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The impact of climate change on agricultural productivity in Zimbabwe (1980- 2022).

BY

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APPROVAL FORM

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Dedication

I dedicate this project to my family and the almighty for the strength and knowledge during the period of my study.

The Abstract

The study is looking into the impact of climate change on agricultural productivity in Zimbabwe. The study first did a literature review on climate change on agricultural productivity around the world and in Zimbabwe. The study aims to investigate empirically from 1980-2022. The background of climate changes around the world was explored to understand the problems that are being faced by those in the agricultural sector. The autoregressive distributed lag (ARDL) model is used in the study to examine the data. The variables under control were, control of corruption, precipitation, government effectiveness, government expenditure, temperature and agricultural productivity and the data is being found on World Bank Development indicators, World Bank's Climate Change Knowledge Portal and Food and the Agricultural organization. The dependent variable in the regression model is agriculture value added as a percentage of GDP.

The findings showed that in the short run, temperature, precipitation, government effectiveness, and control of corruption had a negative impact on agricultural productivity, while government capital expenditure had a positive impact. In the long run, precipitation, control of corruption, and government capital expenditure continued to have a negative impact on agricultural productivity, whereas government effectiveness had a positive impact. Overall, the study provides valuable insights into the relationship between climate change and agricultural productivity in Zimbabwe. It highlights the short and long-term impacts of climate variables and government-related factors on agricultural productivity.

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I am grateful to God for the strength to begin and finish this research project. To my parents Mr and Mrs Mukarombwa , thank you for making this dream come true, my brothers, friends and sisters am grateful for your support during the period of my study.

Many thanks to my supervisor Dr. B. Nkala for the guidance and support throughout the research project into the final product. Additionally, I would like to express my sincere gratitude to the Economics Department, particularly to Dr. S. Mutsvangwa.

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Chapter 1

1.0 Introduction

According to the Intergovernmental Panel on Climate Change (IPCC, 2020), climate change is defined as a long-term alteration in the characteristics of the climate, including its average conditions and variations, which can be detected through statistical analysis and lasts for several decades or more (usually three decades). Climate change is a critical concern that confronts both people and the earth. The ramifications of this have a substantial impact on several industries, particularly agriculture, which relies heavily on climatic conditions (Food and Agricultural Organization, FAO 2020). Agriculture plays a crucial role in providing sustenance and ensuring food security for a significant number of people in Zimbabwe, a developing nation located in Southern Africa (Moyo et al., 2019). The agricultural sector has been negatively impacted by climate change, resulting in higher temperatures, unpredictable rainfall, droughts, floods, and the spread of pests and diseases (Nyamwanza et al., 2020). These variables have diminished agricultural output and animal efficiency, jeopardizing food security and rural growth.

1.1 Background to the study

Globally, the agriculture industry faces significant challenges due to climate change in all areas. This has affected both the supply and demand of food and other ecosystem products. According to the IPCC (2022), climate change impacts on agriculture vary across regions and crops, but generally reduce yields, increase production costs, lower farm incomes, and threaten food security (FAO, 2022). The World Bank (2020) estimates that by 2030, climate change could reduce food consumption by 4% in Europe, with larger effects in a more unequal world. Climate change impacts on agriculture are mostly caused by variations in temperature, precipitation, water availability, pests and diseases, and extreme weather events.

The most significant effects of climate change in the past century occurred globally between 1.8 and 5.8˚C and between 0.09 and 0.88 mm (IPCC, 2020). Furthermore, only South Asia faces a 0.016˚C to 1˚C temperature rise (Lin and Xu, 2018). However, a mere 0.5˚C can result in a 5.14 percent decrease in climate-related production, particularly in agriculture, and a 3˚C increase would put 600 million people in danger (World Bank, 2022). To cope with these impacts, adaptation measures are needed at different levels, from farm to policy. The IPCC (2022) identifies several adaptation options for the agriculture sector, such as improving water management, diversifying crops and livestock, enhancing soil health, reducing greenhouse gas emissions, increasing resilience to shocks, and promoting innovation and cooperation. However, adaptation also faces barriers and limits, such as financial constraints, institutional barriers, knowledge gaps, social norms, and trade-offs with other objectives. Therefore, adaptation requires integrated and participatory approaches that consider the context-specific needs and capacities of farmers and other stakeholders (IPCC, 2022).

Climate change poses a significant risk to the agricultural industry in Southern Africa at a regional level. This sector heavily relies on rain-fed crops and is susceptible to severe weather events. As to research published by the World Bank, the area is projected to see a potential decline of 30% in its maize harvest by the year 2030 as a result of elevated temperatures and less precipitation. Climate change has wide-ranging effects on agriculture, extending beyond only crop output to include cattle, fisheries, forests, and food security. According to the World Food Programme (2020), over 45 million individuals in Southern Africa are now experiencing severe food insecurity as a result of droughts, floods, and storms.

In order to address the difficulties presented by climate change, the agricultural industry in Southern Africa must embrace more robust and sustainable methods that may improve production, broaden sources of revenue, and decrease greenhouse gas emissions. Adaptation possibilities include enhanced irrigation systems, crop types resilient to drought, integrated pest control, agroforestry, conservation agriculture, and diversification of livestock. Furthermore, it is imperative for the sector to enhance its ability to acquire and use climate information and services, as well as engage in regional and national policies and institutions that facilitate climate action (World Bank, 2020).

Zimbabwe relies heavily on rained food production and animal raising at a national level. Based on the World Bank's report in 2020, Zimbabwe has seen a rise in mean temperature of 0.9°C from 1900 to 2015, and a decline in average precipitation of around 5% from 1950 to 2015. The changes have increased the frequency and diseases, pests, floods, and dry spells, which has negatively impacted food security and the livelihoods of many small-scale farmers. According to the World Food Programme (WFP) (2020), about 8.6 million individuals, which accounts for 60% of the population, are experiencing food insecurity in the year 2020/21 as a result of climatic shocks and economic instability.

Zimbabwean farmers must embrace climate-smart agriculture (CSA) techniques to effectively manage the consequences of climate change. These approaches will bolster their ability to withstand challenges, increase their output and revenue, and concurrently decrease greenhouse gas emissions. CSA activities include a range of techniques such as conservation agriculture, cultivation of crops that can withstand drought, small-scale irrigation, agroforestry, management of animal feed, proper handling of waste, generation of biogas, use of better breeds and feeds, weather index insurance, and provision of climate information services. Nevertheless, the implementation of these techniques is hindered by several obstacles, including restricted availability of climate funding, resources, markets, extension services, infrastructure, and policy assistance. Climate change is predicted by the IPCC to continue to negatively impact Zimbabwe's agricultural productivity in the years to come. According to the World Bank (2020), if there are no investments in CSA (Climate-Smart Agriculture), the production of maize is projected to decrease by 33% by the year 2030. Figure 1 below shows the temperature and agricultural productivity trends.

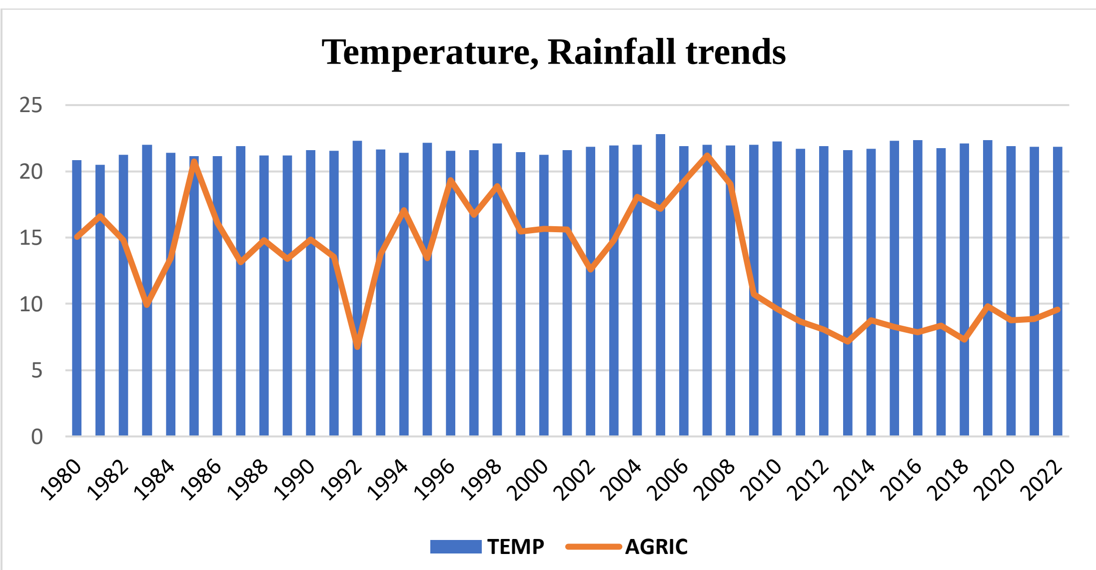


Figure 1 Average surface temperature, Agriculture value added trends

Source: World Bank

The figure above is suggesting a potential relationship between temperature levels and agricultural productivity for the period under study. Between 1980 and 1990 temperature levels increased from 20.85 ˚C to 21.61 ˚C. Agriculture's productivity as a percentage of GDP decreased from 15.07 to 14.8% the same period. The same period according to literature was associated with droughts which could have negatively affected the agricultural sector.

The decade of 1990-2000 registered a decrease in temperatures from 21.61˚C to 21.23.˚C correspondingly the agricultural sector’s value added as a percentage of GDP rose from 14.8 to 15.66. The same trajectory was exhibited for the 2000-2012 decade when the temperature level rose from 21.23˚C to 22.25˚C. In the same decade, agriculture value added as a percent of GDP decreased from 15.66 to 9.60 suggesting that temperature levels have an impact on the agricultural sector.

However, the decade 2010-2020 ushered a new trend with temperatures falling from 22.25˚C to 21.93˚C while agriculture value added moved in the same direction from 9.60 to 8.70 as a percent of GDP. This suggests that there are other variables which were at play. Such variables could entail corruption levels and government’s capital expenditure which all have a potential impact on the performance of the agricultural sector. It is against this backdrop that the research envisages to study the impact of climate change on agricultural productivity in Zimbabwe.

1.2 Statement of the problem

Climate change has had a significant effect on agricultural productivity in Zimbabwe, leading to increased poverty and food insecurity. The World Bank reports that while Zimbabwe has achieved great strides in the 2010s in several areas, poverty and inequality increased at the same time, in contrast to the rest of Sub-Saharan Africa, where there has been a slight decrease in poverty (World Bank, 2022). According to the 2022 ZIMVAC report, the interplay of poverty, increasing low/poor investment as a result of low institutional quality in the agricultural sector, and the inelasticity of the food production sector results in food insecurity in Zimbabwe. These factors are further compounded by the adverse effects of climate change and extreme weather-related events (UNDP, 2022). Approximately two-thirds of Zimbabweans are employed in agriculture, and many more rely on it either directly or indirectly. However, because of its poor productivity and extreme sensitivity to threats associated to climate change, agriculture does not produce the highest income. While more productivity in agriculture is needed for it to play a bigger part in increasing incomes, enhancing food security, and decreasing poverty, climatic variability is hindering the sector's resilience. Thus, it is imperative that the study look into how climate change affects Zimbabwe's agricultural productivity.

1.3 Objectives of the study

1.3.1 To examine the short and long run impact of climate change on agricultural productivity for the period 1980–2022.

1.3.2 To determine how farmers can implement new practices or technological advancement to change weather patterns in the short-term, which will lead to the long-term equilibrium in agricultural productivity.

1.3.3 To determine possible recommendations, for policymakers and farmers to improve climate change resilience sustainable agricultural practices, and food security in Zimbabwe.

1.4 Research questions

1.4.1 To what extent does climate change affect agricultural productivity in Zimbabwe?

1.4.2 How have average surface temperature and annual rainfall impacted agricultural productivity in Zimbabwe?

1.4.3 What is the mediation effect of control of corruption and government effectiveness on agricultural productivity in Zimbabwe?

1.5 Hypothesis

H_0: climate change has no impact on agricultural productivity in Zimbabwe

H_1: climate change has an impact on agricultural productivity in Zimbabwe

1.6 Significance of the study

The study is significant because it highlights the effects of climate change on agricultural productivity in Zimbabwe, which is a critical sector of the country's economy. The study is important because it provides insights into the short and long-run impact of climate change on agricultural productivity in Zimbabwe, which can help policymakers and stakeholders develop effective policies to mitigate the negative effects of climate change on the agricultural sector.

Additionally, most of the available studies on the same subject like Moyo (2014) are over ten years old such that their results may no longer be relevant given the changing rainfall and temperature patterns. Furthermore, the available studies like Moyo (2019, 2020) have utilized OLS regression as a method of estimation, which has limitations in capturing the short and long-period impact of climate change on agricultural productivity in Zimbabwe. The current study will utilize the ARDL to ECM model as a method of estimation, which is more appropriate for capturing the short and long-period impact of climate change on agricultural productivity in Zimbabwe. This will provide more accurate and reliable estimates of the effects of climate change on agricultural productivity in Zimbabwe. Furthermore, the current research will recognize the potential impact of institutional quality, and government capital expenditure on agricultural productivity in Zimbabwe, which are all important factors that have been overlooked in most of the previous studies. This will add more information to the literature repository and provide policymakers and stakeholders with a more comprehensive knowledge of the impact of climate change on agricultural productivity in Zimbabwe.

1.7 Limitations

The major limitation of the study is that it will rely on time series data. Therefore, the study can be negatively affected by the unavailability of data. To mitigate such challenges the study will rely on proxy variables. As a result, the selection was done on the basis of data completeness.

1.8 Delimitations.

The study will use time series data covering the years 1980–2022, focusing on the economy of Zimbabwe with a total of six study variables. The data will be gathered from the World Bank's World Development Indicators and observed annually.

1.9 Chapter Summary

1.9.1 Chapter Two: Literature review

This chapter will review the existing literature on climate change and agricultural productivity. The chapter will identify the key concepts, theories, models, and frameworks that are relevant to the study. The chapter will also highlight the gaps and limitations in the literature that the study intends to fill.

1.9.2 Chapter Three: Research Methodology

This chapter will cover the methodology, model specification, justification of variables, and diagnostic tests. The chapter will justify the adapted/ adopted model and explain it will address the research questions

1.9.3 Chapter Four: Data presentation, Analysis and Discussion

This chapter will present and analyse the data collected from all secondary sources. The chapter will use ARDL to ECM regression analysis, as well as presenting diagnostic results that are pertinent to the method of estimation to answer the research questions. The chapter will also discuss the findings in relation to theoretical and empirical literature.

1.9.4 Chapter 5: Summary, Conclusion and Recommendations

This chapter will summarize the main results of the study, give a conclusion and provide recommendations.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This chapter offers a thorough review of the literature regarding how climate change affects Zimbabwe's agricultural productivity. The study encompasses both theoretical and empirical literature that is pertinent to the research. The chapter starts by examining the primary theories that elucidate the connection between climate change and agricultural production, namely the New Institutional Economics Theory, the Malthusian Theory, and the global warming Theory. The chapter thereafter examines the empirical research undertaken in various countries and circumstances, with a specific emphasis on the estimating methodology, conclusions, and suggestions of each study.

2.1 Theoretical Literature review

2.1.1The New Institutional Economics Theory

The New Institutional Economics (NIE) is an economic discipline that examines the impact of institutions on economic results and explores methods to promote efficiency and welfare via institutional improvements. The emergence of the New Institutional Economics (NIE) in the 1970s was a direct reaction to the shortcomings of neoclassical economics. Neoclassical economics operated under the assumption of perfect rationality, information, and markets, while disregarding the influence of history, culture, and politics on economic growth.

Douglass North, who received the Nobel Prize in Economics in 1993, was a leading advocate of the NIE. He was recognized for his significant contributions to economic history and the examination of institutions. According to North, institutions are the deliberate limitations created by humans that shape political, economic, and social interactions. He contended that institutions provide the guidelines that influence human conduct and motivations, and that altering these institutions is crucial for comprehending historical transformations and economic outcomes.

The central tenet of the NIE is that institutions play a pivotal role in shaping economic outcomes by influencing the costs associated with transactions and output. Transaction costs refer to the expenses associated with engaging in market activities, including activities such as information search, contract negotiation, performance monitoring, and agreement enforcement. Production costs refer to the expenses incurred in converting inputs, such as labour, capital, and technology, into outputs. The NIE operates on the assumption that agents possess rationality, although with cognitive limitations and restricted access to information. Furthermore, it acknowledges the possibility of individuals engaging in opportunistic behaviour to exploit others.

The NIE acknowledges the existence of several sorts of institutions, including official and informal ones, as well as distinct styles of governance, such as markets, hierarchies, and networks. The NIE examines how individuals and organizations make decisions about different ways of organizing themselves and managing their resources to reduce the costs associated with transactions and production. These decisions are influenced by their preferences, beliefs, and limitations. The NIE also investigates the process of institutional change across time, which might be driven by learning, innovation, conflict, or adaptation.

An application of the NIE is to analyze the correlation between institutional quality and agricultural production. Institutional quality pertains to the extent to which institutions foster economic growth and development, including elements such as safeguarding property rights, enforcing contracts, protecting the rule of law, controlling corruption, and maintaining political stability. Agricultural productivity is the measure of how efficiently and effectively agricultural production is carried out, quantified by the amount of output produced per unit of input used. According to the NIE, the quality of institutions has an impact on agricultural output by shaping the motivations and limitations experienced by farmers, merchants, processors, and consumers. For instance, when property rights are secure, farmers are more likely to invest in improving their land and adopting new technologies. Similarly, when contracts are enforced effectively, it becomes easier to engage in trade and reduce transaction costs. Transparent and accountable governance helps prevent rent-seeking and corruption. Lastly, stable and participatory political institutions contribute to the provision of public goods and the promotion of social welfare.

2.1.2 The Malthusian Theory

According to the Malthusian theory, food supply growth follows an arithmetic pattern whereas population expansion follows an exponential pattern. The concept was introduced by the English clergyman and intellectual Thomas Robert Malthus in his 1798 publication, An Essay on the

Principle of Population. According to the hypothesis, there exists an optimal population size that can be sustained by the global food supply. Should the population exceed this threshold, there would be a decline in living conditions, accompanied by measures to control population growth. These occurrences are referred to be positive checks or natural checks, including natural catastrophes, conflicts, food shortages, and illnesses.

The idea also proposes the use of preventive measures to regulate the expansion of the population. These measures include strategies such as contraception, delaying marriage until later in life, and abstaining from sexual activity. Malthus posited that these mechanisms would serve as safeguards against the onset of a Malthusian disaster, characterized by the scenario in which population expansion surpasses agricultural output, leading to pervasive destitution and depopulation. The theory is based on three fundamental assumptions: firstly, that human beings possess an innate inclination to procreate; secondly, that food production exhibits a linear growth pattern; and thirdly, that the principle of diminishing returns is applicable to agricultural output. These assumptions have faced opposition from sceptics and researchers who contend that technology advancements, societal shifts, and environmental influences may impact the dynamics of both population and food supply.

The hypothesis may explain the negative effects of climate change on agricultural output in Zimbabwe and population expansion in a gloomy manner. There could be less arable land available as a result of climate change and water resources for agriculture, resulting in a decrease in food output and an increase in food costs. This will result in a state of food instability and malnutrition throughout the population, particularly affecting the impoverished and susceptible demographics. The idea also posits that population expansion would intensify the strain on finite resources, leading to more instances of disputes, migrations, and fatalities. The idea suggests that Zimbabwe should implement stringent population control measures in order to prevent a Malthusian disaster.

2.1.3 The Global Warming Theory

The term "global warming" describes the observed increase in average air temperature in the vicinity of the Earth's surface over the previous one to two centuries. The phenomenon is a result of the buildup of greenhouse gases in the atmosphere, including carbon dioxide, methane, water vapour, and nitrous oxide. These gases trap the heat emitted by the Earth's surface, preventing it from dissipating into space. Human activity, including the burning of fossil fuels, deforestation, agricultural practices, and industrial operations, is the primary contributor to these greenhouse gases.

In 1896, Swedish physicist Svante Arrhenius introduced the concept of global warming, whereby he determined that if the amount of carbon dioxide in the atmosphere were to double, the Earth's temperature would rise by around 5 degrees Celsius. Subsequently, several scientists have enhanced and verified this idea by the use of diverse methodologies, including climate models, paleoclimate records, and measurements of temperature, precipitation, sea level, ice cover, and other indicators. The Intergovernmental Panel on Climate Change (IPCC), created in 1988 by the United Nations, is the most authoritative source for assessing the scientific data on global warming. Comprised of several specialists from various countries, the IPCC provides a comprehensive evaluation of the subject.

According to the basic assumptions of the global warming theory, human activity is increasing the amounts of greenhouse gases in the atmosphere. These gases intensify the natural greenhouse effect, resulting in the Earth's temperature rising. Consequently, this warming will have substantial consequences for both the environment and human society. Anticipated ramifications of global warming encompass the thawing of glaciers and ice sheets, elevation of sea levels, heightened occurrence and intensity of heat waves, droughts, floods, storms, and wildfires, alterations in precipitation patterns and ecosystems, diminished crop yields, escalated propagation of diseases, and displacement of millions of individuals.

The theory of global warming is based on several assumptions. Firstly, it assumes that the climate system is responsive to variations in greenhouse gas levels. Secondly, it posits that the impact of human activities on climate outweighs natural factors like solar activity and volcanic eruptions. Thirdly, it suggests that feedback mechanisms, such as water vapour and clouds, can either enhance or mitigate the warming effect caused by greenhouse gases. Lastly, it assumes that future greenhouse gas emissions can be predicted based on socio-economic scenarios.

The hypothesis of global warming may elucidate the influence of climatic change on agricultural output in Zimbabwe. According to study by Lobell et al. (2008), Zimbabwe has been among one of the African countries vulnerable to the effects of climate change. This vulnerability is mostly attributed to the nation's heavy reliance on rain-fed agriculture and its limited ability to adapt to changing conditions. According to the report, Zimbabwe is expected to see a decrease in maize production of 10 to 20 percent by 2030 as a result of elevated temperatures and less rainfall. These consequences might significantly impact the country's food security, poverty reduction efforts, and economic growth.

2.2 Empirical Literature review

Bai et al. (2022) examined the relationship between agricultural productivity and climate change by using China's provincial agricultural input-output data from 2000 to 2019 and the climatic data of the ground meteorological stations. The authors analyzed the data they had gathered using the three-stage spatial Durbin model (SDM) model and the entropy method. Additionally, they used SDM and ordinary least square methods to empirically investigate the marginal effects of climate change on agricultural productivity. According to the results of robustness tests such as index replacement, quantile regression, and tail reduction, climate change significantly lowers agricultural productivity. The study's findings also showed that, when the climatic variables were divided, annual precipitation had no discernible effect on the rise in agricultural productivity; in addition, temperature and wind speed had a significant negative impact on productivity. The heterogeneity test showed that climatic changes ominously hinder agricultural productivity growth only in the western region of China, and in the eastern and central regions, climate change had no effect. The study's conclusions emphasize the significance of farm households' diverse social networks in helping to shape policies that would enhance their adaptability to climate change and increase land productivity in different regions. The study also provides a theoretical framework for prioritizing developing regions that need to be carefully considered in order to boost agricultural productivity.

Stadtbäumer et al. (2022) looked at the effects of rainfall on agricultural productivity in Zambia. The study used a quantitative farm planning model to simulate how rural Zambian farmers would adapt to different climate change scenarios and variations in land availability, labour capacity and off-farm work possibility. The study was done using survey data from 277 households collected in 2018.By combining general circulation models, the mathematical optimization method of econometric estimation harmonized top-down and bottom-up approaches. The findings showed that climate change negatively affected farm yields and required land and labour adjustments to prevent losses in wealth. The recommendations included modifying the cropping mix, reallocating planting times, changing farming techniques, increasing agricultural intensification and diversifying income sources through on- and off-farm work. The research concluded that climate change had a significant impact on rural livelihoods and suggested policy interventions to enhance resilience (Stadtbäumer et al., 2022).

Zhang et al. (2022) investigated how China's agricultural output might be affected by climate change using a three-stage SDM model and the entropy technique. The researchers used the entropy approach to assess the climatic indicators, including temperature, precipitation, sunlight length, average wind speed, and average air pressure, in order to compute the provincial agricultural output from 2000 to 2019. A study found that climate change has a substantial detrimental impact on agricultural output in China, particularly in the eastern area. Additionally, it was shown that factors such as human capital, investment in research and development, building of infrastructure, and environmental control had a beneficial impact on agricultural output. The suggestion was made to enhance China's ability to adapt to climate change by boosting its agricultural technology innovation system, expanding the quality of its human capital, and optimizing its regional agricultural structure.

Ogundariand and Onyeaghala (2021) analyzed the impact of climate fluctuations on African agricultural total factor productivity (TFP) growth and tested whether agricultural TFP levels are converging in the region. The research used a technological catch-up model based on the Ricardian analysis and cross-country balanced panel data covering thirty-five countries from 1981 to 2010. The model incorporated historical national rainfall and temperature data as well as potential confounding variables related to education, capital intensity, and arable land with irrigation. The empirical findings demonstrate that agricultural TFP levels in Africa are gradually rising, although at a somewhat slow rate. Additionally, the study discovers that while temperature has no effect on the study's African agricultural TFP development, precipitation considerably boosts it. It was discovered that capital intensity, education, and arable land with irrigation significantly increased the rise of agricultural total factor productivity (TFP). The study recommends that policies should focus on improving education, capital intensity, and irrigation systems to enhance agricultural productivity in Africa.

Ngobeni and Muchopa (2022) examined the impact of population, consumer price index, annual rainfall, government investment on agriculture, and the value of food imports on South Africa's agricultural output between 1983 and 2019. To examine the data, they used a vector autoregressive

(VAR) model. The researchers discovered that long-term agricultural productivity was positively influenced by government spending in agriculture, whereas there was no immediate impact in the short term. Additionally, it was shown that government spending in agriculture did not have a Granger causality effect on the value of agricultural output. However, it was found to be associated with it via other variables in the model. Their suggestion was to advocate for a higher allocation of government funds towards agriculture in order to foster economic expansion and provide employment opportunities.

Alabi and Abu (2020) investigated how public spending on agriculture affected Nigerian agricultural output between 1981 and 2014. They used a co-integration and error correction model as well as a system of equations technique in their analysis. According to the study, agricultural public capital investment had a positive but delayed impact on agricultural output. However, recurrent and total agricultural public expenditure did not have any influence. Additionally, it was shown that governmental spending on agricultural infrastructure helped enhance private investment in agriculture. The recommendation was to reorient agricultural public spending towards investments in irrigation, research and development, and rural development. These areas were shown to have greater benefit-cost ratios and were more effective in stimulating private investment compared to subsidy programs.

Oyinbo et al. (2020) conducted a study to assess the influence of government spending on agriculture on the production of the agricultural sector in Nigeria between 1981 and 2018. They used ordinary least squares (OLS) regression and co-integration analysis for their research. It was discovered that the amount of money the government spends on agriculture has a beneficial and noteworthy effect on the production of the agricultural sector, both in the immediate and extended periods. They also found that government spending on agriculture and agricultural sector production had a stable equilibrium relationship. Their recommendation is for the government to increase its financial allocation to agriculture and guarantee prompt and efficient execution of agricultural policies and programs.

In their study, Mkhabela et al. (2019) examined the influence of government spending on agriculture on agricultural production in South Africa between 1970 and 2016. They examined the data using the bounds testing method and the autoregressive distributed lag (ARDL) model. It was shown that there exists a sustained connection between government spending on agriculture and agricultural production, with a notable beneficial impact that can only be anticipated in the long term. Additionally, it was shown that the allocation of government funds towards agriculture had an adverse impact on agricultural output in the immediate term. This was due to inefficiencies and the improper distribution of resources. They suggested that the government enhance its monitoring and evaluation procedures to guarantee the efficient allocation and usage of public monies for agriculture.

Peicoto .et .al (2022) examined the impact of corruption on agricultural productivity in a study titled "Corruption and Inflation in Agricultural Production: The Problem of the Chicken and the Egg". The study was conducted in 90 countries and aimed to analyze the connection between corruption and inflation in agricultural production prices. The study utilized the panel data cointegration technique. According to the study, there is typically a long-term beneficial correlation between agricultural productivity and corruption control. The direction of causality favours the hypothesis that the inflation of agricultural products promotes incentives that lead to an increase in corruption levels. According to the study, fighting corruption should pay particular focus to reducing failure in agricultural markets that raise prices and can be used as a conduit for corruption.

Lencucha et al (2020) conducted a scoping review of the literature on government strategies and programs that have attempted to shift agricultural production in some way, such as enhancing crop production, inducing crop substitution or shifting to some other type of employment. The authors identified 103 articles that evaluated the impact of various policy tools on different outcomes, such as production, income, efficiency and land allocation. The study discovered that although financial help had mixed results, input, output, and technical support all had an impact on production, revenue, and other outcomes. The study also highlighted the gaps and limitations in the existing literature, such as the lack of attention to the health and environmental impacts of agricultural policies, the need for more rigorous evaluation methods, and the importance of considering the political economy and institutional context of policy implementation. The study concluded by suggesting some directions for future research and policy dialogue on healthy agricultural commodities.

2.3 Chapter Summary

The literature on how climate change affects Zimbabwe's agricultural productivity has been reviewed in this chapter. It has examined three theories that explain the connection between climate change and agricultural productivity: the new institutional economics theory, the global warming theory and the Malthusian theory. The empirical data from earlier research examining the effects of climate fluctuations on different facets of production in agriculture, including crop yields, land usage, farm revenue, and food security, has also been covered in this chapter. The literature review has revealed that climate change poses significant challenges and opportunities for the agricultural sector in Zimbabwe, and that there is a need for more research to understand the complex and dynamic relationship between climate change and agricultural productivity. The research approach that will be applied to solve the study's research objectives and questions is presented in the next chapter.

CHAPTER THREE

METHODOLOGY

3.0 Introduction

Chapter 3 presents the methodology used in this study. It spells out the research design, research instruments, as well as data collection methods.

3.1 Model specification

The model that Ogundariand and Onyeaghala (2021) used to analyze the effects of climate change on the total factor productivity of African agriculture will be employed in this study. Below are the model's specifications.

$$\Delta AGR_t = \varphi_1 + \sum_{i=1}^{p} \beta_0 \Delta AGR_{t-i} + \sum_{i=1}^{p} \beta_1 \Delta TEMP_{t-i} + \sum_{i=1}^{p} \beta_2 \Delta PREC_{t-i} + \sum_{i=1}^{p} \beta_3 \Delta GVT_{t-i} + \sum_{i=1}^{p} \beta_4 \Delta CORR_{t-i} + \sum_{i=1}^{p} \beta_5 \Delta EFF_{t-i} + \sum_{i=1}^{p} \alpha_0 \Delta AGR_{t-i} + \sum_{i=1}^{p} \alpha_1 \Delta TEMP_{t-i} + \sum_{i=1}^{p} \alpha_2 \Delta PREC_{t-i} + \sum_{i=1}^{p} \alpha_3 \Delta GVT_{t-i} + \sum_{i=1}^{p} \alpha_4 \Delta CORR_{t-i} + \sum_{i=1}^{p} \alpha_5 \Delta EFF_{t-i} + \mu_t$$

Where：

AGR: $Agricultural\ value\ added\ as\ a\ percent\ of\ GDP$

$TEMP$: $Annual\ surface\ Tempertature$

$PREC$: *Annual Precipitation*

GVT: *Government capital expenditure*

$CORR$: *Control of Corruption*

EFF: *Government Effectiveness*

β_0: $intercept.$

$\beta_{0,}\beta_1, \beta_2, \beta_3\ \beta_4, \beta_{5,}$: $Short\ Run\ coefficients.$

$\alpha_0, \alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5,$: $Long\ Run\ coefficients.$

Δ: *Difference Operator*

φ_1: *Short Run intercept*

ε: Error term

3.2 Variable justification

3.2.1 Annual Surface Temperature

Annual surface temperature is a measure of the average temperature of the Earth's surface over a year. It is calculated by averaging the monthly mean temperatures of land and ocean surfaces from different sources, such as weather stations, satellites, buoys, and ships (World Bank, 2020). The balance between the heat released from the Earth's system and the incoming solar radiation is reflected in the annual surface temperature, which is a key indicator of climate change. An increase in global temperature means that more heat is trapped in the atmosphere, which can have various impacts on weather patterns, ecosystems, sea level, and human health. The Paris Agreement on climate change aims to limit the long-term temperature increase to no more than 1.5°C above pre-industrial levels, to avoid the most critical consequences of global warming. Bai et al (2022) found a negative relationship between annual surface temperature and agricultural productivity in China. As a result, it is anticipated that this variable will be negative both in the short and long-run periods.

3.2.2 Annual Precipitation

Annual surface precipitation is the amount of water that falls on the Earth's surface in a year, usually measured in millimetres or inches (IPCC, 2022). According to the IPCC, annual surface precipitation has changed over time due to natural variability and human influence on the climate system. The IPCC uses climate models to project future changes in annual surface precipitation under different scenarios of greenhouse gas emissions and socio-economic development. According to IPCC projections, annual surface precipitation is expected to rise in the majority of global regions by the end of the twenty-first century, particularly in high latitudes and certain tropical areas, but it will decline in certain subtropical and semi-arid regions. Stadtbäumer et al. (2022) found a positive relationship between annual precipitation and agricultural productivity. In light of this, it is anticipated that the variable will be positive both in the short- and long-periods.

3.2.3 Government Capital expenditure

Government capital expenditure is the spending by the public sector on fixed assets such as roads, buildings, equipment, and machinery (World Bank, 2022). It is also known as public investment or gross fixed capital formation by the general government. According to the World Bank, it is measured as a percentage of GDP, based on data from national accounts. The World Bank provides data on government capital expenditure for different countries and regions, as well as the global average. For example, in 2019, the global average of government capital expenditure was 7.8% of GDP, while the average for Sub-Saharan Africa was 9.2% of GDP. In their analysis of the relationship between government capital spending and agricultural productivity, Ngobani and Muchopa (2022) found a positive correlation between the variables over both the long and short term. This result indicates that both in the short- and long-term periods, the variable should have a positive sign.

3.2.4 Control of corruption

Control of corruption is one of the indicators used by Transparency International, a global movement that works to end the injustice of corruption by promoting transparency, accountability and integrity. According to their website, control of corruption "captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as 'capture' of the state by elites and private interests. Control of corruption is measured by aggregating data from 13 different sources that provide perceptions of corruption by experts and business people. The sources include surveys, assessments and indices from various institutions, such as the World Bank, the World Economic Forum, the Economist Intelligence Unit and others. The data is then rescaled to a scale of 0 (highly corrupt) to 100 (very clean) and averaged to produce a score for each country or territory. The scores are also accompanied by a standard error and a confidence interval to reflect the level of uncertainty around each score. The latest Corruption Perceptions Index (CPI) was released in January 2022 and showed that most countries are failing to stop corruption. Peiroto et al (2022) found a negative relationship in the short run and a long run positive relationship between control of corruption and agricultural productivity in South Africa. Contrary to this discovery, the variable is projected to have a positive sign in the long run and a negative sign in the short run.

3.2.5 Government effectiveness

Control of government effectiveness is one of the six dimensions of governance measured by the World Bank's Worldwide Governance Indicators (WGI) project. It captures the quality of public services, the quality of the civil service and its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies (World Bank, 2022). The WGI project uses data from various sources, such as surveys of households, firms, experts, and public officials, to construct aggregate indicators for each dimension of governance. Better governance outcomes are indicated by higher values of the indicators, which are given in units between -2.5 and 2.5. The indicators are also accompanied by margins of error reflecting the uncertainty of the estimates. The WGI project provides data for more than 200 countries and regions since 1996, allowing for comparisons over time and across regions. Lencucha et al (2022) found a positive relationship between government efficacy and food output. This implies that government policies have an impact on food output. In light of this, it is anticipated that the variable will have a positive impact over the short and long run.

3.2.6 Error Term

Other elements not covered by this model are captured by the residual, sometimes known as the error term (ε) (Gujarati, 2009).

3.3 Data collection procedures

This research will utilize secondary data from various sources spanning the period 1990-2023. The data will be observed at annual intervals. These sources are the World Bank Development indicators, World Bank's Climate Change Knowledge Portal and Food and Agricultural organization.

3.4 Diagnostic tests

Diagnostic tests in regression analysis are methods to assess whether the assumptions of any regression model are valid or not. These assumptions include linearity, homoscedasticity, and normality of the errors among others. Violating these assumptions may lead to incorrect inference and invalid results often termed spurious regression analysis. Since this research will utilize an ARDL model, only diagnostic results that are peculiar to this method of estimation will be tested and their results will be presented in the subsequent chapter.

3.4.1 Unit root test

Testing for stationarity in time series data used in research is the main goal of the unit root test. The condition is considered optimal when both the mean and variance remain constant, as they should. Gujarati (2004) asserts that this criterion necessitates the two variables to possess enduring qualities across time. Time series data must be used for this research in order to lower the possibility of erroneous regression findings.

The Augmented Dickey Fuller (ADF) test is often used to ascertain the stationarity of research variables. This is the manner in which the assumption is presented.

H_0: there is the unit root problem

H_1: there is no unit root problem

3.4.2 Optimal Lag length

When conducting an ARDL analysis, one important step is to determine the appropriate number of lags to include in the model. The optimum lag selection is crucial to ensure accurate estimation of the relationship between the variables and to avoid issues such as omitted variable bias or overfitting of the model. The criteria that are employed in the process of determining the optimal lag times are the Akaike, Hannan-Quinn, and Schwarz information criteria. The selection of lags has to be approached with caution in order to avoid the occurrence of erroneous regression results. This is because the ARDL restrictions are sensitive to the lags that are used throughout the methodology of model estimate.

3.4.3 Cointegration

The variables in a time series regression analysis must be stationary in order to be considered. In particular, the variables need to demonstrate a similar trend over a longer period of time. This particular scenario has variables that are co-integrated (Gujarati, 2004). Using this test, spurious regression may be reduced. It is possible to do an analysis of multivariate linear regression equations using the Johansen co-integration approach. A comparison between the F stat value and the upper and lower limit values is included in the research. This is because the model is an ARDL.

H_0: there is co-integration

H_1: there is no co-integration

Decision Rule: reject H_0 if the F statistic is greater than the upper and lower bound values, if not accept.

3.4.4 Autocorrelation

A phenomenon known as autocorrelation takes place when the residuals that are created are connected to one another (Gujarati, 2004). In the event that such a phenomenon occurred, the CLRM assumptions would be violated, which would result in the results that were predicted being incorrect.

In order to answer the question of whether or not there is autocorrelation, the Bruesch-Godfrey will be used. Listed below is the theory that will be put to the test.

H_0: there is autocorrelation

H_1: there is no autocorrelation

Decision rule: Reject H_0 if the p-value of Chi-Square is greater than 0.05, if not do not reject.

3.4.5 Heteroscedasticity test

To determine whether or not the residuals generated by a regression model are equal, a test for heteroscedasticity is conducted (Gujarati, 2004).

H_0: the generated residuals are equal

H_1: the generated residuals are unequal

Decision rule: Reject H_0 if the p-value of Chi-Square is greater than 0.05, if not do not reject.

3.4.6 ARCH test

In ARDL regression, the ARCH (Autoregressive Conditional heteroscedasticity) is used to help detect and account for non-Constance variance in the generated residuals.

H_0: There is no ARCH in the generated residuals

H_1: there is ARCH in the generated residuals

Decision rule: Reject the null hypothesis if the P Value is less than 0.05 level of significance.

3.4.7 Normality Test

One of the regression assumptions in ARDL regression is that the generated residuals should have a normal distribution, so testing for normality is essential (Gujarati, 2004).The regression's results might not be accurate if the residuals are not normally distributed.

H_0: There is no normality

H_1: there is normality

Decision rule: Reject the null hypothesis if the P Value is less than 0.05 level of significance.

3.4.8 CUSUM test

In ARDL regression, the cumulative sum of squares is utilized for checking structural changes in the regression model (Gujarati, 2004). These are adjustments to the regressor-regresant relationship.

H_0: There are no structural changes

H_1: There are structural changes

Decision rule: Reject the null hypothesis if the cumulative sum of squares falls outside of the 5% critical region.

3.4.9 CUSUM of squares.

The CUSUM of squares test is like the CUSUM test, but it uses the sum of squared residuals instead of the cumulative sum of squares. The purpose of the test is to check for structural changes in the regression model.

H_0: There are no structural changes

H_1: there are structural changes

Decision rule: Reject the null hypothesis if the cumulative sum of squares falls outside of the 5% critical region.

3.4.10 Model Specification Test

The Ramsey RESET (regression specification error test) is used to check for misspecification of the model (Gujarati, 2004).

H_0: The model is correctly specified

H_1: The model is incorrectly specified

Decision rule: Reject the null hypothesis if the p-value is less than 0.05 level of significance.

3.5 Chapter Summary

This chapter has presented the justification of the variables used in the study, as well as the diagnostic tests performed to ensure the validity and reliability of the econometric model. The variables were selected based on the theoretical and empirical literature, and their sources and definitions were provided. The diagnostic tests comprised the unit root test, the optimal lag length test, the cointegration test, the autocorrelation test, the heteroscedasticity test, the ARCH test, the normality test, the CUSUM test and the model specification test. The findings of these tests showed that the model was well-specified, stable, and free from major econometric problems. In the following chapter, the empirical results of the model estimation will be presented and analyzed.

CHAPTER FOUR

RESULTS PRESENTATION, ANALYSIS AND DISCUSSION

4.0 Introduction

This chapter presents and analyses the results of the study on the impact of climate change on agricultural productivity in Zimbabwe. The chapter presents the results of the autoregressive distributed lag (ARDL) diagnostic tests, which assess the validity and reliability of the model. The chapter also discusses the inference of the findings for policy and practice.

Table 1 Descriptive statistics

	AGRIC	TEMP	PRECI	CORRU	EFFECTIVE	GCE
Mean	13.52609	21.73683	657.8537	-0.449289	-0.617486	12.80976
Median	13.73791	21.73000	657.0000	-1.127275	-0.757243	13.00000
Maximum	21.19769	22.79000	692.0000	1.528792	0.529872	31.00000
Minimum	6.751570	20.50000	657.0000	-1.425627	-1.553131	1.000000
Std. Dev.	4.159720	0.456494	5.466082	1.004906	0.688818	5.135650
Skewness	-0.041930	-0.331648	6.166441	0.607953	0.185380	0.629901
Kurtosis	1.887542	3.217469	39.02500	1.844082	1.528876	6.079296
Jarque-Bera	2.126183	0.832394	2476.914	4.808229	3.932019	18.90982
Probability	0.345386	0.659550	0.000000	0.090345	0.140014	0.000078
Sum	554.5695	891.2100	26972.00	-18.42085	-25.31693	525.2000
Sum Sq. Dev.	692.1307	8.335488	1195.122	40.39347	18.97883	1054.996
Observations	41	41	41	41	41	41

The agriculture value added as a percentage of GDP is represented by the variable AGRIC. The mean value of 13.52609 indicates that, on average, agriculture contributes approximately 13.53%

to Zimbabwe's GDP. The median value of 13.73791 suggests that the distribution of agriculture's contribution to GDP is relatively symmetrical. The maximum observation of 21.19769 indicates that there have been instances where agriculture's value added reached as high as 21.20% of GDP. Conversely, the minimum value of 6.751570 indicates that there have been periods where agriculture's contribution has been as low as 6.75% of GDP. The standard deviation of 4.159720 indicates a moderate amount of variability in agriculture's value added over the study period. The negative skewness of -0.041930 suggests a slightly left-skewed distribution, indicating that there may have been more instances of higher values of agriculture's value added. The positive kurtosis of 1.887542 indicates a leptokurtic distribution, suggesting that the data may have exhibited heavier tails and a more peaked distribution compared to the normal distribution. The Jarque-Bera test statistic of 2.126183 with a probability of 0.345386 suggests that the distribution of agriculture's value added may not significantly deviate from a normal distribution. The sum of 554.5695 indicates the total value added by agriculture over the study period, and the Sum Sq. Dev. of 692.1307 represents the sum of squared deviations from the mean

.The variable TEMP represents annual surface temperature. The mean temperature of 21.73683 indicates the average annual temperature in Zimbabwe. The median value of 21.73683 suggests a symmetrical distribution of temperature data. The maximum temperature of 22.79000 indicates the highest recorded annual temperature, while the minimum temperature of 20.50000 represents the lowest recorded annual temperature. The standard deviation of 0.456494 denotes a relatively low variability in annual temperature. The negative skewness of -0.331648 suggests a slightly left-skewed distribution, indicating more instances of higher temperatures. The positive kurtosis of 3.217469 indicates a leptokurtic distribution, suggesting heavier tails and a more peaked distribution compared to the normal distribution. The Jarque-Bera test statistic of 0.832394 with a probability of 0.659550 suggests that the distribution of annual temperature data may not significantly deviate from a normal distribution. The sum of 891.2100 represents the total annual temperature recorded over the study period.

The variable PRECI represents annual precipitation. The mean precipitation of 657.8537 represents the average annual rainfall in Zimbabwe. The median value of 657.0000 indicates a relatively symmetrical distribution of precipitation data. The maximum precipitation value of 692 represents the highest recorded annual rainfall, while the minimum value of 657 represents the lowest recorded annual rainfall. The standard deviation of 5.466082 indicates a moderate amount of variability in annual precipitation. The positive skewness of 6.166441 suggests a highly right-skewed distribution, indicating more instances of lower precipitation values and occasional extreme rainfall events. The positive kurtosis of 39.02500 denotes a highly leptokurtic distribution, suggesting heavier tails and a more peaked distribution compared to the normal distribution. The Jarque-Bera test statistic of 2476.914 with a probability of 0.00000 indicates a significant deviation from a normal distribution for the precipitation data. The sum of 26972.00 represents the total annual precipitation recorded over the study period and the Sum Sq. Dev. of 1195.122 represents the sum of squared deviations from the mean.

The variable CORR represents the control of corruption. The mean value of -0.449289 denotes a relatively low level of corruption control in Zimbabwe. The median value of -1.127275 suggests a skewed distribution with more instances of lower corruption control scores. The maximum value of 1.528792 represents a relatively higher level of corruption control, while the minimum value of -1.425627 indicates a lower level of corruption control. The standard deviation of 1.004906 indicates a moderate variability in corruption control scores. The positive skewness of 0.607953 suggests a slightly right-skewed distribution, indicating more instances of lower corruption control scores. The positive kurtosis of 1.844082 indicates a positive kurtosis, suggesting heavier tails and a more peaked distribution compared to the normal distribution. The Jarque-Bera test statistic of 4.808229 with a probability of 0.090345 suggests a slight deviation from a normal distribution for the corruption control data. The sum of -18.42085 represents the cumulative corruption control scores over the study period, and the Sum Sq. Dev. of 40.39347 represents the sum of squared deviations from the mean.

The variable EFF represents government effectiveness. The mean value of -0.617486 indicates a relatively low level of government effectiveness in Zimbabwe. The median value of -0.757243 suggests a skewed distribution with more instances of lower government effectiveness scores. The maximum value of 0.529872 represents a relatively higher level of government effectiveness, while the minimum value of -1.553131 indicates a lower level of government effectiveness. The standard deviation of 0.688818 indicates a moderate variability in government effectiveness scores. The positive skewness of 0.185380 suggests a slightly right-skewed distribution, indicating more instances of lower government effectiveness scores. The positive kurtosis of 1.528876 indicates a leptokurtic distribution, suggesting heavier tails and a more peaked distribution compared to the normal distribution. The Jarque-Bera test statistic of -25.31693 with a probability of 0.140014 suggests a slight deviation from a normal distribution for the government effectiveness data. The sum of -18.42085 represents the cumulative government effectiveness scores over the study period, and the Sum Sq. Dev. of 40.39347 represents the sum of squared deviations from the mean.

The variable GCE represents government capital expenditure. The mean value of 12.80976 indicates the average level of government capital expenditure in Zimbabwe. The median value of 13.00000 suggests a relatively symmetrical distribution of government capital expenditure data. The maximum value of 31.000000 represents a relatively high level of government capital expenditure, while the minimum value of 1.000000 denote a lower level of government capital expenditure. The standard deviation of 5.135650 indicates a moderate variability in government capital expenditure. The positive skewness of 0.629901 suggests a slightly right-skewed distribution, indicating more instances of lower government capital expenditure values. The positive kurtosis of 6.079296 indicates a leptokurtic distribution, suggesting heavier tails and a more peaked distribution compared to the normal distribution. The Jarque-Bera test statistic of 18.90982 with a probability of 0.000078 indicates a significant deviation from a normal distribution for the government capital expenditure data. The sum of 525.2000 represents the total government capital expenditure over the study period and the Sum Sq. Dev. of 1054.996 represents the sum of squared deviations from the mean.

4.1 Diagnostic tests

One of the essential steps in conducting an autoregressive distributed lag (ARDL) model was to perform diagnostic tests on the adapted regression equation. These tests involve determining whether the coefficients are stable, normal, and serially correlated. The purpose of these tests was to ensure that the ARDL model was well-specified and did not suffer from any econometric problems that could invalidate the inference and interpretation of the results. By carrying out these diagnostic tests, it reduced the chances of generating spurious regression results, which are misleading and unreliable. Therefore, it is important to verify that the ARDL model produces reliable, accurate, and consistent estimates of the short- and long-period impacts among the variables of interest while also satisfying the requirements of the traditional linear regression model.

4.2 Unit root test

Before running regression, the study variables had to be tested for unit root. The results that were obtained are listed below.

Table 2: Unit root results

Variable	ADF Stat	Critical Value		Intercept	Trend	P-Value	Integration Order
AGRI	-7.595465***	1%	-2.622585	NO	NO	0.0000	I (1)
		5%	-1.949097				
		10%	-1.611824				
TEMP	-5.492611***	1%	-4.192337	YES	YES	0.0003	I (0)
		5%	-3.520787				
		10%	-3.191277				
PREC	-6.240490***	1%	-4.205004	YES	YES	0.0000	I (0)
		5%	-3.526609				
		10%	-3.194611				
GCE	-4.121773***	1%	-4.198503	YES	YES	0.0121	I (0)
		5%	-3.523623				
		10%	-3.192902				
CORR	-2.276895***	1%	-2.622585	NO	NO	0.0237	1(1)
		5%	-1.949097				
		10%	-1.611824				
EFF	-4.453134***	1%	-2.622585	NO	NO	0.0000	I(1)
		5%	-1.949097				
		10%	-1.611824				

**, ** and ***means significant at 10%, 5%and 1% respectively.*

The unit root results above shows that the research variables are not stationery at the same level. In the autoregressive distributed lag (ARDL) model, it is assumed that the variables are integrated of order I (0) or I (1), i.e., zero or one. This means that the variables are either stationary at level or after first differencing. However, having variables that are I (1) does not imply that there is a long-term relationship among them. To test for the existence of a cointegration relationship, there is a need to apply a cointegration test. There are different methods of cointegration testing, such as the Johansen test, the Engle-Granger test, and the bound testing approach. In this study, the researcher chooses the bound testing approach, which relies on the F-test of the significance of the lagged levels of the variables in an error correction model (ECM). The advantage of this approach is that it can be applied regardless of whether the variables are I (0) or I (1), or a mixture of both. The bound testing approach involves estimating an unrestricted ECM that includes both the lagged levels and the lagged differences of the variables.

4.3 Cointegration results

The research sought to establish long-run association among the study variables. Using the bounding testing approach, the results are presented below.

Table 3: Cointegration results

Test Statistic	**Value**	**Signif**	**I(0)**	**I(1)**
		Asymptotic: n=1000		
F Statistic	6.966569	10%	2.26	3.35
K	5	5%	2.62	3.79
		2.5%	2.96	4.18
		1%	3.41	4.68

The results in table 3 above exhibit a long run relationship among the study variables. A value of 6.966569 for the F statistic means that it is greater than the lower bound values which are 2.26, 2.62, 2.96, and 3. 41 at 10%, 5%, 2.5% and 1% respectively. The F statistic value is also greater than the upper bound values at 3.35, 3.79, 4.18, and 4.68 at 10%, 5%, 2.5% and 1% respectively. It can therefore be concluded that the study variables are co-integrated thus eliminating the chances of generating spurious regression results

4.4 Optimal Lag Length Results

Before estimating the long and short run impact of climate change on agricultural productivity, the study sought to establish first the optimal lag length to eliminate the chances of generating superficial good results. Below are the obtained results.

Table 4: Optimal Lag results

Lag	**Log L**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
3	-209.8862	313.6996*	0.012142*	12.59431*	14.36764*	13.23549*

The optimal lag results in table 4 above suggest that the optimum lag is three, which means that including three lagged values of the variables in the model provides the best balance between capturing the short-term dynamics and avoiding excessive complexity. This is important because including too few lags may result in a model that fails to capture important short-term effects while including too many lags can lead to overfitting and loss of statistical efficiency.

4.5 Autocorrelation Results

In econometric analysis, detecting and addressing autocorrelation is important as it can affect the reliability of the estimated coefficients and lead to biased inference. Below are the obtained results for autocorrelation.

Table 5: Autocorrelation results

F-Statistic	0.432318	Prob. F(3,14)	0.7332
Obs*R-squared	3.221836	Prob. Chi-Square(3)	0.3587

The results in table 5 above show that the F statistic value is 0.432318, and its associated probability value (often referred to as the p-value) is 0.7332. Interpreting the F statistic and its p-value involves comparing the calculated F statistic with a critical value. If the calculated F statistic is greater than the critical value, it suggests evidence of autocorrelation. However, in this case, the calculated F statistic is 0.432318, which is smaller than the critical value. This indicates that there is insufficient evidence to conclude the presence of autocorrelation in the data. Additionally, the associated p-value of 0.7332 further supports this interpretation. The p-value represents the probability of observing a test statistic as extreme as the calculated F statistic, assuming that there is no autocorrelation in the data. In this case, the high p-value of 0.7332 indicates that the observed F statistic is not statistically significant and falls within the range of values expected under the assumption of no autocorrelation. In summary, based on the given F statistic and its associated p-value, there is no significant evidence of autocorrelation in the data.

4.6 Heteroscedasticity Results

Heteroscedasticity was done to ensure the efficiency of parameter estimates, correct standard errors, and valid hypothesis tests. By addressing heteroscedasticity, the researcher sought to improve the reliability and accuracy of the ARDL regression analysis. Below are the obtained results.

Table 6 : Heteroscedasticity results

F-Statistic	1.230344	Prob. F(3,14)	0.3358
Obs*R-squared	22.47372	Prob. Chi-Square(3)	0.3154

The results in table 6 above indicate that the calculated F statistic is 1.230344 and the associated probability value (p-value) is 0.3358. To interpret these results, we compare the calculated F statistic with a critical value or a significance level. The critical value is determined based on the desired level of significance, and in this case it was determined at 5% (or 0.05). If the calculated F statistic is greater than the critical value, it suggests evidence of heteroscedasticity. However, in this case, the calculated F statistic of 1.230344 is smaller than the critical value. This indicates that there is insufficient evidence to conclude the presence of heteroscedasticity in the data. Furthermore, the associated p-value of 0.3358 provides additional information. The p-value represents the probability of observing a test statistic as extreme as the calculated F statistic, assuming that there is no heteroscedasticity in the data. In this case, the relatively high p-value of 0.3358 indicates that the observed F statistic is not statistically significant and falls within the range of values expected under the assumption of no heteroscedasticity. Therefore, based on the given F statistic and its associated p-value, we fail to reject the null hypothesis of no heteroscedasticity. This suggests that there is no significant evidence to support the presence of heteroscedasticity in the regression model thus eliminating the chances of generating spurious ARDL results.

4.7 ARCH Results

While the Breusch-Godfrey Serial Correlation LM and ARCH tests are both measures of heteroscedasticity, this researcher had to test both of them for confirmatory purposes. Below are the generated results for ARCH test.

Table 7: ARCH results

F-Statistic	0.448280	Prob. F(3,31)	0.7203
Obs*R-squared	1.455238	Prob. Chi-Square(3)	0.6926

The ARCH test results above indicate that the calculated F statistic is 0.448280, and the associated probability value (p-value) is 0.7203. To interpret these results, we compare the calculated F statistic with a critical value or a significance level, in this case it was set at 5% (or 0.05). If the calculated F statistic is greater than the critical value, it suggests evidence of conditional heteroscedasticity. However, in this case, the calculated F statistic of 0.448280 is smaller than the critical value. This indicates that there is insufficient evidence to conclude the presence of conditional heteroscedasticity in the data. Furthermore, the associated p-value of 0.7203 provides additional information. The p-value represents the probability of observing a test statistic as extreme as the calculated F statistic, assuming that there is no conditional heteroscedasticity in the data. In this case, the relatively high p-value of 0.7203 indicates that the observed F statistic is not statistically significant and falls within the range of values expected under the assumption of no conditional heteroscedasticity. Therefore, based on the given F statistic and its associated p-value, we fail to reject the null hypothesis of no conditional heteroscedasticity. This suggests that there is no significant evidence to support the presence of time-varying volatility in the model.

4.8 Normality Results

The Jarque-Bera test statistical test was used to assess the normality assumption of the residuals in this study. It examines whether the distribution of the residuals follows a normal distribution, which is an important assumption for many statistical inference procedures. Below are the generated results.

Table 8 : Normality results

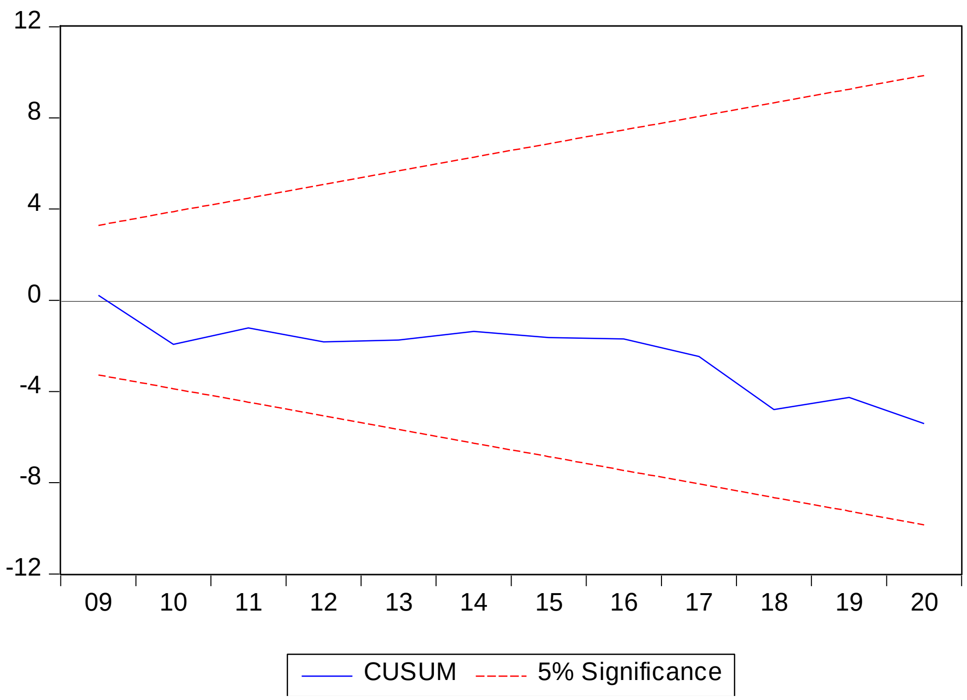
Jarque-Bera	0.942433
Probability	0.624243

The Jarque-Bera test results above indicate that the calculated Jarque-Bera statistic is 0.942433, and the associated probability value (p-value) is 0.624243. To interpret these results, we compare the calculated Jarque-Bera statistic with a critical value or a significance level, usually set at 5% (or 0.05). If the calculated Jarque-Bera statistic exceeds the critical value, it suggests evidence of non-normality in the residuals. However, in this case, the calculated Jarque-Bera statistic of 0.942433 is smaller than the critical value. This indicates that there is insufficient evidence to conclude that the residuals deviate significantly from a normal distribution. Furthermore, the associated p-value of 0.624243 provides additional information. The p-value represents the probability of observing a test statistic as extreme as the calculated Jarque-Bera statistic, assuming that the residuals follow a normal distribution. In this case, the relatively high p-value of 0.624243 indicates that the observed Jarque-Bera statistic is not statistically significant and falls within the range of values expected under the assumption of normality. Therefore, based on the given Jarque-Bera statistic and its associated p-value, we fail to reject the null hypothesis of normality. This suggests that there is no significant evidence to suggest that the residuals deviate from a normal distribution.

4.9 CUSUM Results

The CUSUM (Cumulative Sum) test is a statistical test used to assess the stability of a regression model over time. It examines whether there are significant changes in the coefficients of the model over the observed period. Below are the obtained results.

Table 9 : CUSUM results

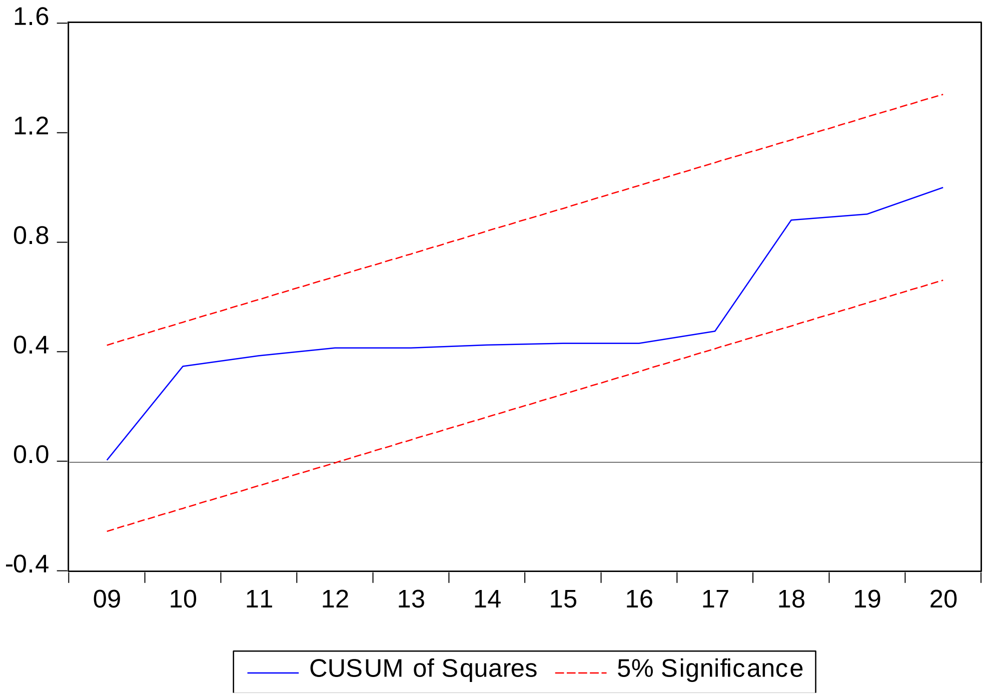


The CUSUM test results above indicate that the test statistic fell within the 5% critical range over the entire observed period. This implies that there is no evidence of significant structural change or instability in the regression model. When the CUSUM test statistic falls within the critical range, it suggests that the coefficients of the model remain stable and that there are no significant shifts or breaks in the relationship between the independent variables and the dependent variable over time. This result provides confidence in the stability of the regression model and supports the assumption that the estimated coefficients can be relied upon for inference and prediction throughout the observed period.

4.10 CUSUM of Squares Results

The CUSUM of squares test was done to assess the stability of the variance or error structure in the adapted ARDL regression model over time. It examined whether there were significant changes in the variance of the residuals over the observed period. Below are the obtained results.

Table 10: CUSUM of squares results



The CUSUM of squares test results above indicate that the test statistic fell within the 5% critical range over the entire observed period. This suggests that there is no evidence of significant changes in the variance or error structure of the model over time. When the CUSUM of squares test statistic falls within the critical range, it indicates that the variance of the residuals remains stable and that there are no significant shifts or breaks in the error structure of the regression model over the observed period. This result provides confidence in the stability of the error term and supports the assumption that the variance of the residuals should be constant over time, which is an important assumption for many statistical inference procedures.

4.11 Model Specification results.

The functional form of the study's regression model was assessed for adequacy using the Ramsey RESET (Regression Equation Specification Error Test). It sought to examine whether there are omitted variables or functional misspecifications that may impact the model's performance. Below are the obtained results.

Table 11: Model Specification results

	Value	DF	Probability
F-statistic	1.971654	(3, 14)	0.1646

The Ramsey RESET test results above indicate that the calculated F statistic is 1.971654, and the associated probability value (p-value) is 0.1646. To interpret these results, we compare the calculated F statistic with a critical value or a significance level, typically set at 5% (or 0.05). If the calculated F statistic exceeds the critical value, it suggests evidence of model misspecification or the need to include additional variables. However, in this case, the calculated F statistic of 1.971654 is smaller than the critical value. This indicates that there is insufficient evidence to conclude that the model has significant functional misspecification or omitted variables. Furthermore, the associated p-value of 0.1646 provides additional information. The p-value represents the probability of observing a test statistic as extreme as the calculated F statistic, assuming that the model is correctly specified. In this case, the relatively high p-value of 0.1646 indicates that the observed F statistic is not statistically significant and falls within the range of values expected under the assumption of a correctly specified model. Therefore, based on the given F statistic and its associated p-value, we fail to reject the null hypothesis of a correctly specified model. This suggests that there is no significant evidence to support the presence of functional misspecification or omitted variables in the regression model.

4. 12 estimated short run results

Table 12 : Estimated short-run results

C	802.8296	290.6781	2.761920	0.0133
AGRIC(-1)*	-0.952182	0.199770	-4.766399	0.0002
TEMP(-1)	-1.029004	3.739734	-0.275154	0.7865
PRECI(-1)	-1.155004	0.359831	-3.209851	0.0051
CORRU(-1)	-9.530392	2.616055	-3.643040	0.0020
EFFECTIVE(-1)	15.51671	4.314053	3.596782	0.0022

GCE(-1)	-0.398648	0.150810	-2.643384	0.0171
D(TEMP)	-4.432420	2.060698	-2.150932	0.0462
D(TEMP(-1))	-2.532153	1.862437	-1.359591	0.1917
D(TEMP(-2))	-2.667842	1.309720	-2.036956	0.0575
D(PRECI)	-0.115857	0.129993	-0.891252	0.3852
D(PRECI(-1))	0.489789	0.154369	3.172844	0.0056
D(CORRU)	29.66306	10.99385	2.698150	0.0152
D(CORRU(-1))	5.075882	13.60670	0.373043	0.7137
D(CORRU(-2))	-32.51181	15.14734	-2.146370	0.0466
D(EFFECTIVE)	-10.56486	7.876236	-1.341358	0.1975
D(EFFECTIVE(-1))	-19.94380	7.932460	-2.514201	0.0223
D(EFFECTIVE(-2))	-29.48558	7.301232	-4.038439	0.0009
D(GCE)	-0.125912	0.102986	-1.222611	0.2382
D(GCE(-1))	0.314342	0.144973	2.168281	0.0446
D(GCE(-2))	0.266025	0.128351	2.072634	0.0537

4.13 Estimated long Run Results

Table 13: Estimated long-run results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TEMP	-1.080680	3.852131	-0.280541	0.7824
PRECI	-1.213008	0.291331	-4.163669	0.0007
CORRU	-10.00901	3.261653	-3.068691	0.0070
EFFECTIVE	16.29595	5.888410	2.767463	0.0132
GCE	-0.418668	0.148896	-2.811816	0.0120

4.14Average Annual Temperature (TEMP)

The ARDL results indicate the impact of average annual temperature on agriculture value added in Zimbabwe, covering the period 1980-2022. In the short run, the coefficient for average annual temperature is -4.432420. This coefficient suggests that, on average, a one-unit increase in average annual temperature is associated with a decrease of 4.432420 units in agriculture value added in Zimbabwe, holding other variables constant. The T-statistic of -2.150932 denote that the estimated coefficient is statistically significant at a 5% significance level, with a probability value of 0.0462. In the short run, higher average annual temperatures might negatively impact agricultural productivity due to heat stress, increased water demand, or changes in pest and disease patterns. These factors can lead to reduced crop yields and livestock productivity, resulting in lower agricultural value added. This finding supports evidence from reviewed literature where Bai et al found a negative relationship between average annual temperature and agricultural productivity in China.

In the long-run, the coefficient for average annual temperature is -1.080680. This coefficient suggests that, on average, a one-unit increase in average annual temperature is associated with a decrease of 1.080680 units in agriculture value added in Zimbabwe in the long-term. However, the T-statistic of -0.280541 indicates that the estimated coefficient is not statistically significant at conventional levels, with a probability value of 0.7824. In the long run, other factors may come into play, such as adaptive strategies, technological advancements, and changes in agricultural practices. These factors could mitigate the adverse effects of temperature on agriculture value added, leading to the non-significant relationship observed in the long term.

4.15 Average Annual Precipitation (PREC)

The ARDL results indicate the impact of average annual precipitation on agriculture value added in Zimbabwe over the period 1980-2022. The short-run coefficient for average annual precipitation is 0.489789, with a T-statistic value of 3.172844 and a probability value of 0.0056. In the long run, the coefficient for average annual precipitation is -1.213008, with a T-statistic value of -4.163669 and a probability value of 0.0007.

Holding other variables constant, the positive short-term coefficient of 0.489789 indicates that, on average, an increase of one unit in average annual precipitation is linked to an increase of 0.489789 units in Zimbabwe's value added from agriculture. The statistically significant T-statistic (with a probability value of 0.0056) indicates that this relationship is unlikely to have occurred by chance. The negative coefficient of -1.213008, in the long run, suggests that, on average, a one-unit increase in average annual precipitation is associated with a decrease of 1.213008 units in agricultural value added in Zimbabwe in the long term. The statistically significant T-statistic (with a probability value of 0.0007) indicates that this relationship is unlikely to have occurred by chance. This goes against empirical evidence where Bai (2022) et al found a positive relationship between average annual precipitation and agricultural productivity in China.

In the context of Zimbabwe, several factors could explain these such as rainfall variability: Zimbabwe experiences rainfall variability, with periods of both droughts and excessive rainfall. In the short run, increased precipitation can have positive impacts on agriculture, as it replenishes soil moisture and enhances crop growth. However, in the long run, excessive or poorly distributed precipitation can lead to waterlogging, soil erosion, and increased risks of pests and diseases. These factors can contribute to decreased agricultural productivity and, subsequently, lower agriculture value added.

Additionally agricultural practices and infrastructure are other factors that can explain such results. The impact of precipitation on agriculture value added can also be influenced by agricultural practices and infrastructure. Proper water management systems, such as irrigation facilities and drainage systems, can help mitigate the negative effects of excessive rainfall and enhance productivity. However, if such infrastructure is lacking or poorly maintained, the negative impacts of excessive precipitation on agriculture value added may be more pronounced.

4.16 Control of corruption

. The ARDL results indicate the impact of control of corruption on agriculture value added in Zimbabwe over the period 1980-2022. The short-run coefficient for control of corruption is -9.530392, with a T-statistic value of -3.643040 and a probability value of 0.0020. In the long run, the coefficient for control of corruption is -10.00901, with a T-statistic value of -3.068691 and a probability value of 0.0070.

The negative coefficient of -9.530392 in the short run implies that, on average, a one-unit decrease in control of corruption is associated with a decrease of 9.530392 units in agriculture value added in Zimbabwe, holding other variables constant. The statistically significant T-statistic (with a probability value of 0.0020) indicates that this relationship is unlikely to have occurred by chance. The negative coefficient of -10.00901 in the long run suggests that, on average, a one-unit decrease in control of corruption is associated with a decrease of 10.00901 units in agriculture value added in Zimbabwe in the long term. The statistically significant T-statistic (with a probability value of 0.0070) indicates that this relationship is unlikely to have occurred by chance. These results go against the reviewed literature where Peicoto et al (2020) found a positive impact of control of corruption on agricultural productivity.

In the context of Zimbabwe, several factors could explain these results and one of them is corruption and mismanagement of resources. Corruption can undermine the efficiency and effectiveness of agricultural policies, programs, and institutions. It can lead to misallocation of resources, lack of transparency, and weak enforcement of regulations, which can negatively impact agriculture value added. Limited control of corruption may result in reduced investment in the agricultural sector, hindering its growth and productivity. Additionally, a high level of corruption can erode investor confidence in the agricultural sector. When corruption is prevalent, businesses and investors may be reluctant to engage in agricultural activities, resulting in reduced agricultural value added. This can hinder the development of the sector, limit technology transfer, and impede innovation and productivity improvements.

4.17 Government Effectiveness

The ARDL results indicate the impact of government effectiveness on agriculture value added in Zimbabwe over the period 1980-2022. The short-run coefficient for government effectiveness is -29.48558, with a T-statistic value of -4.038439 and a probability value of 0.0009. In the long run, the coefficient for government effectiveness is 16.29595, with a T-statistic value of 2.767463 and a probability value of 0.0132. The negative coefficient of -29.48558 in the short run implies that, on average, a one-unit decrease in government effectiveness is associated with a decrease of 29.48558 units in agriculture value added in Zimbabwe, holding other variables constant. The statistically significant T-statistic with a probability value of 0.0009 indicates that this relationship is unlikely to have occurred by chance. These results support reviewed literature where Lencucha et al (2022) found a positive relationship between government expenditure and agricultural productivity.

The positive coefficient of 16.29595, in the long term, suggests that, on average, a one unit increase in government effectiveness is associated with an increase of 16.29595 units in agriculture value added in Zimbabwe in the long term. The statistically significant T-statistic with a probability value of 0.0132 indicates that this relationship is unlikely to have occurred by chance. These results could be explained by several factors such as good governance and policy effectiveness: Government effectiveness can play a crucial role in promoting agricultural development. In the short run, a decrease in government effectiveness may indicate challenges in implementing effective policies, providing necessary support to farmers, and ensuring efficient resource allocation. These factors can negatively impact agriculture value added. In the long run, an increase in government effectiveness can indicate improved governance, policy formulation, and resource allocation. Effective governance can lead to better planning, financing in infrastructure, research and development, and targeted support to the agricultural sector. These factors can contribute to increased productivity and growth in agriculture value added.

4.18 Government Capital Expenditure (GCE)

The ARDL results indicate the impact of Government Capital Expenditure on agriculture value added in Zimbabwe over the period 1980-2022. The short-run coefficient for Government Capital Expenditure is -0.398648, with a T-statistic value of -2.643384 and a probability value of 0.0171. In the long run, the coefficient for Government Capital Expenditure is -0.418668, with a T-statistic value of -2.811816 and a probability value of 0.0120.

The negative coefficient of -0.398648 in the short run implies that, on average, a one-unit decrease in Government Capital Expenditure is associated with a decrease of 0.398648 units in agriculture value added in Zimbabwe, holding other variables constant. The statistically significant T-statistic with a probability value of 0.0171 indicates that this relationship is unlikely to have occurred by chance. The negative coefficient of -0.418668, in the long run, suggests that, on average, a one-unit decrease in Government Capital Expenditure is associated with a decrease of 0.418668 units in agriculture value added in Zimbabwe in the long term. The statistically significant T-statistic with a probability value of 0.0120 indicates that this relationship is unlikely to have occurred by chance. The unexpected negative sign of government capital expenditure implies that the findings contradict the reviewed literature. According to Alabi and Abu (2020), government capital spending and agricultural productivity are positively correlated.

In the context of Zimbabwe, several factors could explain these results can be explained by factors such as poor investment in agriculture. Government Capital Expenditure represents the investment made by the government in the agricultural sector. A decrease in Government Capital Expenditure suggests reduced investment in agriculture, such as infrastructure development, research and development, and capacity building. These investment activities are crucial for promoting agricultural productivity and value-added. Therefore, a decrease in Government Capital Expenditure can have a negative impact on agriculture value added. Also the decrease in Government Capital Expenditure may be influenced by economic constraints faced by the government. Limited financial resources, budgetary constraints, or competing priorities may lead to reduced capital expenditure in the agricultural sector. As a result, agricultural development may be hindered, leading to a decrease in agriculture value added.

4.14 Chapter Summary

This chapter presented results on various diagnostic tests, including unit root, cointegration, optimal lag length, autocorrelation, heteroscedasticity, normality test, model specification test, CUSUM test results, and CUSUM of squares results. The results established that average annual temperature poses a negative impact on agricultural productivity in both the short and long run. However, the variable was not significant in the long-term. The variable control of corruption was significant in explaining its short and long-term negative impact on agricultural productivity. The same results were established for government capital expenditure. Precipitation was found to have a positive impact in the short run and a negative impact in the long run. Government effectiveness was found to have a negative impact in the short-term and a positive in the long-term. The findings, conclusion, and recommendations will be discussed in the following chapter.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary

This research aimed to examine the short and long-run effects of climate change on agricultural productivity from 1980 to 2022, to determine possible recommendations, for policymakers and farmers to improve climate change resilience sustainable agricultural practices, and food security in Zimbabwe and to determine how farmers can implement new practices or technological advancement to change weather patterns in the short run, which will bring agricultural production to its equilibrium over the long run. To achieve these objectives, the study utilized three major theories: The New Institutional Economics Theory, the Malthusian Theory, and The Global Warming Theory. The study adopted an Autoregressive Distributed Lag (ARDL) model, which was previously used by Ogundariand and Onyeaghala (2021) in analyzing the effects of climate change on African agricultural total factor productivity. The dependent variable in the regression model was agriculture value added as a percentage of GDP. The explanatory variables included annual surface temperature, annual precipitation, government capital expenditure, control of corruption, and government effectiveness. The data for the study was obtained from the World Bank and Transparency International. The study conducted various diagnostic tests specific to the ARDL model. These tests included the unit root test, optimal lag length determination, cointegration test, autocorrelation test, heteroscedasticity test, ARCH test, normality test, CUSUM test, CUSUM of squares test, and model specification test.

The regression results revealed the following findings: In the short run, temperature, precipitation, government effectiveness, and control of corruption had adverse effects on agricultural productivity, while government capital expenditure had a positive impact. In the long-run, precipitation, control of corruption, and government capital expenditure continued to have a adverse impact on agricultural productivity, although government effectiveness had a positive impact. Overall, the research provides valuable insights into the relationship between climate change and agricultural production in Zimbabwe and it answers its research objectives. It highlights the short and long-run impacts of climate variables and government-related factors on agricultural productivity.

5.2 Conclusion

In conclusion, the study examined the impact of climate change on agricultural productivity in Zimbabwe from 1980 to 2022 and aimed to determine the short and long-run effects of climate variables on agricultural productivity. By utilizing the New Institutional Economics Theory, the Malthusian Theory, and the Global Warming Theory, the research employed an ARDL model to analyze the data. The results indicated that temperature, precipitation, government effectiveness, and control of corruption had a negative impact on agricultural productivity in the short-run, while government capital expenditure had a positive impact. In the long-run, precipitation, control of corruption, and government capital expenditure continued to have a negative impact, while government effectiveness had a positive impact. These findings underscore the importance of addressing climate change and implementing effective policies to promote sustainable agricultural practices in Zimbabwe in order to mitigate the negative effects on agricultural productivity.

5.3 Recommendations

Based on the findings of the study titled "The Impact of Climate on Agricultural Productivity in Zimbabwe," which revealed the impacts of various variables on agricultural productivity, the following variable-specific policy recommendations are proposed:

Given the unfavourable impact of temperature on agricultural productivity in the short period, the Ministry of Agriculture, in collaboration with research institutions, should develop and disseminate heat-tolerant crop varieties suitable for Zimbabwe's climate. Additionally, farmers should be educated on proper crop management practices, such as adjusting planting schedules, technology advancements and implementing shading techniques, to mitigate the adverse effects of high temperatures on crop yields.

The government should invest in sustainable water management systems in collaboration with the Ministry of Agriculture and water management agencies, given the detrimental effects of precipitation on agricultural output in the short-period and long-period. This includes improving irrigation infrastructure, promoting water-efficient agricultural practices, improving the dams for irrigation purposes and implementing rainwater harvesting techniques to ensure adequate water supply for agricultural activities during periods of low precipitation.

As government efficacy was found to have a positive impact on agricultural productivity, it is crucial for the government to prioritize good governance and efficient service delivery in the agricultural sector to improve food security. The Ministry of Agriculture, in collaboration with the Ministry of Public Service and Administration, should focus on streamlining administrative processes, reducing bureaucratic hurdles, reducing corruption and ensuring timely and effective delivery of agricultural services to farmers.

Given the negative impact of corruption on agricultural productivity, the government, in coordination with anti-corruption agencies, should strengthen measures to curb corruption in the agricultural sector. This includes enforcing anti-corruption laws, increasing transparency in resource allocation, and implementing strict accountability mechanisms to ensure that agricultural resources and subsidies reach the intended beneficiaries to increase food security in the country.

Considering the positive impact of government capital expenditure on agricultural productivity in both the short and long-run, the government should allocate adequate funds for agricultural infrastructure development and investment. The Ministry of Finance, in collaboration with the Ministry of Agriculture, should prioritize budgetary allocations for improving rural roads, irrigation systems, storage facilities, and other necessary agricultural infrastructure to enhance productivity and facilitate market access for farmers.

These variable-specific policy recommendations call for the involvement and collaboration of key authorities, including the Ministry of Agriculture, Ministry of Finance, Ministry of Public Service and Administration, research institutions, water management authorities, anti-corruption agencies, and agricultural extension services. By implementing these measures, Zimbabwe can address the specific challenges related to temperature, precipitation, government effectiveness, control of corruption, and government capital expenditure, leading to improved agricultural productivity and ability to face climate changes.

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APPENDICES

APPENDIX 1: Dataset

YEAR	AGRIC	TEMP	PRECI	CORRU	EFFECTIVE	GCE
1980	15.0775	20.8500	657.0000	1.5288	0.5299	13.0000
1981	16.6081	20.5000	657.0000	1.4158	0.4768	10.0000
1982	14.8085	21.2500	657.0000	1.3028	0.4238	9.7000
1983	9.9239	22.0300	657.0000	1.1899	0.3708	13.0000
1984	13.4366	21.4200	657.0000	1.0769	0.3177	14.7000
1985	20.7266	21.1300	657.0000	0.9639	0.2647	15.0000
1986	16.1359	21.1500	657.0000	0.8509	0.2116	14.0000
1987	13.1238	21.9100	657.0000	0.7380	0.1586	21.0000
1988	14.8253	21.2000	657.0000	0.6250	0.1056	20.0000
1989	13.3988	21.1900	657.0000	0.5120	0.0525	19.0000
1990	14.8320	21.6100	657.0000	0.3990	-0.0005	19.0000
1991	13.5469	21.5400	657.0000	0.2860	-0.0536	16.0000
1992	6.7516	22.3000	657.0000	0.1731	-0.1066	31.0000
1993	13.7379	21.6700	657.0000	0.0601	-0.1597	11.5000
1994	17.0801	21.4000	657.0000	-0.0529	-0.2127	13.0000
1995	13.4660	22.1400	657.0000	-0.1659	-0.2657	10.0000
1996	19.3426	21.5600	657.0000	-0.2788	-0.3188	8.0000
1997	16.6957	21.6000	657.0000	-0.3918	-0.3718	1.0000
1998	18.8903	22.0900	657.0000	-0.5048	-0.4249	12.0000
1999	15.4813	21.4400	657.0000	-0.8160	-0.5910	13.0000
2000	15.6671	21.2300	692.0000	-1.1273	-0.7572	16.0000
2001	15.6271	21.6000	657.0000	-1.1420	-0.7986	10.0000
2002	12.5684	21.8500	657.0000	-1.1568	-0.8399	14.0000
2003	14.7934	21.9600	657.0000	-1.1889	-0.9268	13.0000
2004	18.0638	22.0300	657.0000	-1.2536	-1.0015	10.0000
2005	17.1482	22.7900	657.0000	-1.3146	-1.3542	10.6000

2006	19.2301	21.8800	657.0000	-1.3729	-1.2564	15.0000
2007	21.1977	22.0100	657.0000	-1.4048	-1.2924	14.0000
2008	19.0211	21.9400	657.0000	-1.3488	-1.5427	5.0000
2009	10.7426	22.0200	657.0000	-1.3579	-1.5531	7.0000
2010	9.6099	22.2500	657.0000	-1.3733	-1.5382	10.0000
2011	8.6659	21.6800	657.0000	-1.4256	-1.4197	11.0000
2012	8.0445	21.9100	657.0000	-1.3818	-1.3752	12.0000
2013	7.1445	21.5800	657.0000	-1.4197	-1.3090	13.0000
2014	8.7453	21.7100	657.0000	-1.4044	-1.2790	11.0000
2015	8.2842	22.3200	657.0000	-1.3178	-1.2022	11.7000
2016	7.8740	22.3500	657.0000	-1.2713	-1.2099	12.0000
2017	8.3410	21.7300	657.0000	-1.2811	-1.2387	1.0000
2018	7.3194	22.0900	657.0000	-1.2276	-1.2618	12.0000
2019	9.8193	22.3700	657.0000	-1.2733	-1.2673	16.0000
2020	8.7729	21.9300	657.0000	-1.2894	-1.2998	17.0000
2021	8.8499	21.8700	657.0000	-1.2579	-1.2429	19.0000
2022	9.5589	21.8300	657.0000	-1.2264	-1.1861	14.0000

APPENDIX 2: Unit Root

Null Hypothesis: D(AGRIC) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, max lag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.595465	0.0000
Test critical values:	1% level	-2.622585	
	5% level	-1.949097	
	10% level	-1.611824	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(AGRIC,2)
Method: Least Squares
Date: 04/19/24 Time: 02:23
Sample (adjusted): 1982 2022

Included observations: 41 after adjustments

Null Hypothesis: TEMP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, max lag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.492611	0.0003
Test critical values:	1% level	-4.192337	
	5% level	-3.520787	
	10% level	-3.191277	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(TEMP)
Method: Least Squares
Date: 04/19/24 Time: 02:25
Sample (adjusted): 1981 2022
Included observations: 42 after adjustments

Null Hypothesis: PRECI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, max lag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.240490	0.0000
Test critical values:	1% level	-4.205004	
	5% level	-3.526609	
	10% level	-3.194611	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(PRECI)
Method: Least Squares
Date: 04/19/24 Time: 02:26
Sample (adjusted): 1981 2020
Included observations: 40 after adjustments

Null Hypothesis: GCE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, max lag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.121773	0.0121
Test critical values:	1% level	-4.198503	
	5% level	-3.523623	
	10% level	-3.192902	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GCE)
Method: Least Squares
Date: 04/19/24 Time: 02:27
Sample (adjusted): 1981 2021
Included observations: 41 after adjustments

Null Hypothesis: D(CORRU) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, max lag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.276895	0.0237
Test critical values:	1% level	-2.622585	
	5% level	-1.949097	
	10% level	-1.611824	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CORRU,2)
Method: Least Squares
Date: 04/19/24 Time: 02:29
Sample (adjusted): 1982 2022
Included observations: 41 after adjustments

Lag Length: 0 (Automatic - based on SIC, max lag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.453134	0.0000
Test critical values:	1% level	-2.622585	
	5% level	-1.949097	
	10% level	-1.611824	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(EFFECTIVE,2)
Method: Least Squares
Date: 04/19/24 Time: 02:30
Sample (adjusted): 1982 2022
Included observations: 41 after adjustments

APPENDIX 3: Optimal Lag Length

VAR Lag Order Selection Criteria
Endogenous variables: AGRIC CORRU EFFECTIVE GCE PRECI TEMP
Exogenous variables: C
Date: 04/19/24 Time: 02:39

Sample: 1980 2022
Included observations: 38

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-375.4919	NA	21.14345	20.07852	20.33709	20.17052
1	-199.0222	287.9242	0.013348	12.68538	14.49534	13.32935
2	-160.0596	51.26654	0.013229	12.52945	15.89081	13.72540
3	-109.5243	50.53534*	0.009361*	11.76444*	16.67719*	13.51236*

* 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 4: Multicollinearity

	AGRIC	CORRU	EFFECTIVE	GCE	PRECI	TEMP
AGRIC	1	0.25486099...	0.31691028...	-0.1430277...	0.08239102...	-0.3306869...
CORRU	0.25486099...	1	0.97075008...	0.29861315...	-0.1080008...	-0.6262567...
EFFECTIVE	0.31691028...	0.97075008...	1	0.32558448...	-0.0324787...	-0.6358792...
GCE	-0.1430277...	0.29861315...	0.32558448...	1	0.09943983...	-0.0054463...
PRECI	0.08239102...	-0.1080008...	-0.0324787...	0.09943983...	1	-0.1777289...
TEMP	-0.3306869...	-0.6262567...	-0.6358792...	-0.0054463...	-0.1777289...	1

APPENDIX 5: Cointegration

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
		Asymptotic: n=1000		
F-statistic	6.966569	10%	2.26	3.35
k	5	5%	2.62	3.79
		2.5%	2.96	4.18
		1%	3.41	4.68

APPENDIX 6: Autocorrelation

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.432318	Prob. F(3,14)	0.7332
Obs*R-squared	3.221836	Prob. Chi-Square(3)	0.3587

APPENDIX 7: Heteroscedasticity

Heteroscedasticity Test: Breusch-Pagan-Godfrey

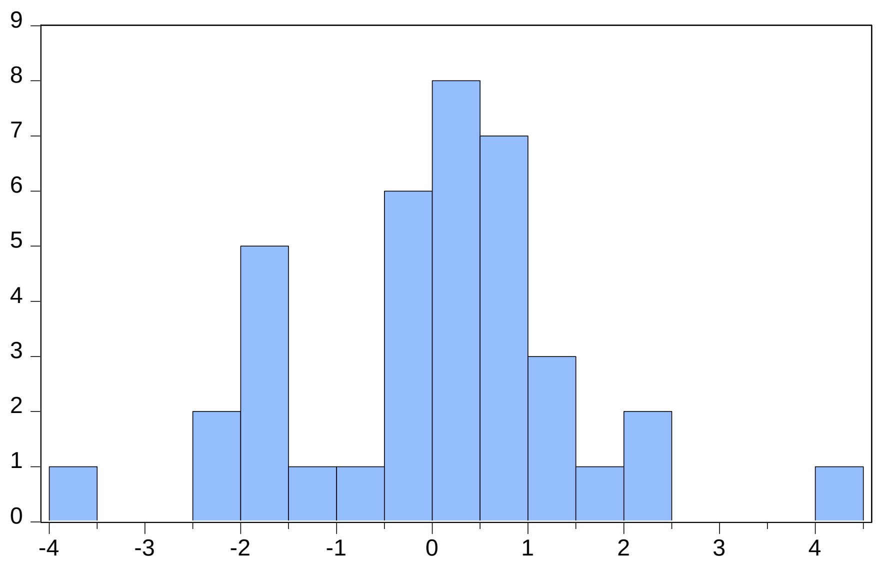
F-statistic	1.230344	Prob. F(20,17)	0.3358
Obs*R-squared	22.47372	Prob. Chi-Square(20)	0.3154
Scaled explained SS	6.120296	Prob. Chi-Square(20)	0.9987

APPENDIX 8: ARCH Test

Heteroscedasticity Test: ARCH

F-statistic	0.448280	Prob. F(3,31)	0.7203
Obs*R-squared	1.455238	Prob. Chi-Square(3)	0.6926

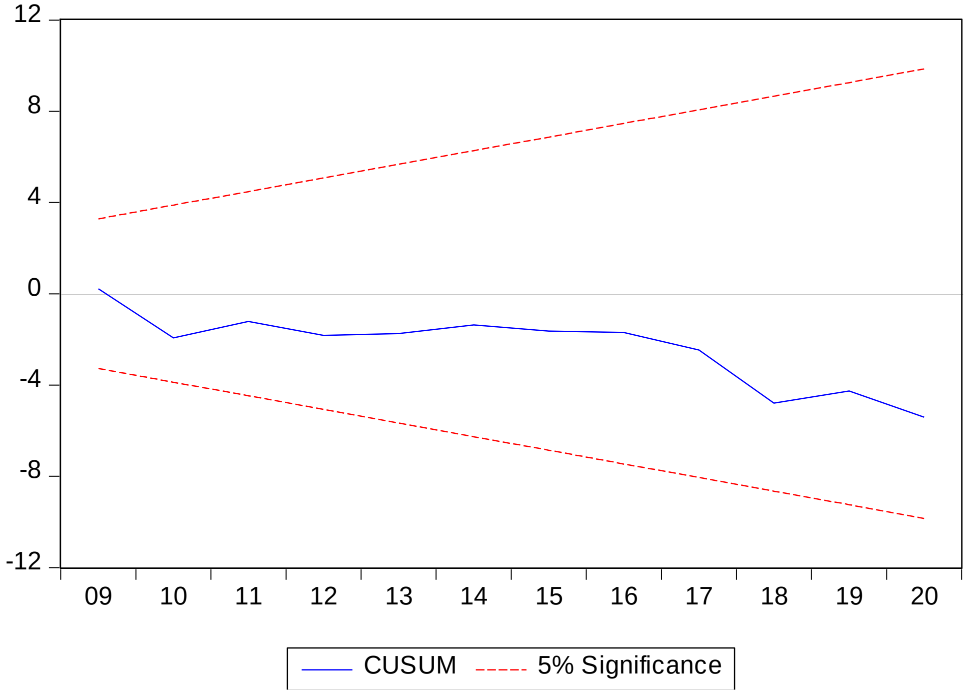
APPENDIX 9: Normality Test



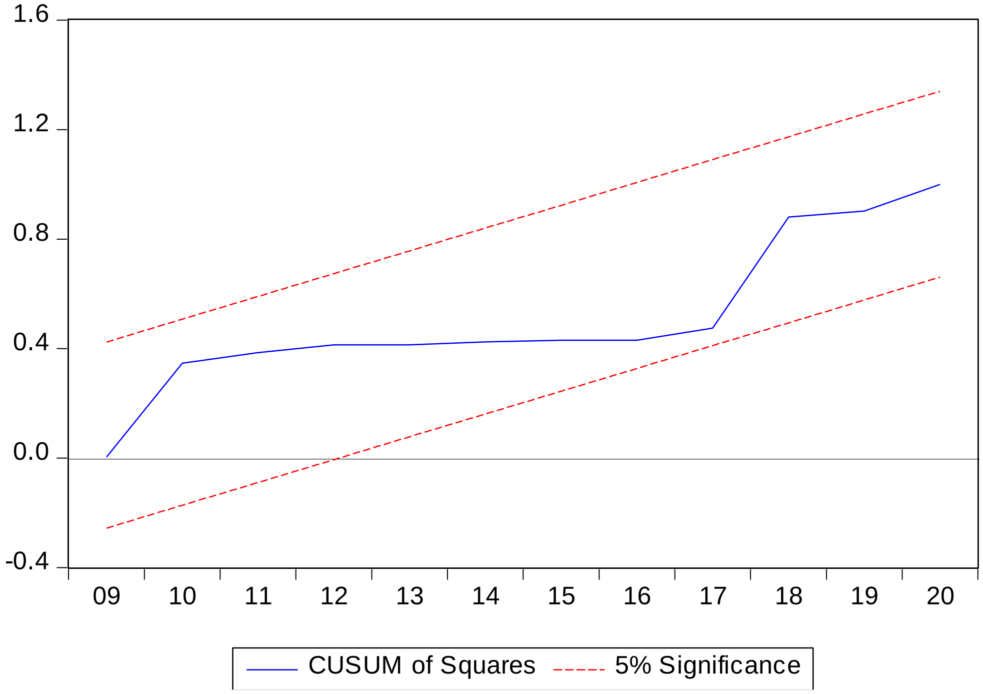
Series: Residuals
Sample 1983 2020
Observations 38

Mean	-1.80e-13
Median	0.003205
Maximum	4.272431
Minimum	-3.502581
Std. Dev.	1.487985
Skewness	0.136714
Kurtosis	3.721427
Jarque-Bera	0.942433
Probability	0.624243

APPENDIX 10: CUSUM



APPENDIX 11: CUSUM of squares



APPENDIX 12: Model Specification

	Value	df	Probability
F-statistic	1.971654	(3, 14)	0.1646

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	24.33163	3	8.110544
Restricted SSR	81.92166	17	4.818921
Unrestricted SSR	57.59003	14	4.113574

APPENDIX 13: Short Run Results

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	802.8296	290.6781	2.761920	0.0133
AGRIC(-1)*	-0.952182	0.199770	-4.766399	0.0002
CORRU(-1)	-9.530392	2.616055	-3.643040	0.0020
EFFECTIVE(-1)	15.51671	4.314053	3.596782	0.0022
GCE(-1)	-0.398648	0.150810	-2.643384	0.0171
PRECI(-1)	-1.155004	0.359831	-3.209851	0.0051
TEMP(-1)	-1.029004	3.739734	-0.275154	0.7865
D(CORRU)	29.66306	10.99385	2.698150	0.0152
D(CORRU(-1))	5.075882	13.60670	0.373043	0.7137
D(CORRU(-2))	-32.51181	15.14734	-2.146370	0.0466
D(EFFECTIVE)	-10.56486	7.876236	-1.341358	0.1975
D(EFFECTIVE(-1))	-19.94380	7.932460	-2.514201	0.0223
D(EFFECTIVE(-2))	-29.48558	7.301232	-4.038439	0.0009
D(GCE)	-0.125912	0.102986	-1.222611	0.2382
D(GCE(-1))	0.314342	0.144973	2.168281	0.0446
D(GCE(-2))	0.266025	0.128351	2.072634	0.0537
D(PRECI)	-0.115857	0.129993	-0.891252	0.3852
D(PRECI(-1))	0.489789	0.154369	3.172844	0.0056
D(TEMP)	-4.432420	2.060698	-2.150932	0.0462
D(TEMP(-1))	-2.532153	1.862437	-1.359591	0.1917
D(TEMP(-2))	-2.667842	1.309720	-2.036956	0.0575

* P-value incompatible with t-Bounds distribution.

APPENDIX 14: Long Run Results

Levels Equation
Case 3: Unrestricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CORRU	-10.00901	3.261653	-3.068691	0.0070
EFFECTIVE	16.29595	5.888410	2.767463	0.0132
GCE	-0.418668	0.148896	-2.811816	0.0120
PRECI	-1.213008	0.291331	-4.163669	0.0007
TEMP	-1.080680	3.852131	-0.280541	0.7824

EC = AGRIC - (-10.0090*CORRU + 16.2960*EFFECTIVE -0.4187*GCE
-1.2130*PRECI -1.0807*TEMP)

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