlation of 0.0749 with food inflation suggesting that increased crop yield does not necessarily result in reduced food prices, considering post-harvest inefficiencies that outweigh the advantages of higher production. There is an extremely weak positive relationship between food exports (FEX) and food inflation. ARMI (agricultural raw material imports) and food inflation exhibit a weak positive correlation of 0.1325, which suggests that more imports may increase food prices as they directly affect production costs.

Fertiliser consumption (FCON) exhibits a weak positive correlation of 0.0937 with food inflation, potentially indicating the cost-push effect of input costs on food prices. Rainfall exhibits a negative correlation of -0.0901 with food inflation, consistent with the theoretical expectation which asserts that favorable rainfall enhances agricultural output and alleviates food price pressures. Temperature exhibits a weak positive correlation of 0.0185, indicating a minor linear impact on food inflation. These correlations are relatively low, suggesting that individual variables have minimal direct impact, however, their cumulative effects may be more accurately captured through advanced econometric models.

5.11. Unit Root Test

Table 5.13 illustrates the unit-root test results when assessing the stationarity of model variables. Before determining whether agricultural output and climate variables are cointegrated, the study evaluated the order of integration for each series. Three different unit root tests were employed to assess the integration order of the series: (i) Levin, Lin and Chu (LLC); (ii) Im-Pesaran-Shin (IPS) and (iii) Augmented Dickey-Fuller (ADF) test. The probabilities of the three-unit root tests are significant for all the variables in question, thus indicating stationarity of the variables. Based on the depicted unit root results, the null hypothesis which states that there is unit root among the variables is rejected.

Table 5.13: Panel Unit-Root Test Results

H_0: all variables have unit root (non-stationary)						
Variables		**LLC P-value**	**IPS P-value**	**ADF P-value**	**Order of Integration**	**Acceptance Region P <0.05**
FCPI	*Level: Intercept*	P = 0.0000***	P = 0.0000***	P = 0.0000***	I(0)	Reject H_0
CROP	*1st Difference: Intercept*	P = 0.0000***	P = 0.0000***	P = 0.0000***	I(1)	Reject H_0
FEX	*Level: Intercept*	P = 0.0000***	P = 0.0000***	P = 0.0000***	I(0)	Reject H_0
ARMI	*1st Difference: Intercept*	P = 0.0000***	P = 0.0000***	P = 0.0000***	I(1)	Reject H_0
FCON	*Level: Intercept*	P = 0.0000***	P = 0.0000***	P = 0.0000***	I(0)	Reject H_0
RAIN	*Level: Intercept*	P = 0.0000***	P = 0.0000***	P = 0.0000***	I(0)	Reject H_0
TEMP	*Level: None*	P = 0.0000***	P = 0.0000***	P = 0.0000***	I(0)	Reject H_0
		NB: (***) Denotes significance at 1% level of significance				

Source: Author's computation using EViews

The study used the unit root test at the level and first difference forms, as illustrated, with an order of integration that combines I(0) and I(1). Due to the existence of mixed levels of integration among the variables, the study proceeds to apply the Panel PMG/ARDL approach. However, prior running the ARDL model, panel cointegration is performed to check whether the model variables are cointegrated in the long run.

5.12. Panel PMG/ARDL Results

5.12.1. Optimal Lag Selection

Generally, the lag length selected is based on values for which either Akaike Information Criterion (AIC) or Schwarz Criterion (SC) are minimized, indicated by the asterisks in Table 5.14. From the table, the best criterion that best fits the model is the Akaike Information Criterion with the lowest figure of 51.82 in contrast to that of the Schwarz Criterion which is 53.78. It is therefore concluded that the lag length selection is made based on the AIC value because the lower the AIC value, the better the model. According to the results below as shown by the asterisk sign of AIC, the optimal lag length is 3 and the best criterion to adopt for the model is AIC.

Table 5.14. Optimal Lag Length Results

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-7961.898	NA	2.57e+18	62.257	62.353	62.296
1	-6729.808	2387.174	2.49e+14	53.014	53.789*	53.326
2	-6610.450	224.727	1.44e+14	52.464	53.918	53.049
3	-6479.207	239.929	7.58e+13*	51.821*	53.954	52.679*

Source: Author's computation using EViews

5.13. Panel Cointegration Test

After determining the order of integration of each variable, ARDL is estimated through cointegration to examine the long-run relationship between the variables of interest.

5.13.1. Pedroni test

Table 5.15. Pedroni Residual Co-integration Test Results

H_0: No cointegration		
Panel cointegration statistics(within-dimension)		
	Statistic	Probabilities
Panel v-statistic	-4.287462	1.0000
Panel rho-statistic	-1.300491	0.0967*
Panel PP-statistic	-6.637621	0.0000***
Panel ADF-Statistic	-6.715991	0.0000***
Group mean cointegration statistics (between-dimension)		
Group rho-statistic	1.170329	0.8791
Group PP-statistic	-7.504847	0.0000***
Group ADF-statistic	-5.505580	0.0000***
NB: (***) and (*) indicate rejection of the null hypothesis of no co-integration at 1% and 10% significance level.		

Source: Author's computation using EViews

The null hypothesis of no cointegration was tested under both the within-dimension and between-dimension of the Pedroni test. The panel cointegration results suggest mixed presence of cointegration across the different test statistics and dimensions.

For the within-dimension statistics, only three statistics in the panel co-integration statistics are found to be significant at both 1 and 10% level of significance, thus, strongly supporting the rejection of the null hypothesis of no cointegration. In the between-dimension framework, the Group rho-Statistic is not significant with a probability of 0.87, hence weak evidence against the null hypothesis is suggested. On the contrary, the Group PP-Statistic and Group ADF-Statistic are highly significant at the 1% level of significance, indicating strong evidence for variable cointegration. The combined findings thus indicate that for five of the seven Pedroni statistics, there is adequate evidence to reject the null hypothesis of no cointegration, implying the presence of a long-run equilibrium relationship between these variables.

5.12.2. Kao test

Table 5.16: Kao Cointegration Test Results

H_0: No cointegration		
	t-Statistics	**Prob.**
ADF	-3.542043	0.0002*
(***) indicates rejection of the null hypothesis of no co-integration at 1% significance level.		

Source: Author's computation using EViews

The Kao cointegration test yields an ADF t-statistic of -3.542043 with a p-value of 0.0002, which is significant at the 1% level. This leads to the rejection of the null hypothesis of no cointegration, providing strong evidence of a long-run equilibrium relationship among the variables. The result suggests that the variables in the panel are cointegrated and move together over time, despite any short-run deviations.

5.13.2 Long run panel ARDL empirical results

The panel Autoregressive Distributed Lag (ARDL) model is applied to investigate the long- and short-run effects of various factors, including climate variables, on food inflation in Southern Africa over the period 1981 to 2020. Due to unavailability of data at regional scale, the oil price index variable has been omitted, while the fertilizer price index variable is replaced by fertilizer consumption. The dependent variable in the model is food consumption price index (FCPI) and the independent variables include crop production index (CROP), food exports (FEX), agricultural raw material imports (ARMI), fertilizer consumption (FCON), rainfall (RAIN) and temperature (TEMP).

Table 5.17: Long-run panel ARDL estimates

Long Run: Dependent Variable: D(AGRP)				
Variable	**Coefficient**	**Std. Error**	**t-statistics**	**Prob***
CROP	0.0209	0.0130	1.6012	0.1127
FEX	0.1272	0.0417	3.0532	0.0030***
ARMI	-3.6974	0.4193	-8.8180	0.0000***
FCON	0.6121	0.0720	8.5062	0.0000***
RAIN	-0.0198	0.0151	-1.3085	0.1940
TEMP	0.3015	0.0673	4.4819	0.0000***
NB: (***) Denotes significance at 1% level of significance				

Source: Author's computation using EViews

Crop Production (Index)

The coefficient for CROP has a positive value, contrary to the expected negative sign, and it is not statistically significant. This positive value of the coefficient implies that increased crop production does not lead to a decrease in food prices, as initially assumed. Instead, factors such as poor distribution or concentration on exporting instead of being concerned about domestic supply might be increasing the price of food, regardless of the improved production.

Food Exports (% of merchandise exports)

FEX has a positive coefficient, 0.12, which is statistically significant at the 1% level of significance as expected, meaning that a 1% increase in food exports leads to a 0.12% increase in domestic food consumption prices. These findings suggest that an increase in agricultural production by the region for export may decrease the domestic supply of food, hence exerting upward pressure on food prices. In the Southern African context, this observation represents a key trade-off, while exports bring economic benefits, they can limit domestic food availability in the selected countries, especially where surpluses in production are being used to supply exports rather than being sold in local markets. This stresses the need for policies that ensure domestic food security while expanding exports to be in place.

These findings are consistent with those obtained in the study by Qayyum and Sultana (2018), which seeks to examine the factors influencing food price inflation in Pakistan from 1970 to 2017. To evaluate food inflation, the study examined the following independent determinants: GDP, food exports, food imports, taxes, and money supply. The estimation findings showed that there is a positive and significant link between food prices and export imports. Keeping all other variables fixed, a one-percent increase in export imports raises food prices by 10% and 20%. When food exports grow, supply within the country falls, increasing demand for food in the country and, as a result, food inflation rises.

Agricultural Raw Material Imports (% merchandise exports)

The results show a negative and significant coefficient value of -3.6974, meaning an increase in the import of agricultural raw materials is associated with a 3.70% reduction in prices of food consumption. This means that increased imported agricultural inputs most likely increase agricultural productivity, which subsequently leads to lower production costs and hence reduced prices of foods. This outcome is in sharp contrast to the expected positive impact, where increased import costs would translate into higher production costs and, consequently, higher food prices. The findings instead suggest that access to these raw materials, whether imported or not, may temper domestic supply constraints and improve yield quality, thus helping to reduce prices of food. In Southern Africa, the supply of these raw materials at lower prices could help to stabilize market prices, so improving the importation of agricultural produce may help to improve food affordability.

These results are in line with those of the study by Erdogan et al. (2024), which analyzed the relationship between climate change and food prices in Nigeria using different nonlinear and quantile-based methods with data covering the period 2008 to 2020. The results obtained empirically indicated that there is a negative and significant relationship between ARMI and food inflation. The study recommended that, given the declining impact of agricultural raw material imports, which are critical for the production of food and affect food prices in Nigeria, combined with the increasing impact of food exportation on food prices, it would be more sensible to encourage agricultural material imports while restricting food product exports. Reducing tariffs on agricultural product imports could thus assist to lower food prices in Nigeria by increasing supply. Furthermore, an increase in food export duties may stimulate the Nigerian food industry to produce more food for the domestic market.

Fertilizer Consumption (kilograms per hectare of arable land (kg/ha))

FCON has a positive coefficient and is statistically significant at the 1% level of significance as expected due to the hypothesized positive relationship. The result shows that for every 1 kg/ha increase in fertilizer application, food consumption prices would go up by 0.61%. This indicates that while increased use of fertilizers promotes agricultural production, the associated cost pulls up the food price level. This result flags an important concern for Southern Africa, where the high fertilizer prices are mostly borne by import costs. The effect on food prices shows that bringing in subsidies or seeking for alternative inputs that could decrease reliance on expensive fertilizers may lower their ability to drive up food prices.

The findings obtained are in close agreement with the findings of a study by Zhang et al. (2014), which initiated an inquiry into the relationship between food pricing and inflationary trends in China. The empirical results suggested that the relationship between consumer price inflation and food prices has not weakened; besides, food price inflation, specifically in cereals due to increased fertilizer costs, remains a key driver of overall consumer price inflation. In addition, international food prices also play an essential role in driving the inflation process in China.

Rainfall (mm per year)

The majority of the sample countries rely on agriculture that depends on rainfall to meet their food and cash crop production needs. Thus, variations in the quantity and frequency of precipitation throughout the season, combined with an increase in weather changes, reduce agricultural quantity, particularly food commodities, resulting in high food prices and overall inflation. Precipitation in millimeters yields a coefficient of -0.01 with the expected negative sign. This negative coefficient implies that adequate rainfall reduces production costs by improving agricultural yield without the adoption of costly irrigation practices. However, its insignificance at standard levels implies that precipitation alone might not have a long-run significant effect on food prices unless accompanied by other complementary support systems including water infrastructure and drought resilience approaches.

These results corroborate with findings from Odongo et al. (2022), except that the coefficient of rainfall in the aforementioned study was both negative and significant as expected. The study concluded that, based on its findings, the importance of precipitation levels in lowering prices highlighted a need to prioritize investment in policies that contribute to regular water supplies, such as irrigation and food self-sufficiency programs. Some of these measures have been implemented in some of the study's sample countries, however they continue to be far away from achieving independence from agriculture, as was the case in Israel, where irrigation proved effective. Even if this policy is advised, it may be necessary to assess the impact of irrigation on food yield against national expenditures, and possibly to include the expertise of different countries with successful irrigation projects. At the macro level, the study highlights the need for additional research to build successful climate change policies and best practices in other nations that can be adapted for Africa.

Temperature (°C per year)

The positive coefficient of 0.30 implies that, holding other factors constant, a rise of 1°C leads to an increase of approximately 30.15% food inflation, and this effect is statistically significant, as indicated by the p-value of 0.00.

This means that temperature plays a role in influencing food inflation in the long run. A positive relationship indicates that high temperatures may contribute to the rise in food prices through various mechanisms, such as reduced agricultural production and increased energy costs related to food production. Temperature has become the prima facia agent as a basic input to determine crop yields; hence, rising temperatures can potentially hurt the growth process of many staple crops either by causing heat stress or by lessening the water supply through altered precipitation patterns. This decline in the production of agriculture may lead to reduced supply of food, hence rising food prices. For example, main staple crops such as wheat, maize, and rice are quite sensitive to extreme temperatures; therefore, even a slight rise in average temperatures may cause a reduction in yields, which finally rises food prices.

5.13.3. Short run panel ARDL empirical results

Table 5.18: Short run results of panel ARDL

Short Run: Dependent Variable: D(AGRP)				
Variables	**Coefficient**	**Std. Error**	**t-statistic**	**Prob**
CointEq(-1)	-0.453458	0.215064	-2.108484	0.0378**
D(FCPI(-3))	0.302569	0.177608	1.703576	0.0919*
D(CROP(-1))	-0.482499	0.269738	-1.788771	0.0770*
D(TEMP(-2))	-8.054747	4.129310	-1.950628	0.0542*
NB: (**) and (*) Denote significance at 5% and 10% level of significance				

Source: Author's computation using EViews

The ECT coefficient of -0.453 implies a fair speed of adjustment back towards the long-run equilibrium after some short-run shock. Its value is statistically significant at 5%, meaning that roughly 45% of every deviation from equilibrium is being corrected each year. Short-run panel ARDL results show that with a 3-year increase in food inflation, the current food inflation increases by 0.30%. A lagged crop production increase is associated with falling food prices, reflecting the downward price impact of the output increase in the previous year. Lagged temperature increases tend to negatively affect food prices; this may indicate that in the year following hot conditions, prices stabilize or go down.

5.14. Hausman test results

Table 5.19: Hausman test results – Random Effects Model

H_0: REM is appropriate		
Variables	**Coeff**	**Prob**
CROP	-0.202	0.8849
FEX	-5.465	0.0331**
ARMI	131.546	0.0043***
FCON	2.234	0.3154
RAIN	0.824	0.5120
TEMP	45.006	0.2151
C	-1477.464	0.2994
Obs	320	-
R-squared	0.097033	-
F-stat	2.529445	0.0025***
Chi-square	3.472834	0.6275
NB: (***) and (**) indicate rejection of the null hypothesis of no co-integration at 1% and 5% significance level.		

Source: Author's computation using EViews

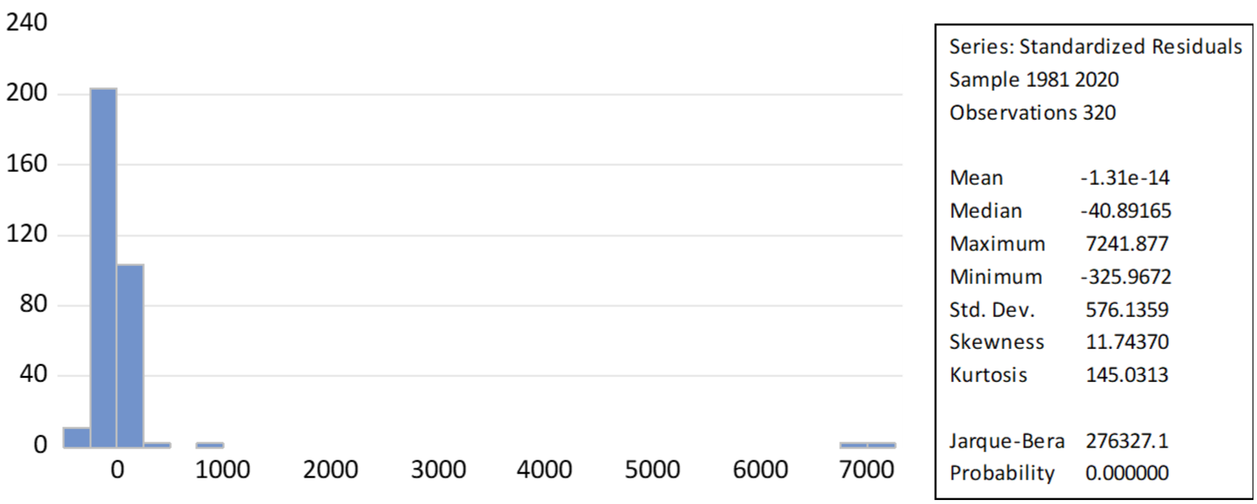
The Hausman test results support the null hypothesis of the REM being appropriate in this data. The signs of significance of FEX and ARMI at 5% and 1%, respectively, suggest that these variables have statistically significant impacts under REM, but other variables are not statistically significant in explaining the variation in the food price. With an R-squared of 0.097, the model explains approximately 9.7% of the variance in food prices.

5.15. Diagnostic Tests

The diagnostic tests namely, normality and cross section dependence test are employed to verify the variable evaluation of the outcomes obtained by the model.

5.15.1. Normality Test

Figure 5.2. Normality Test



Source: EViews Computation

Results from the normality test of the food inflation model show that residuals are not normally distributed; the Jarque-Bera test statistic is high, at 276327.1, while its probability is 0.00, thus leading to a rejection of the null hypothesis because the p-value obtained was below the acceptance region of 0.05. The histogram confirms this non-normality, with residuals concentrated around the lower end and few extreme positive outliers. Overall, these results imply that the model's residuals are not normally distributed, which may affect the reliability of standard inferential statistics in the model. However, according to Frain (2007), large sample sizes are not necessarily normally distributed, which in this case often results in an inability to fail to reject the null hypothesis of normality. Meaning that, with great samples, the distribution does not stay constant, and over time, regression results might not be the same. According to Kundu et al. (2011), tests of normality are sensitive when samples are large, which may lead to the rejection of the null hypothesis more frequently than it deserves. Chen and Kuan (2003) added that normality tests on large samples may overestimate the deviation from normality and question the robustness of some statistical models in such situations.

5.15.2. Cross Section Dependence

Table 5.20: Cross Section Dependence results

H0: No cross section dependence			
Test	**Statistics**	**Degrees of freedom**	**Probability**
Breusch-Pagan LM	151.5026	28	0.0000***
Pesaran Scaled LM	16.50373		0.0000***
Pesaran CD	9.410627		0.0000***
NB: (***) Denotes significance at 1% level of significance			

Source: Author's computation using EViews

The cross-section dependence test results for the food inflation model indicates significant evidence of cross-sectional dependence across the countries in the panel data. All three tests, the Breusch-Pagan LM, Pesaran Scaled LM and Pesaran CD have extremely low p-values, leading to the rejection of the null hypothesis of no cross-sectional dependence at the 1% significance level. These selected countries all have similar climate conditions, while agricultural production and the price of food in each varies according to shared variables such as droughts and variable rain conditions. Furthermore, the selected countries are economically interconnected as they exchange agricultural commodities and food produce. Regional policies, including those determined by trade agreements within the region and common socio-economic issues such as fluctuating currency, inflationary pressures, and reliance on the same staple crops, further help in dismissing the null hypothesis. Such dynamics explain the situation whereby food inflation in one country is highly likely to have strong effects on another country in the region.

5.16. Chapter summary

This chapter sought to employ a series of tests to investigate the impact of climate change on agricultural production and food inflation in Southern Africa over the period 1981 to 2020. The chapter began by analyzing the agricultural production model, followed by a focus on the food inflation model. Descriptive statistics and data trends for both models were then presented, followed by the panel unit root tests: LLC by Levin, Lin and Chu, IPS by Im, Pesaran and Shin, and Augmented Dickey Fuller tests to determine the stability of the variables. The Panel cointegration test established the equation for long-run estimation. Empirical results within the

Panel ARDL framework using the Pooled Mean Group estimator are then estimated. Diagnostic test results were also provided with regard to residual issues that could affect model accuracy.

Results indicate that climate change, as measured by average rainfall and temperature, significantly affects agricultural production and food inflation. While rainfall has a negative and insignificant effect in model 2, temperature has a negative and significant effect on the agricultural output model and a positive significant effect on food inflation as expected. In the agricultural production model, temperature impact implies that, for Southern Africa, the rise in temperature has a significant negative effect on agricultural productivity.

CHAPTER 6: SUMMARY, RECOMMENDATIONS AND CONCLUSION

6.1. Introduction

This study investigated the relationship between climate change, agricultural production and food inflation in Southern Africa using panel data from 1981 and 2020. This chapter therefore commences with the summary of the study. This is followed by recommendations for both models analyzed in the study. Furthermore, conclusion is based on the findings of the study and lastly opportunities for further research are presented.

6.2. Summary of the findings

The results demonstrate how climate variables significantly affect agricultural productivity in Southern Africa, according to the agricultural production model. Of particular concern are rising temperatures, which cause a significant drop in agricultural productivity. This emphasizes the pressing need for adaptation strategies, including better irrigation and drought-resistant crop variations, to mitigate the negative consequences of rising temperatures, which increase pest pressures, decrease soil moisture, and hasten evapotranspiration. Rainfall also has a negative correlation with production, high levels of rainfall cause crop diseases, waterlogging, and soil erosion, highlighting the need for climate-resilient farming methods and water management systems.

The findings from the food inflation model indicate that climate variables have a substantial impact on food inflation in Southern Africa. Particularly, increasing temperatures have a major impact on food inflation as the findings point out the negative consequences of heat stress on crop yields, resulting in lower agricultural productivity and higher production costs, all of which contribute to a tighter food supply and higher prices. The negative coefficient of rainfall implies that adequate rainfall can reduce food prices by enhancing crop growth and lowering dependency on costly irrigation. However, the lack of significance implies that rainfall by itself is inadequate to stabilize food prices in the absence of further investment in water supply systems and drought-resistant measures. These findings, therefore, emphasize the crucial need for comprehensive climate mitigation strategies to reduce the price increases on the region's food systems caused by higher temperatures and irregular rainfall patterns.

6.3. Policy Recommendations

6.3.1. Model 1: Agricultural Production Model

The agricultural sector faces a challenging task in adapting to changing weather conditions while lowering greenhouse gas (GHG) emissions, conserving biodiversity, and maintaining food security. According to Bezner et al. (2022), a wide range of initiatives have been established to assist agriculture in adapting to climate change, however, greater emphasis may have to be placed on implementation, monitoring, and evaluation. In order to address the challenges brought about by worldwide climate change, agricultural sector must apply an extensive array of strategies. These strategies can be divided into short-term (I), mid-term (II), and long-term strategies (III) and (IV), as illustrated below. Consequently, the study recommends the following:

(I) Targeted interventions to strengthen climate change adaptation

Agricultural support programs in Southern Africa should be more tailored to meet the requirements of farmers in an equitable manner. Current policies frequently result in inadequate transfers of revenue and fail to empower farmers to change their farming practices effectively. Support strategies should therefore include various adaptation methods, such as increasing sustainable productivity, increasing farm household incomes, and transitioning to non-agricultural livelihoods when appropriate. For instance, Malawi's Farm Input Subsidy Programme (FISP), which aims to strengthen food security by subsidizing fertilizers and seeds, has experienced inefficiencies and unforeseen consequences (Walls et al., 2023). The program's emphasis on maize production limited the diversification of crops, whereas larger farmers disproportionately benefited from asymmetrical access compared to smaller and more vulnerable farmers.

When farming becomes unsustainable, policies such as these must change to incorporate more comprehensive tactics that enable farmers to switch to alternate livelihoods, diversify their sources of income, or embrace climate-resilient techniques. The ability of farmers to adapt can be improved by investments in research, extension services, entrepreneurship, human capital, and climate-resilient technologies. Payments linked to ecosystem services, such as the preservation of biodiversity and the management of invasive species, can have dual benefits, but their efficacy has to be carefully evaluated to ensure effectiveness. Furthermore, planned adaptation projects that lower risks and improve long-term resilience should be given priority when budgetary resources are limited.

(II) Feasible solutions for sustainable fertilizer production

Environmental contamination and large GHG emissions are frequently linked with the manufacture and use of traditional fertilizers. Sustainable fertilizer production systems, on the other hand, efficiently lower carbon footprints through material selection and production process optimization. The findings of the present study demonstrate a significant relationship between total fertilizer consumption and agricultural production. However, the model conveys that extensive dependence on fertilizers may reach a point of diminishing returns, indicating that a more balanced, sustainable approach to fertilizer consumption is mandatory. A transition toward organic and bio-based fertilizers can help improve soil fertility, mitigate long-term degradation of the environment, and enhance agricultural yield or production. According to Avsar (2024), using bio-fertilizers and organic fertilizers entails recycling organic matter and agricultural waste, increasing soil fertility, decreasing greenhouse gas emissions and fossil fuel consumption, and improving resource efficiency and material recyclability. Additionally, microbial fertilizers and sophisticated synthetic biology processes greatly improve the efficiency of nutrient utilization, lower fertilizer runoff and water contamination, and improve soil, all of which increase crop yields.

Furthermore, smart fertilization technologies and environmentally friendly chemical processes are part of sustainable fertilizer production. Green chemical methods minimize the environmental impact of chemical synthesis and manufacture by reducing dependency on fossil fuels for chemical and fuel production (Ganesh et al., 2021). Through reliable fertilization and release control, intelligent fertilization systems reduce excess fertilizer usage while optimizing fertilizer efficiency and minimizing impact on the environment (Ahsan et al., 2024). By decreasing dependence on chemical fertilizers and GHG emissions, these creative solutions not only boost the quantity and quality of crops and strengthen the resilience of agricultural systems, however, they also promote sustainability of agriculture and climate change adaptation. All things considered, sustainable fertilizer production technologies are essential to maintaining security of food, safeguarding the environment, and advancing agricultural sustainability.

(III) Smart agriculture water reuse and recycling

Alternative solutions of recycling and reusing water are important and comprehensive in reducing the negative effects of climate change on agricultural output. These techniques efficiently lower the agricultural water demand by streamlining water resource management, therefore mitigating climate change-related water scarcity challenges. For example, the adoption of technologies such as trickle irrigation and rainwater-harvesting systems in farmland irrigation systems may substantially improve water use efficiency, reduce waste, and guarantee that crops receive sufficient water even during droughts (Freng et al., 2024). By turning household and commercial wastewater into irrigation water, wastewater regeneration and treatment technologies can lessen the need for freshwater resources and the pollution that wastewater discharge causes to the environment. Furthermore, the study's findings revealed that rainfall, although statistically significant, adversely affects agricultural productivity, thus, indicating that excessive or irregular rainfall, which is prevalent in Southern Africa, can result in diminished productivity due to soil erosion, waterlogging, and increased susceptibility of crops to disease. This requires water management strategies that not only respond to water scarcity but also mitigate the detrimental impacts of excessive rainfall.

By recycling and reducing pollution, water reuse techniques improve the stability and health of agricultural ecosystems in addition to preserving soil moisture, increasing soil fertility, and supplying nutrients for crops to support growth (Leonel and Tonetti, 2021). In general, water reuse and recycling programs are essential for combating climate change, protecting the environment, and guaranteeing food security in addition to improving the sustainability and efficiency of agricultural output. Thus, promoting and implementing these water resource management technologies are practical ways to address the issues of climate change and achieve sustainable agricultural development.

(IV) Establishing Sustainable Closed-Loop Systems

The development of sustainable closed-loop systems seeks to minimize waste production and pollution in the environment while achieving effective resource recycling. Closed-loop systems can minimize greenhouse gas emissions, lessen dependency on fossil fuels and chemical fertilizers, and turn agricultural waste into useful resources by combining waste management, energy production, and agricultural output. Although the study did not directly assess closed-loop systems, it suggests that minimizing inefficiencies in agricultural production (AGRP) is essential for achieving sustainable outcomes. By optimizing resource use and reducing waste, closed-loop systems could significantly reduce production costs, increase efficiency, and enhance the long-term resilience of agricultural systems, indirectly stabilizing food prices. Furthermore, irrigation water can be efficiently collected and recycled in closed-loop systems, giving crops sufficient protection from weather fluctuations. Food safety is improved, and the environmental impact of chemicals is decreased as plants are grown in controlled settings without the need for pesticides, fertilizers, or herbicides (Sharma et al., 2024).

Worldwide research on closed-loop ecosystems shows that this comprehensive management strategy improves agricultural production resilience and resource efficiency while simultaneously offering crucial data and technology support for prospective space exploration (Nelson, 2021). Conclusively, the development of sustainable closed-loop systems presents innovative strategies to combat climate change and advance agricultural sustainability, with important ecological and financial considerations.

6.3.2. Model 2: Food Inflation Model

According to the results obtained from this study, severe weather occurrences have an impact on inflation through agricultural productivity. As demonstrated by increasing temperatures and unpredictable weather patterns that have a direct impact on agricultural productivity and food costs, climate change is a major contributor to food inflation in Southern Africa. Therefore, the study recommends the following:

(I) Enhancing climate-resilient agricultural practices

Policymakers should urgently address these challenges by strengthening adaptive capacity to climate hazards in alignment with Sustainable Development Goals (SDGs).

This necessitates prioritizing investments in climate-resilient agricultural technologies and practices, including diversification of crops, enhanced systems for irrigation, and climate-smart agriculture. Governments should also fund research and development to encourage innovations such as hydroponic and vertical farming, which allow farmers to produce more effectively in climate-vulnerable regions. The study determined that temperature increase significantly impacts food prices, with prices increasing by about 30.15% with each 1°C increase, indicating the need for adaptive measures to mitigate the heat stress on crops and stabilize food inflation. As recommended by Seppelt et al. (2022), modifying cropping patterns and aligning planting seasons with local climatic conditions might improve resource efficiency while lowering food production losses, providing an uninterrupted supply of food and minimizing inflationary pressures.

(II) Addressing structural barriers in agricultural inputs and trade

To combat food inflation, the selected Southern African countries have to tackle the structural factors that affect agricultural input availability and trade dynamics. According to the results of this study, lowering tariffs on agricultural raw material imports (ARMI) is key to increasing access to critical inputs such as fertilizers and seeds, which are essential for increasing productivity. The findings of the study further reveal that availability of agricultural raw materials could reduce food prices considerably, and therefore it is mandatory to improve supply chains for such inputs. Simultaneously, limiting food exports by means of export levies and temporary limitations during domestic shortages can help prioritize local markets and stabilize food prices. The positive export coefficient shows that high food exports could trigger rising food prices in the local market, and therefore policymakers need to regulate exports in periods of scarcity of food to prevent inflationary surges. As further recommended in the study by Abraham (2018), improving regional trade integration through SADC-supported initiatives will improve food security by encouraging equitable trade and minimizing supply disruptions across member states.

(III) Promoting energy diversification for agricultural sustainability

Another crucial tactic for the region is energy diversification, since reliance on fossil fuels not only contributes to climate change but also links food inflation to fluctuating oil prices worldwide. Food inflation can be indirectly lowered by transitioning to renewable energy sources, such as solar, wind, and hydroelectric power, which can minimize operating costs in transportation and agriculture. Governments should, therefore, encourage the use of green technologies by providing tax incentives and subsidies for renewable energy projects in the agricultural sector, as suggested by McIntyre and Ashram (2017). In addition to promoting long-term environmental sustainability, investments in extending Southern Africa's renewable energy infrastructure would help decouple food inflation from fluctuations in the price of fossil fuels.

(IV) Adapting monetary policies to food price volatility

The study recommends that monetary policymakers consider the short- and long-term effects of supply shocks caused by major weather events on food prices and the overall price level. Given that central banks' primary responsibilities are price and production stability, even short-term effects of extreme weather events could have catastrophic consequences for poor households in

Southern Africa, as well as long-term ramifications for macroeconomic policy in general. Findings of this study suggest that climate factors, specifically, rainfall and temperature, account for food inflation. While rainfall had a forecasted negative coefficient, its statistical insignificance suggests the contribution of rainfall is conditional based on additional factors such as water infrastructure. Monetary policy should subsequently incorporate climate risk assessments into forecasting inflation dynamics. The findings further suggest that food price volatility, which is driven by trade and climate, presents a structural challenge to inflation targeting frameworks for central banks in the region.

Therefore, in order to effectively forecast and reduce increases in food prices, inflation targeting should be supplemented with increased monitoring of agricultural and trade conditions. For instance, the study indicates that trade variables such as agricultural raw material imports (ARMI) and food exports (FEX) directly influence food prices, emphasizing the need for central banks to monitor these variables alongside traditional inflation indicators. In order to anchor inflation, a study by Kunawotor et al. (2022), further recommends that a buffer of food items should be regularly maintained to serve as a reprieve during weather-related disasters. It is important to note that this study does not in any way imply that monetary policy should be the remedy to climate change, but instead suggests that monetary policy authorities should take climate change into account in their decision-making process.

6.4. Conclusion

The purpose of this study was to determine the influence of climate change on agricultural production and food inflation in the selected Southern African countries. The study applied various theoretical and empirical objectives outlined at the onset of this study. Theoretical objectives included a provision of literature review on inflation theories, climate-related factors that give rise to inflation and a conceptual approach that aims to narrate then impact of climate change on agricultural production. On the other hand, empirical literature was cited as a source of information from previous studies on how the findings varied with respect to how climate change impacts agricultural output and food inflation.

The results showed that temperature and rainfall patterns, indicators of climatic change, had massive impacts on agricultural productivity and the costs of food. It could therefore be contended that the agricultural sector in Southern Africa is particularly at risk from climate change because of the unique geology and farming systems of this region. To mitigate these challenges, this study recommends climate-resilient farming practices, input tariff reductions, enhancement of regional trade integration, and support for renewable energies to answer these challenges, so that productivity improves while food prices remain stable. Flexible monetary policies and increased social protection measures will thus be very instrumental in safeguarding livelihoods and food security for the people, fostering a strong agricultural economy against both structural and climatic challenges.

6.5. Future Directions

This study adopted the production function approach since the available input data for Southern African countries is aggregated and hence detailed analysis at commodity level is restricted. This, however, can be improved upon in future research using more detailed datasets or devising methods to disaggregate input data for major crops such as rice, maize, millet, and wheat. Besides, the inconsistent time-series data on temperature and precipitation limited alternative models. Future research could integrate satellite-derived climate data or embed regional climate models in this framework to bring down the analysis to higher resolutions. The inclusion of other modelling approaches, such as crop-climate interaction models, could further expand the scope and offer more holistic insights into climate change and agricultural productivity. Having this limitation overcome by data, future research would further polish the methodologies and bring out more exact and tailor-made recommendations for policy and practice.

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APPENDIX

Model 1: Agricultural Production

Appendix 1: Descriptive Statistics

	AGRP	LIV	LNAGRL	LAB	TFC	AMAC	RAIN	TEMP
Mean	80.55353	75.85794	14.40618	36.92003	25.99124	10820.62	63.10138	32.15822
Median	82.04000	87.04000	14.83976	30.80857	20.25891	0.000000	47.89917	32.85000
Maximum	178.3300	183.6900	16.44105	85.06357	99.87735	175557.0	276.6742	39.81917
Minimum	19.07000	13.97000	12.11176	0.000000	0.000000	0.000000	0.878333	20.44917
Std. Dev.	31.88167	34.97479	1.259591	29.32446	24.05584	34588.60	61.29251	4.190739
Skewness	0.011120	-0.119093	-0.202321	0.095373	0.798552	3.633117	1.785385	-1.378189
Kurtosis	2.322160	2.303285	1.872605	1.481961	2.779997	15.18967	5.784460	4.411737
Jarque-Bera	6.132827	7.228597	19.13006	31.21103	34.65526	2685.148	273.3815	127.8750
Probability	0.046588	0.026936	0.000070	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	25777.13	24274.54	4609.979	11814.41	8317.197	3462598.	20192.44	10290.63
Sum Sq. Dev.	324244.7	390212.3	506.1153	274315.7	184600.1	3.82E+11	1198410.	5602.373
Observations	320	320	320	320	320	320	320	320

Appendix 2: Unit Root Test

AGRP: 1st Difference

Panel unit root test: Summary
Series: D(AGRP)
Date: 10/30/24 Time: 08:42
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-10.0512	0.0000	8	296
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-15.8759	0.0000	8	296
ADF - Fisher Chi-square	199.940	0.0000	8	296
PP - Fisher Chi-square	244.029	0.0000	8	304

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

LIV: 1st Difference

Panel unit root test: Summary
Series: D(LIV)
Date: 10/30/24 Time: 08:51
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-11.4862	0.0000	8	296
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-11.0965	0.0000	8	296
ADF - Fisher Chi-square	137.996	0.0000	8	296
PP - Fisher Chi-square	193.278	0.0000	8	304

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

LNAGRL: 1st Difference

Panel unit root test: Summary
Series: D(LNAGRL)
Date: 10/30/24 Time: 08:52
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-7.80772	0.0000	8	296
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-9.08513	0.0000	8	296
ADF - Fisher Chi-square	109.675	0.0000	8	296
PP - Fisher Chi-square	205.987	0.0000	8	304

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

LAB: 1st Difference

Panel unit root test: Summary
Series: D(LAB)
Date: 10/30/24 Time: 08:54
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-10.4143	0.0000	8	296
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-8.33837	0.0000	8	296
ADF - Fisher Chi-square	97.1372	0.0000	8	296
PP - Fisher Chi-square	181.752	0.0000	8	304

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

TFC: 1st Difference

Panel unit root test: Summary
Series: D(TFC)
Date: 10/30/24 Time: 08:54
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-6.45917	0.0000	8	296
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-12.1624	0.0000	8	296
ADF - Fisher Chi-square	152.745	0.0000	8	296
PP - Fisher Chi-square	214.803	0.0000	8	304

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

AMAC: 1st Difference

Panel unit root test: Summary
Series: D(AMAC)
Date: 10/30/24 Time: 08:55
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-8.65260	0.0000	5	185
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-7.06068	0.0000	5	185
ADF - Fisher Chi-square	65.9217	0.0000	5	185
PP - Fisher Chi-square	126.000	0.0000	5	190

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

RAIN: Level

Panel unit root test: Summary
Series: RAIN
Date: 10/30/24 Time: 08:56
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-4.70422	0.0000	8	304
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-8.18039	0.0000	8	304
ADF - Fisher Chi-square	102.889	0.0000	8	304
PP - Fisher Chi-square	158.078	0.0000	8	312

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

TEMP: Level

Panel unit root test: Summary
Series: TEMP
Date: 10/30/24 Time: 09:01
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-8.85009	0.0000	8	304
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-9.85671	0.0000	8	304
ADF - Fisher Chi-square	120.569	0.0000	8	304
PP - Fisher Chi-square	188.975	0.0000	8	312

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Appendix 3: Panel Cointegration

Pedroni Residual Cointegration Test
Series: AGRP LIV LAB TFC RAIN TEMP
Date: 10/30/24 Time: 10:27
Sample: 1981 2020
Included observations: 320
Cross-sections included: 8
Null Hypothesis: No cointegration
Trend assumption: Deterministic intercept and trend
Automatic lag length selection based on SIC with a max lag of 8
Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

			Weighted	
	Statistic	Prob.	Statistic	Prob.
Panel v-Statistic	1.780535	0.0375	2.041157	0.0206
Panel rho-Statistic	-2.516770	0.0059	-1.844263	0.0326
Panel PP-Statistic	-6.862833	0.0000	-6.688734	0.0000
Panel ADF-Statistic	-7.031124	0.0000	-6.852969	0.0000

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	-0.990628	0.1609
Group PP-Statistic	-8.069380	0.0000
Group ADF-Statistic	-7.049184	0.0000

Cross section specific results

Phillips-Peron results (non-parametric)

Cross ID	AR(1)	Variance	HAC	Bandwidth	Obs
Zimbabwe	0.103	160.1336	159.1767	1.00	39
Mozambique	0.454	55.68151	59.17648	2.00	39
Malawi	0.091	21.03540	18.67217	3.00	39
South Africa	-0.193	34.41887	32.34102	3.00	39
Lesotho	-0.092	278.8772	232.3517	5.00	39
Botswana	0.189	156.7008	156.7008	0.00	39
Namibia	0.094	16.42088	16.12177	3.00	39
Zambia	0.235	31.70737	2.834864	38.00	39

Augmented Dickey-Fuller results (parametric)

Cross ID	AR(1)	Variance	Lag	Max lag	Obs
Zimbabwe	0.103	160.1336	0	8	39
Mozambique	0.454	55.68151	0	8	39
Malawi	0.091	21.03540	0	8	39
South Africa	-0.193	34.41887	0	8	39
Lesotho	-0.092	278.8772	0	8	39
Botswana	0.189	156.7008	0	8	39
Namibia	0.094	16.42088	0	8	39
Zambia	0.235	31.70737	0	8	39

Appendix 4: Optimal lag length

VAR Lag Order Selection Criteria
Endogenous variables: AGRP LIV LAB TFC RAIN TEMP
Exogenous variables: C
Date: 12/02/24 Time: 06:45
Sample: 1981 2020
Included observations: 256

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-6809.479	NA	5.36e+15	53.24593	53.32902	53.27935
1	-5425.115	2693.022	1.43e+11	42.71183	43.29346*	42.94576
2	-5329.135	182.2107	8.94e+10	42.24324	43.32342	42.67768
3	-5239.089	166.7267	5.87e+10*	41.82101*	43.39972	42.45596*
4	-5210.524	51.54988	6.23e+10	41.87910	43.95635	42.71456
5	-5187.729	40.07059	6.93e+10	41.98225	44.55805	43.01823
6	-5165.069	38.76863	7.73e+10	42.08648	45.16081	43.32296
7	-5144.197	34.73296	8.77e+10	42.20466	45.77754	43.64166
8	-5107.925	58.65775*	8.83e+10	42.20254	46.27396	43.84005

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Appendix 5: PMG/Panel ARDL

Dependent Variable: D(AGRP)
Method: ARDL
Date: 12/02/24 Time: 05:45
Sample: 1984 2020
Included observations: 296
Dependent lags: 3 (Fixed)
Dynamic regressors (3 lags, fixed): LIV LAB TFC RAIN TEMP
Fixed regressors: C

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
	Long Run Equation			
LIV	0.339199	0.086921	3.902397	0.0001
LAB	0.234819	0.066067	3.554273	0.0005
TFC	1.365937	0.139044	9.823762	0.0000
RAIN	-1.111003	0.274359	-4.049444	0.0001
TEMP	-16.63122	3.763963	-4.418541	0.0000
	Short Run Equation			
COINTEQ01	-0.260199	0.132078	-1.970034	0.0505
D(AGRP(-1))	-0.270735	0.107602	-2.516075	0.0128
D(AGRP(-2))	-0.200158	0.071946	-2.782056	0.0060
D(LIV)	-0.144108	0.225894	-0.637945	0.5244
D(LIV(-1))	-0.156617	0.214831	-0.729023	0.4670
D(LIV(-2))	0.009541	0.166479	0.057310	0.9544
D(LAB)	-0.224834	0.162205	-1.386109	0.1676
D(LAB(-1))	-0.851849	0.319426	-2.666814	0.0084
D(LAB(-2))	0.059659	0.245419	0.243089	0.8082
D(TFC)	-0.073550	0.129995	-0.565793	0.5723
D(TFC(-1))	0.029784	0.158228	0.188238	0.8509
D(TFC(-2))	0.279678	0.145041	1.928263	0.0556
D(RAIN)	0.544487	0.510425	1.066733	0.2877
D(RAIN(-1))	0.618320	0.505360	1.223525	0.2229
D(RAIN(-2))	-0.519872	0.651990	-0.797363	0.4264
D(TEMP)	-0.627595	1.236193	-0.507684	0.6124
D(TEMP(-1))	-0.187486	0.963928	-0.194502	0.8460
D(TEMP(-2))	0.322429	0.539589	0.597546	0.5510
C	144.6408	69.93051	2.068351	0.0402

Root MSE	7.118829	Mean dependent var	2.068007
S.D. dependent var	14.88309	S.E. of regression	9.974468
Akaike info criterion	6.770562	Sum squared resid	16216.87
Schwarz criterion	8.619395	Log likelihood	-926.2900
Hannan-Quinn criter.	7.508836		

*Note: p-values and any subsequent tests do not account for model selection.

Appendix 6: Hausman Test of the Four versions of the Model

(I) Model 1: RAIN and TEMP

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	3.754370	5	0.5853

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
LIV	0.348593	0.350120	0.000038	0.8032
LAB	0.208152	0.205734	0.000064	0.7624
TFC	0.700773	0.686881	0.000229	0.3582
RAIN	-0.119758	-0.114620	0.000164	0.6885
TEMP	-3.934629	-3.276017	0.424648	0.3122

Cross-section random effects test equation:
Dependent Variable: AGRP
Method: Panel Least Squares
Date: 12/02/24 Time: 05:57
Sample: 1981 2020
Periods included: 40
Cross-sections included: 8
Total panel (balanced) observations: 320

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	162.2986	38.93338	4.168624	0.0000
LIV	0.348593	0.043510	8.011806	0.0000
LAB	0.208152	0.048421	4.298794	0.0000
TFC	0.700773	0.073527	9.530857	0.0000
RAIN	-0.119758	0.040428	-2.962256	0.0033
TEMP	-3.934629	1.174523	-3.349980	0.0009

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.683231	Mean dependent var	80.55353
Adjusted R-squared	0.670849	S.D. dependent var	31.88167
S.E. of regression	18.29104	Akaike info criterion	8.690476
Sum squared resid	102710.6	Schwarz criterion	8.843564
Log likelihood	-1377.476	Hannan-Quinn criter.	8.751607
F-statistic	55.18013	Durbin-Watson stat	0.749157
Prob(F-statistic)	0.000000		

(II) Model 2: RAIN, SQRAIN and TEMP

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	156.082699	6	0.0000

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
LIV	0.348554	0.312482	0.000702	0.1733
LAB	0.208159	0.284704	0.000944	0.0127
TFC	0.700732	0.407369	0.003318	0.0000
RAIN	-0.118864	-0.218844	0.022373	0.5039
SQRAIN	-0.000003	0.000208	0.000000	0.6417
TEMP	-3.930427	-1.915848	1.849544	0.1385

Cross-section random effects test equation:
Dependent Variable: AGRP
Method: Panel Least Squares
Date: 12/02/24 Time: 06:05
Sample: 1981 2020
Periods included: 40
Cross-sections included: 8
Total panel (balanced) observations: 320

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	162.1334	48.49598	3.343235	0.0009
LIV	0.348554	0.044100	7.903687	0.0000
LAB	0.208159	0.048517	4.290422	0.0000
TFC	0.700732	0.074000	9.469350	0.0000
RAIN	-0.118864	0.161138	-0.737657	0.4613
SQRAIN	-2.92E-06	0.000510	-0.005730	0.9954
TEMP	-3.930427	1.386298	-2.835197	0.0049

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.683231	Mean dependent var	80.55353
Adjusted R-squared	0.669774	S.D. dependent var	31.88167
S.E. of regression	18.32090	Akaike info criterion	8.696726
Sum squared resid	102710.6	Schwarz criterion	8.861590
Log likelihood	-1377.476	Hannan-Quinn criter.	8.762560
F-statistic	50.76959	Durbin-Watson stat	0.749204
Prob(F-statistic)	0.000000		

(III) Model 3: RAIN, TEMP, SQTEMP

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	114.423067	6	0.0000

** WARNING: estimated cross-section random effects variance is zero.

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
LIV	0.349687	0.299405	0.000696	0.0567
LAB	0.206628	0.283816	0.001014	0.0154
TFC	0.699160	0.581044	0.002941	0.0294
RAIN	-0.118703	-0.151363	0.001221	0.3499
SQTEMP	0.071725	0.423720	0.012217	0.0014
TEMP	-8.500043	-26.693703	52.654628	0.0122

Cross-section random effects test equation:
Dependent Variable: AGRP
Method: Panel Least Squares
Date: 12/02/24 Time: 06:14
Sample: 1981 2020
Periods included: 40
Cross-sections included: 8
Total panel (balanced) observations: 320

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	233.6326	128.5873	1.816918	0.0702
LIV	0.349687	0.043597	8.020830	0.0000
LAB	0.206628	0.048544	4.256526	0.0000
TFC	0.699160	0.073658	9.491960	0.0000
RAIN	-0.118703	0.040512	-2.930063	0.0036
SQTEMP	0.071725	0.123210	0.582136	0.5609
TEMP	-8.500043	7.930167	-1.071862	0.2846

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.683582	Mean dependent var	80.55353
Adjusted R-squared	0.670139	S.D. dependent var	31.88167
S.E. of regression	18.31077	Akaike info criterion	8.695620
Sum squared resid	102596.9	Schwarz criterion	8.860484
Log likelihood	-1377.299	Hannan-Quinn criter.	8.761453
F-statistic	50.85188	Durbin-Watson stat	0.753739
Prob(F-statistic)	0.000000		

(IV) Model 4: RAIN, SQRAIN, TEMP, SQTEMP

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	103.853222	7	0.0000

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
LIV	0.349550	0.301722	0.000743	0.0793
LAB	0.206653	0.294632	0.001008	0.0056
TFC	0.699012	0.570687	0.002994	0.0190
RAIN	-0.115517	-0.331983	0.022588	0.1498
SQRAIN	-0.000010	0.000767	0.000000	0.0873
SQTEMP	0.071789	0.472677	0.012043	0.0003
TEMP	-8.489110	-29.696327	52.273236	0.0034

Cross-section random effects test equation:
Dependent Variable: AGRP
Method: Panel Least Squares
Date: 12/02/24 Time: 06:13
Sample: 1981 2020
Periods included: 40
Cross-sections included: 8
Total panel (balanced) observations: 320

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	233.1071	131.3511	1.774688	0.0769
LIV	0.349550	0.044181	7.911742	0.0000
LAB	0.206653	0.048639	4.248732	0.0000
TFC	0.699012	0.074139	9.428372	0.0000
RAIN	-0.115517	0.161415	-0.715656	0.4748
SQRAIN	-1.04E-05	0.000511	-0.020390	0.9837
SQTEMP	0.071789	0.123451	0.581514	0.5613
TEMP	-8.489110	7.961227	-1.066307	0.2871

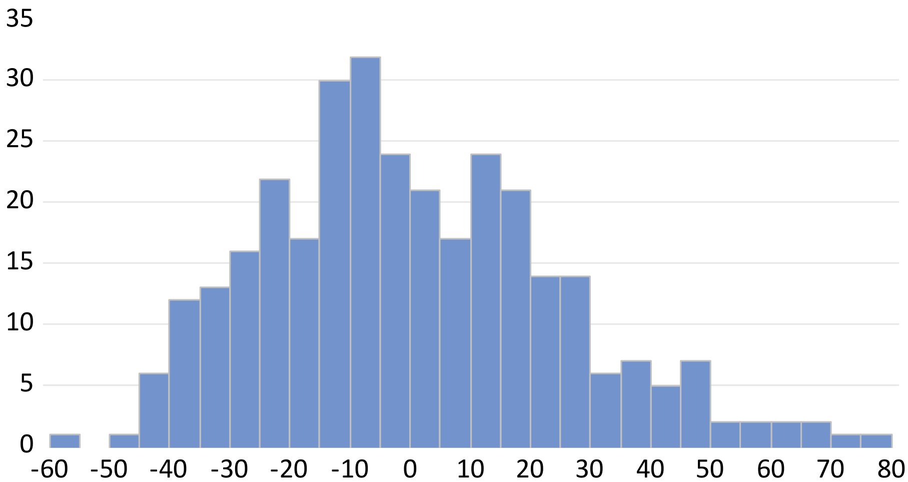
Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.683582	Mean dependent var	80.55353
Adjusted R-squared	0.669058	S.D. dependent var	31.88167
S.E. of regression	18.34075	Akaike info criterion	8.701868
Sum squared resid	102596.8	Schwarz criterion	8.878508
Log likelihood	-1377.299	Hannan-Quinn criter.	8.772404
F-statistic	47.06538	Durbin-Watson stat	0.753911
Prob(F-statistic)	0.000000		

Appendix 7: Diagnostic Tests

(I) Normality Test



Series: Standardized Residuals
Sample 1981 2020
Observations 320

Mean	2.45e-14
Median	-2.840938
Maximum	75.39412
Minimum	-55.43050
Std. Dev.	24.49417
Skewness	0.487771
Kurtosis	2.983650
Jarque-Bera	12.69268
Probability	0.001753

(II) Cross Section Dependence Test

Residual Cross-Section Dependence Test
Null hypothesis: No cross-section dependence (correlation) in weighted residuals
Equation: Untitled
Periods included: 40
Cross-sections included: 8
Total panel observations: 320
Note: non-zero cross-section means detected in data
Cross-section means were removed during computation of correlations

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	28.10603	28	0.4588
Pesaran scaled LM	0.014169		0.9887
Pesaran CD	0.715967		0.4740

Model 2: Food Inflation

Appendix 1: Descriptive Statistics

	FCPI	CROP	FEX	ARMI	FCON	RAIN	TEMP
Mean	69.74708	80.55353	19.80734	0.851625	25.99124	63.10138	32.15822
Median	10.78271	82.04000	8.665654	0.684363	20.25891	47.89917	32.85000
Maximum	7375.300	178.3300	96.02369	4.153999	99.87735	276.6742	39.81917
Minimum	-15.08000	19.07000	0.000000	0.000000	0.000000	0.878333	20.44917
Std. Dev.	585.1390	31.88167	27.73022	0.881837	24.05584	61.29251	4.190739
Skewness	12.23730	0.011120	1.612010	1.031663	0.798552	1.785385	-1.378189
Kurtosis	152.8441	2.322160	4.348777	3.497080	2.779997	5.784460	4.411737
Jarque-Bera	307363.3	6.132827	162.8467	60.05871	34.65526	273.3815	127.8750
Probability	0.000000	0.046588	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	22319.07	25777.13	6338.350	272.5200	8317.197	20192.44	10290.63
Sum Sq. Dev.	1.09E+08	324244.7	245299.8	248.0659	184600.1	1198410.	5602.373
Observations	320	320	320	320	320	320	320

Appendix 2: Unit Root Test

FCPI: Level

Panel unit root test: Summary
Series: FCPI
Date: 10/30/24 Time: 19:28
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-6.19515	0.0000	8	304
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-6.12046	0.0000	8	304
ADF - Fisher Chi-square	70.5727	0.0000	8	304
PP - Fisher Chi-square	73.9673	0.0000	8	312

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

CROP: 1st difference

Panel unit root test: Summary
Series: D(CROP)
Date: 10/30/24 Time: 19:27
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-10.0512	0.0000	8	296
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-15.8759	0.0000	8	296
ADF - Fisher Chi-square	199.940	0.0000	8	296
PP - Fisher Chi-square	244.029	0.0000	8	304

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

FEX: Level

Panel unit root test: Summary
Series: FEX
Date: 10/30/24 Time: 19:59
Sample: 1981 2020
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.97599	0.1645	8	304
Breitung t-stat	-3.89343	0.0000	8	296
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-2.52724	0.0057	8	304
ADF - Fisher Chi-square	34.7582	0.0043	8	304
PP - Fisher Chi-square	33.3163	0.0067	8	312

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

ARMI: 1st difference

Panel unit root test: Summary
Series: D(ARMI)
Date: 10/30/24 Time: 20:02
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-8.43096	0.0000	8	296
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-9.59015	0.0000	8	296
ADF - Fisher Chi-square	115.224	0.0000	8	296
PP - Fisher Chi-square	245.518	0.0000	8	304

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

FCON: Level

Panel unit root test: Summary
Series: FCON
Date: 10/30/24 Time: 20:02
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.64008	0.0041	8	304
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.09203	0.0000	8	304
ADF - Fisher Chi-square	45.9171	0.0001	8	304
PP - Fisher Chi-square	80.3911	0.0000	8	312

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

RAIN: Level

Panel unit root test: Summary
Series: RAIN
Date: 10/30/24 Time: 08:56
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-4.70422	0.0000	8	304
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-8.18039	0.0000	8	304
ADF - Fisher Chi-square	102.889	0.0000	8	304
PP - Fisher Chi-square	158.078	0.0000	8	312

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

TEMP: Level

Panel unit root test: Summary
Series: TEMP
Date: 10/30/24 Time: 09:01
Sample: 1981 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-8.85009	0.0000	8	304
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-9.85671	0.0000	8	304
ADF - Fisher Chi-square	120.569	0.0000	8	304
PP - Fisher Chi-square	188.975	0.0000	8	312

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Appendix 3: Panel Cointegration Test

Pedroni Residual Cointegration Test
Series: FCPI CROP FEX ARMI FCON RAIN TEMP
Date: 10/30/24 Time: 20:09
Sample: 1981 2020
Included observations: 320
Cross-sections included: 8
Null Hypothesis: No cointegration
Trend assumption: Deterministic intercept and trend
Automatic lag length selection based on SIC with a max lag of 8
Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	-4.287462	1.0000	-4.013769	1.0000
Panel rho-Statistic	-1.300491	0.0967	0.398372	0.6548
Panel PP-Statistic	-6.637621	0.0000	-5.014555	0.0000
Panel ADF-Statistic	-6.715991	0.0000	-5.138696	0.0000

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	1.170329	0.8791
Group PP-Statistic	-7.504847	0.0000
Group ADF-Statistic	-5.505580	0.0000

Cross section specific results

Phillips-Peron results (non-parametric)

Cross ID	AR(1)	Variance	HAC	Bandwidth	Obs
Zimbabwe	0.094	1255035.	1139294.	3.00	39
Mozambique	0.129	110.2592	110.2592	0.00	39
Malawi	0.388	170.4616	157.6640	4.00	39
South Africa	0.051	16.88796	10.28619	10.00	39
Lesotho	0.053	16.25854	1.414972	28.00	39
Botswana	0.348	11.42278	11.64736	2.00	39
Namibia	0.036	17.34003	11.55476	6.00	39
Zambia	0.362	773.3316	681.2801	2.00	39

Augmented Dickey-Fuller results (parametric)

Cross ID	AR(1)	Variance	Lag	Max lag	Obs
Zimbabwe	0.094	1255035.	0	8	39
Mozambique	0.129	110.2592	0	8	39
Malawi	0.388	170.4616	0	8	39
South Africa	0.051	16.88796	0	8	39
Lesotho	-0.295	14.35394	1	8	38
Botswana	0.348	11.42278	0	8	39
Namibia	0.036	17.34003	0	8	39
Zambia	0.362	773.3316	0	8	39

Appendix 4: Optimal lag length

VAR Lag Order Selection Criteria
Endogenous variables: FCPI CROP FEX ARMI FCON RAIN TEMP
Exogenous variables: C
Date: 12/02/24 Time: 07:17
Sample: 1981 2020
Included observations: 256

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-7961.898	NA	2.57e+18	62.25701	62.35395	62.29600
1	-6729.808	2387.174	2.49e+14	53.01412	53.78963*	53.32603
2	-6610.450	224.7274	1.44e+14	52.46446	53.91853	53.04928
3	-6479.207	239.9292	7.58e+13*	51.82193*	53.95458	52.67967*
4	-6436.731	75.32789*	8.01e+13	51.87290	54.68412	53.00356
5	-6405.297	54.02726	9.25e+13	52.01014	55.49992	53.41371
6	-6371.465	56.29993	1.05e+14	52.12863	56.29698	53.80513
7	-6344.938	42.69191	1.27e+14	52.30420	57.15112	54.25361
8	-6316.451	44.28779	1.52e+14	52.46446	57.98995	54.68679

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Appendix 5: PMG/Panel ARDL

Dependent Variable: D(FCPI)
Method: ARDL
Date: 12/02/24 Time: 07:25
Sample: 1984 2020
Included observations: 296
Dependent lags: 3 (Fixed)
Dynamic regressors (3 lags, fixed): CROP FEX ARMI FCON RAIN TEMP
Fixed regressors:

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
		Long Run Equation		
CROP	0.020886	0.013041	1.601605	0.1127
FEX	0.127261	0.041682	3.053161	0.0030
ARMI	-3.697446	0.419302	-8.818091	0.0000
FCON	0.612101	0.071959	8.506206	0.0000
RAIN	-0.019810	0.015140	-1.308472	0.1940
TEMP	0.301518	0.067274	4.481925	0.0000
		Short Run Equation		
COINTEQ01	-0.453458	0.215064	-2.108484	0.0378
D(FCPI(-1))	0.287511	0.235392	1.221415	0.2251
D(FCPI(-2))	-0.068349	0.158440	-0.431389	0.6672
D(FCPI(-3))	0.302569	0.177608	1.703576	0.0919
D(CROP)	-1.522149	1.179497	-1.290508	0.2002
D(CROP(-1))	-0.482499	0.269738	-1.788771	0.0770
D(CROP(-2))	0.054536	0.486677	0.112059	0.9110
D(CROP(-3))	3.085577	2.924944	1.054918	0.2943
D(FEX)	-10.86789	12.19591	-0.891110	0.3752
D(FEX(-1))	-7.095231	5.622147	-1.262014	0.2102
D(FEX(-2))	4.310921	4.416176	0.976166	0.3316
D(FEX(-3))	-1.020080	0.825297	-1.236016	0.2197
D(ARMI)	263.1718	248.1145	1.060687	0.2917
D(ARMI(-1))	97.67005	99.33121	0.983277	0.3281
D(ARMI(-2))	-75.29501	80.72050	-0.932787	0.3534
D(ARMI(-3))	38.11176	35.87968	1.062210	0.2910
D(FCON)	1.917229	1.882651	1.018367	0.3112
D(FCON(-1))	-0.781687	0.903747	-0.864940	0.3894
D(FCON(-2))	-2.672423	2.533380	-1.054885	0.2943
D(FCON(-3))	-3.196884	3.125143	-1.022956	0.3091
D(RAIN)	-55.68692	55.14847	-1.009764	0.3153
D(RAIN(-1))	36.92729	37.31937	0.989494	0.3251
D(RAIN(-2))	15.11163	15.56062	0.971146	0.3341
D(RAIN(-3))	65.83740	65.96584	0.998053	0.3209
D(TEMP)	-28.69005	23.86817	-1.202021	0.2325
D(TEMP(-1))	23.79896	27.79379	0.856269	0.3941
D(TEMP(-2))	-8.054747	4.129310	-1.950628	0.0542
D(TEMP(-3))	61.16259	63.22871	0.967323	0.3360

Root MSE	91.46366	Mean dependent var	1.901882
S.D. dependent var	578.0528	S.E. of regression	172.4655
Akaike info criterion	7.013033	Sum squared resid	2676992.
Schwarz criterion	9.721514	Log likelihood	-892.0853
Hannan-Quinn criter.	8.094581		

*Note: p-values and any subsequent tests do not account for model selection.

Appendix 6: Hausman Test

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	3.472834	5	0.6275

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
RAIN	0.769388	-0.321120	0.756317	0.2099
TEMP	48.575792	8.354478	1079.130123	0.2208
FCON	2.199265	2.053559	1.617083	0.9088
ARMI	85.633105	80.355877	73.896949	0.5393
CROP	-0.662882	-0.454205	0.117836	0.5433

Cross-section random effects test equation:
Dependent Variable: FCPI
Method: Panel Least Squares
Date: 10/30/24 Time: 20:20
Sample: 1981 2020
Periods included: 40
Cross-sections included: 8
Total panel (balanced) observations: 320

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1617.605	1232.132	-1.312850	0.1902
RAIN	0.769388	1.263310	0.609025	0.5430
TEMP	48.57579	36.40209	1.334423	0.1831
FCON	2.199265	2.324568	0.946096	0.3448
ARMI	85.63310	40.66473	2.105832	0.0360
CROP	-0.662882	1.391145	-0.476501	0.6341

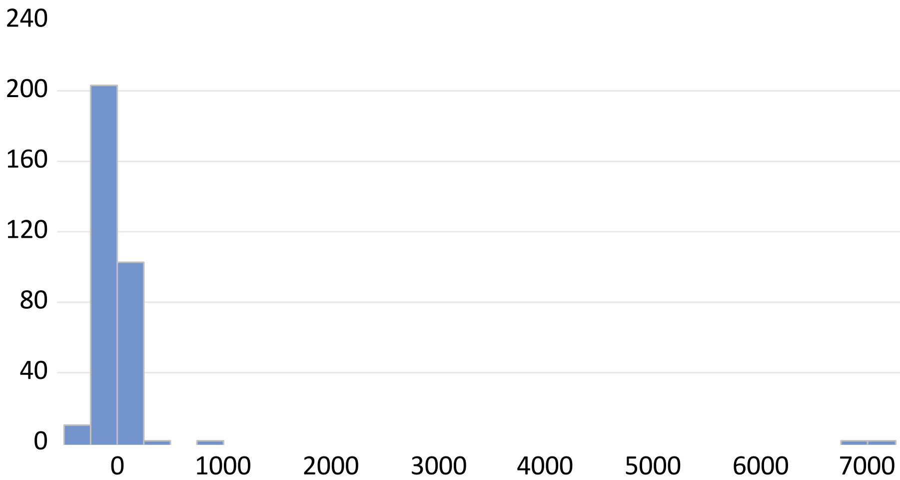
Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.083516	Mean dependent var	69.74708
Adjusted R-squared	0.047692	S.D. dependent var	585.1390
S.E. of regression	571.0153	Akaike info criterion	15.57249
Sum squared resid	1.00E+08	Schwarz criterion	15.72557
Log likelihood	-2478.598	Hannan-Quinn criter.	15.63362
F-statistic	2.331307	Durbin-Watson stat	0.943727
Prob(F-statistic)	0.007219		

Appendix 7: Diagnostic Tests

(I) Normality Test



Series: Standardized Residuals
Sample 1981 2020
Observations 320

Mean	-1.31e-14
Median	-40.89165
Maximum	7241.877
Minimum	-325.9672
Std. Dev.	576.1359
Skewness	11.74370
Kurtosis	145.0313
Jarque-Bera	276327.1
Probability	0.000000

(II) Cross Section Dependence Test

Residual Cross-Section Dependence Test
Null hypothesis: No cross-section dependence (correlation) in weighted residuals
Equation: Untitled
Periods included: 40
Cross-sections included: 8
Total panel observations: 320
Note: non-zero cross-section means detected in data
Cross-section means were removed during computation of correlations

Test	Statistic	d.f.	Prob.
Breusch-Pagan LM	303.5008	28	0.0000
Pesaran scaled LM	36.81534		0.0000
Pesaran CD	3.977204		0.0001