UNIVERSITY OF CAPE COAST

VECTOR AUTO-REGRESSIVE MODEL WITH EXOGENOUS CLIMATE CONDITIONS FOR RICE VARIETIES IN NORTHERN GHANA

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BY

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DECLARATION

Candidate's Declaration

I hereby declare that this thesis is the result of my own original research and that no part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature.................................. Date……………………………….

Name: Dawaal Ahamed

Supervisors' Declaration

We hereby declare that the preparation and presentation of the thesis were supervised in accordance with the guidelines on supervision of thesis laid down by the University of Cape Coast.

Principal Supervisor's Signature.................................. Date……………………

Name: Dr. Bismark Kwao Nkansah

Co-Supervisor's Signature.. Date……………………

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ABSTRACT

Multivariate time series analysis is one of the complex technique for studying a consistent time-dependent data on different variables. The data used for the study, which is obtained from the Centre for Scientific and Industrial Research (CSIR), cover the period 1957 to 2016 and involved two sets of variables: one set is made up of yield of four varieties of rice (Mandii, Bazulgu, O.Sativa and Kpukpula) and the second set consist five climate conditions(Annual Rainfall, Temperature, Evapo-tranpiration, Wind speed and Sunshine). As a result of the composition of the data,the classical Vector Auto-Regressive (VAR) model for the yield of rice varieties extended to include two sets of variables. An order-3 lag model is found appropriate for both sets of variables.It is found that inclusion of the climate conditions provides a better model for rice yield than the lagged rice varieties alone. It is also found that temperature and sunshine have a more consistent positive influence on rice yield, particularly for O.Sativa. The study therefore recommends the right varieties that can perform well under shocks of identified best-subset weather conditions.

KEY WORDS

Augmented Dickey-Fuller

Climate Conditions

Impulse Response Functions

Lag Order Selection

Rice Yield

Vector Autoregressive Model

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DEDICATION

To my family

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LIST OF ACRONYMS

ADF: Augmented Dickey-Fuller

CCC: Canadian Climate Change

CEEPA: Centre for Environmental Economics and Policy in Africa

CGE: Computational General Equilibrium

CSIR: Centre for Scientific and Industrial Research

DF: Dickey-Fuller

ECM: Error Correction Mechanism

FAO: Food and Agriculture Organization

GMST: Global Mean Surface Temperature

IPCC: Internation Panel for Climate Change

IRF: Impulse Response Function

MDB: Murray Darling Basin

MDGs: Millennium Development Goals

NISER: Nigeria Institute for Social and Economic Research

OSU: Oregon State University

PDR: People Democratic Republic

SARI: Savanna Agriculture Research Institute

TWAIE: Total Water Allocated for Irrigation and Evaporation

UKTR: United Kingdom Transient

UNDP: United Nation Development Program

UNEP: United Nation Environmental Program

UNFCCC: United Nation Frame Work Conference on Climate Change

IVAR: Incorporated Vector Auto Regression.

CHAPTER ONE

INTRODUCTION

Background to the Study

Climate change is a long-term and significant change in the average weather condition of a region and can last for a significant time (Nzuma, Waithaka, Mulwa, Kyotalimye & Nelson, 2010). Furthermore, Alley, Berntsen, Bindoff, Chen, Chidthaisong, Friedlingstein and Hoskins, (2007) argued that climate change as explained by International Panel for Climate Change (IPCC,2007) can be seen as a change in the climate that is characterized by variability of its properties and that remains for an extended period, typically decades or longer, the classical period being 30 years. The condition is further defined as a change in the average weather conditions especially average temperature and precipitation of an area (Mabe, Sarpong & Osei-Asare, 2012). It is the result of the combination of several factors, such as Earth's dynamic processes, external forces (forcings), and more recently, human activity. The external forces that result in changes in climate processes include variations in solar radiation, volcanic eruptions, deviations in Earth's orbit, and variations in the level of greenhouse gas concentrations . Extreme climate and weather events in recent decades have been a critical global issue due to the severity of the impact on natural environments, economy, and human life. These extreme events are unpredictable and destructive, especially, on agriculture production. For example, it affects the crops we grow and causes diseases in particular locations.

It also determines the physical infrastructure we need to build to survive comfortably in the face of extremes of heat, cold, drought and flood.

Society has thrown the composition of the atmosphere out of gear in the last two decades and is expected to change the earth climate out of relatively stable range which characterizes the earth in the last few thousand years. This causes more of the heat from the Sun to be retained on Earth, warming the atmosphere and ocean. Warming greater than the global annual average ($1^{o}C$) is being experienced in many land regions and seasons, including two to three times higher in the Arctic. Warming is generally higher over land than over the ocean Zhai, Portner,Skea,Robert & Shuckler (2018). Trends in intensity and frequency of some climate and weather extremes have been detected over periods during which about 0.5°C of global warming occurred (medium confidence). This assessment is based on several lines of evidence, including attribution studies for changes. The sea, which is very vital in regulating the climate absorbed about 25% of anthropogenic carbon dioxide emissions and about 90% of Earth's additional heat since the 1970s. This makes the oceans to become more acidic, warm and decrease oxygen content (due to reduced oxygen solubility caused by warming and decreased supply to the ocean interior due to less mixing). These changes have important consequences not only for marine biodiversity and ecosystems but also for the goods and services they provide, including protein and other nutrients from fish and shellfish, coastal protection, and livelihoods for hundreds of millions of people. Increasing carbon dioxide can increase crop yields while high temperature and drought in some regions can decrease them. The aggregate impact at the global level is for climate change above 2°C to reduce yields.Ianchovichina, Darwin, and Shoemaker, (2001) explains that general precipitation and temperature model results indicate that global warming shortens growing seasons in the Tropics and lengthens growing seasons at high latitudes. He further argued that in comparing with 1990 economic conditions, the model shows that these land resource changes reduce agricultural output in equatorial regions where many developing countries are located. This affects the food chain, and the quantities and types of food produced and the adequacy (Yaro, 2013). Climate change poses a range of effects: the increased concentration of carbon dioxide can increase crop yields, while changes in temperature and rainfall will have a variety of effects, with very high temperatures and drought both adversely affecting yield. Taking all factors into account, Zhai et al., (2018) concluded that a change of 2°C or more above late-20th-century levels will adversely affect yields and food production. A lot of effort and resources are committed to reducing the impacts of climate change from the international levels to the household levels. Following the evidence discovered by scientists about human interference with the climate in 1979, governments grew more concerned about the issue. World Meteorological Organization under United Nations Environment Program [UNEP] has created a new body called Intergovernmental Panel for Climate Change (IPCC) in 1980 to deal with the issues. IPCC in its first annual report confirms that the threat of climate change is real (Herold, & Johns, 2007).

Effects of Climate Change and Soil Parameters on Rice Growth and Yield

The yield potential of rice mainly depends on the climate. The most important factors that influence growth, development and yield of crops are temperature, precipitation and solar radiation. These influential variables are examined in this section.

Temperature

Rice is a cold-sensitive plant that originates from tropical or sub-tropical zones. The growth of rice is impressed by a limited period that favour its growth in temperate regions. Optimum temperature is required for maximum dry accumulation. All crops have maximum, optimum and minimum temperature limits. The response of the rice plant to daily mean temperatures at different growth stages are provided in Appendix A. A high temperature for rice beyond the optimum range affects mineral nutrition, pollen development resulting in low yields. The nutrient uptake is also affected by both soil and air temperature in rice. The high temperature $38^{\circ}C$ can reduce the plant height, and make smaller roots.

Precipitation

Rainfall is one of the key climate parameters for rice cultivation because large volumes of water are needed to produce rice. Rainless days have a direct impact on rice yield as two weeks without rain in lowland areas and about a week in upland areas can significantly reduce yields. Extreme drought for years can reduce the average yield from 17% to 40% leading to production losses and food scarcity. The intensity and frequency of droughts are predicted to increase in rain-fed lands and droughts could extend further into water-short irrigated areas. In rain-fed cultivation, crops are planted according to the season and rice is planted during the wet season. The production yield has a direct dependency on rainfall received during the crop season. Heavy rains with short frequencies will result in floods and decrease yield whereas excess rainfall can cause an alteration of chemical and biophysical processes. Heavy rainfall can cause problems in drainage of roots which can block the free movement of oxygen and also can result in the formation of toxic compounds harmful for roots. Inadequate rainfall causes water stress which reduces the size of inflorescence, and finally affects fertilization, gain filling and reduce final yield (Khadka, 2016). Both low and excessive rainfalls can have a negative impact on rice yield. Excessive rainfall can interfere with different farming activities such as seedbed preparation, harvesting, processing and drying of seed. It can also increase the chance of spreading diseases in the plants. The fertilization and grain formation of rice plant is also affected due to the continuous rainfall for a longer time (Basnayake, Inthavong, Kam, Fukai, Schiller, & Chanphengxay, 2006).

Solar Radiation

Solar radiation is an important factor needed for the growth and development of rice plant. Solar energy provides light required for seed germination of seed, expansion and growth of leaf, stem and shoot. Sun also provides thermal energy necessary for the physiological development of the plant. Solar radiation is low in the wet season under tropical conditions because the radiation is trapped or intercepted by clouds. But low radiation does not have a significant effect during the early vegetative stage of rice plant. However, it can have an effect during the reproductive phase (Datta, 1981).

Soil Stress

Soil stress relates to the characteristics of the soil, such as water holding capacity, drainage, depth, texture, organic matter and fertility. High soil stress can decrease the rice yield. Various forces acting on the soil water decrease the soil potential energy and make it less available for root extraction. In wet soils, the potential energy of water is relatively high. This allows water to move freely in wet soils and water can be easily extracted by plant roots. The potential energy of water in the dry soil is very low compared to wet soil and is strongly bound by capillary and absorptive forces to the soil matrix, making it difficult for crops to absorb water. Excessive soil water stress can result in pollination failure, and trigger early canopy senescence (Steduto, Hsiao, Fereres, & Raes, 2012)

Potential Evapo-transpiration and Length of Growing Period

Potential evapo-transpiration is a measure of the ability of the atmosphere to remove water from the soil and plant surface through evapo-transpiration(evaporation and transpiration) without the limitation of water supply. It is a very important parameter for the growth of rice plant. If petcorr exceeds rainfall, then irrigation is required for optimum growth of rice plant. The usual petcorr level used by FAO for upland crops is 50% but for Lao PDR, it is estimated to be 75% (Basnayake et al., 2006). Day length also plays a vital role in rice growth. The growth of rice is favoured by shorter days. Lao PDR have relatively smaller day length variation than other countries and due to these; the wet season is very productive for the flowering of rice. During short days, the flowering and reproduction of plant are developed quickly. The traditional rice varieties of Lao PDR are usually highly photo-period sensitive and rice plant flowers from September to mid-October (Basnayake, et al., 2006).

Statement of the Problem

Considering the widespread effect of climate change on livelihoods of people and communities, there has been a concerted effort towards reducing the impact. Through research and exploration, several strategies are espoused aimed at building resilience and reducing vulnerabilities of individual, households and communities to climate change. The impact of climate change is dire, proven not to have bounds and has come to stay. This impact cuts across all ecological zones of the globe and all spheres of human and environmental life. Studies suggest that maintaining ecosystem resilience, focusing on the underlying structure, functions, and processes of ecosystems should be a priority. Good environmental conservation practices, such as creating protected areas and biodiversity networks, minimizing habitat fragmentation and managing invasive species, is the obvious starting point for biodiversity management in response to climate change (Heller, & Zavaleta, 2009).

Increased temperature and a concurrent reduction in annual rainfall have incremental effect on crop evapo-transpiration which will further cause an increase in the irrigation requirements for all the crops between 1.4% and 9.8%. (Fischer, Tubiello, Van Velthuizen, & Wiberg, 2007). The projected effect of this is that for instance in the case the Vea dam, which is an irrigation dam purposely for the cultivation of crops will experience water abstraction above the Total Water Allocated for Irrigation and Evaporation losses (TWAIE) for the dam about 20.20% to 27.30% (Kusi, 2013). Yaro, (2013) argued for the integration of climate change adaptation and mitigation into an overall development agenda through stakeholder engagements. He canvasses for a holistic approach which is household-specific due to the differences in the vulnerabilities in individual households. Generally, the government and the citizenry at large have not been proactive in putting adaptation mechanism in place to minimise the impact of climate change. There are scientific evidence to demonstrate (i) rising temperatures, (ii) declining rainfall totals and variability, (iii) rising sea levels and (iv) high incidence of weather extremes and disasters. These are increasingly projected to have a disastrous impact on all facets of life of current and future generation (Apuri, Peprah, & Achana, 2018). Quite a number of studies conducted about climate change, a lot of them is geared towards finding human factors that influence the change in climate, its effects on food security, strategies to mitigate the impact and coping strategies, among others. There are still grey areas that need to be carefully espoused to determine how it affects a variety of crops. Ghana spends so much on importing rice, which could have served as capital for farmers to improve and expand rice production for local consumption and export. It is against this backdrop that the study seeks to investigate the impact of climate conditions on the yield of varieties of rice produced in the context of multivariate timeseries.

Objective of the Study

The purpose of the study is to examine the yield of rice varieties in Northern Ghana by incorporating the effect of climate conditions. The study is guided by the following specific objectives:

(1) Examine the level of influence climate conditions exert on the yield of varieties of rice.

(2) Develop an appropriate multivariate model for the yield of varieties of rice that incorporates climate conditions.

Significance of the Study

The result of this study is expected to make a significant contribution towards the application of suitable multivariate model that incorporates two sets of multivariate time series variables. The study again would determine the most suitable rice variety that maximises yield for farmers over a long time. This study is also expected to add to the pool of knowledge on the impact of climate change on farming and the strategies to ameliorate it.

Scope and Delimitations of the Study

The geographical scope of this study is limited to the Tolon District of the Northern Region of Ghana. The target beneficiary population of the study would be the rice farmers and District Agric Department.

Organisation of the Study

The study is structured into five chapters: Chapter One entails the introductory part of the study, which sets the stage for the entire research work. Chapter Two presents the literature review of studies on the topic. The Chapter Three reviews the research methodology employed to accomplish the study. Chapter Four and Five, respectively, look at data analysis and discussion on one breadth and summary conclusion and recommendations, on the other hand.

Chapter Summary

Climate conditions changing over time, and resulting in destructions of lives, properties and loss of farm products are on the increase. These are the effects of climate change over time on human life especially the total harvest farmers get from the farm at the end of the farming season. The topic under study which is the vector autoregressive model with incorporated exogenous climate conditions on varieties of rice in Northern Ghana seeks to examine the influence of climate conditions on the production of rice varieties and to develop appropriate multivariate time series model. The model to be developed comprise two parts, the first model would be developed from only yields of the rice varieties and the second model to would be extended vector autoregressive model to include climate conditions. This approach is informed by the impact of weather conditions on various spheres of livelihoods including agriculture.

CHAPTER TWO

LITERATURE REVIEW

Introduction

This chapter discusses the sources of information that relate to global climate change, climate change in Ghana and the effect of climate change on rice production in Ghana. The review includes the effect of climate factors and soil parameters on rice production and yield. The empirical literature on the factors that influence climate change on rice production is also reviewed.

Climate Change

Climate change is now one of the greatest environmental, social, and economic problems that face the planet (Nzuma et al., 2010). The Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), (2007) indicates that most land areas will have warmer and fewer cold days and nights. Fancherean, Rouault, and Richard, (2003) also pointed out that the earth in times past have observed significant increases in temperature and decreased rainfall as a result of climate change.

(IPCC,2007) has shown that Africa would experience a more severe global warming as compared to the rest of the world in the 21st century. This is expected to cause rainfall in some parts of the region to decline (IPCC, 2007). Recent research indicates that decreased precipitation is expected to be recorded even in East Africa where increased rainfalls were often recorded due to climate change (Funk, Dettinger, Michaelsen, Verdin, Brown, Barlow, & Hoell, 2008). These expected climate changes remain a great challenge to food and water security, public health, natural resources, and biodiversity (McCarthy, Canziani, Leary, Dokken, & White, 2001). According to Nzuma et al. (2010), climate change is expected to have a significant impact on the livelihoods and living conditions of the poor and thus threaten the attainment of the Millennium Development Goals (MDGs) and sustainable development in Sub-Saharan Africa. In Ghana, the following climate indicators reveal that the climate has changed; rising temperatures, declining and increased variability of rainfall, rising sea levels and high incidence of weather extremes such as floods and droughts .

According to De Pinto, Demirag and Haruna (2012), Ghana records increased mean annual temperature and decreased monthly rainfall per decade since 1960, though rainfall over Ghana was particularly high in the 1960s. The increase in temperature and decrease in rainfall is 1°C per decade and about 2.4% per decade, respectively (Pinto et al., 2012). Records further indicate that temperatures are likely to continue rising in the future with an average annual temperature increase between 0.8°C and 5.4°C for the years 2020 and 2080, respectively. Rainfall is also predicted to decrease in all the agro-ecological zones with an average annual rainfall total within the same period of 2020 and 2080 estimated to decline by between 1.1%, and 20.5% (www.ccdare.org). Based on the review of some climate models, Pinto et al. (2012) concluded that by 2060, the mean annual temperature will increase by 1.0°C -3.0°C, and further increase to 1.5°C -5.2°C by 2090 with changes being expected to be more severe in northern Ghana. Other studies such as Owusu and Waylen (2009) report that the decline in the annual mean rainfall of the southwestern regions of the country has been the most severe. In the remaining parts of the country such as the Volta Basin, shorter dry spells have been replaced by prolonged dry seasons, indicating changes in the climate condition (Owusu, Waylen, & Qiu, 2008). Such predicted changes in climate are expected to significantly affect estimates for future crop yields (Pinto et al., 2012).

Evidence of Climate Change

Ghana is a tropical country which experiences changes in weather elements. Ghana is documented to have completed its first National Communication to the United Nations Framework on Climate Change (UNFCCC) in 2000, which predicted the impacts of climate change. Furthermore, findings from Centre for Environmental Economics and Policy in Africa (CEEPA) studies carried out in 2006 revealed changes in some of the climate elements such as temperature, rainfall and sea levels in Africa, including Ghana. According to Daze (2007), the temperature in Ghana was expected to increase by $2.5^{\circ}C$ to $3.2^{\circ}C$ by 2100. This increase in temperature would, however, differ according to the agro-ecological zones in Ghana. Daze (2007) further documents that Sudan savannah zone in the Upper East Region is predicted to experience the maximum temperature of $3^{\circ}C$ by 2100, followed by the Guinea savannah in the Northern Region of $2.5^{\circ}C$. In contrast, the Sudan Savannah is however predicted to experience the least minimum temperature with the Transitional zone found in the Brong-Ahafo Region of Ghana expected to experience the highest minimum temperature of $2.7^{\circ}C$ by the year 2100 (Anim-Kwapong & Frimpong, 2004). They further document predictions in the changes in rainfall to be expected by

2100 mainly due to human activities. Evidently, rainfall amount and distribution in Ghana has fluctuated over the years. A study conducted by Anim-Kwapong and Frimpong (2004) indicates that there has indeed been a 10 per cent increase and 15 percent decrease in the seasonal rainfall pattern and distribution globally especially in the south coastal regions of West Africa between the years of 1931-1960 and 1961-1990. These changes are however reported to have been caused by changes in land cover in the region, change in global ocean circulation due to changes in the surface temperatures of seas and finally changes in global atmospheric composition (Hulme, 1992). In Ghana, the rainfall amount and runoff have been reported to decrease by 20% and 30%, respectively, within the past 30 years (Daze, 2007).

Again, Daze (2007), reports that the annual rainfall in Ghana is projected to decrease between 9-27% by the year 2100. Not withstanding, the Sudan savannah agro-ecological zone is however predicted to experience the highest decline in the amount of rainfall of 170.0mm by that year, followed by Deciduous Forest, Transitional zone and Guinea savannah, by 99.0mm, 78.0mm and 74.0mm, respectively, by the year 2100 with rainforest predicted to experience an increase of 110.0mm in the amount of rainfall by the year 2100. Contrary to this, Daze (2007) reports that although the amount of rainfall has decreased over the years and expected to decrease more in the coming years in Ghana, the level of the sea has been reported to have increased by 2.1mm per year over the past 30 years. And this has been estimated to further increase by 1mm by the year 2100. A transect study (Torgbor, Stern, Nkansah & Stern, 2018) that made use of rainfall data over 53 years, selected 15 meteorological stations on a five-tier basis from north to south, and three-tier basis from west to east across Ghana. One remarkable finding was the high variability of rainfall within the region. This observation was consistent with the result from Uganda (Osbahr, Dorward, Stern & Cooper, 2011) and southern Zambia (Stern & Cooper, 2011). In that study by (Torgbor, Stern, Nkansah & Stern, 2018), which identified a first-order Markov process as sufficient for rainfall modelling in Ghana, no visible changes were observed in rainfall patterns over the period. It notes however that the identification of rainfall changes would require more detailed procedures.

Climate Change and Rice Production in Ghana

Climate is found to be one of the major components that significantly influence agricultural production, with large-scale impact on food production and the overall economy (Parthasarathy & Pant, 1985). Both natural and human activities such as emission of greenhouse gases (IPCC, 2007) cause various climate-related disasters that adversely affect agriculture, food security, water resources and biodiversity as a whole (Tirado, Clarke, Jaykus, McQuatters-Gollop, & Frank, 2010). Rice is a staple food which constitutes a major part of the diet of many countries in the world (Oteng & Anna, 1999). It is widely cultivated with high production in South-East Asia, and largely exported by the United States of America and Southern Europe regions (Longtau, 2000). In Sub-Saharan Africa, West Africa is the leading producer and consumer of rice. The crop is widely produced in Ghana, Cote d'Ivoire, the Gambia, Guinea, Guinea Bissau, Liberia, Burkina Faso, Senegal and Sierra Leone (NISER, 2002). The sub-region produces 42% of all the rice produced in Africa while the other four regions North Africa, East Africa, Central Africa and Southern Africa produce 32%, 23.8%, 1.2% and 1%, respectively (Oteng & Anna, 1999).

In Ghana, the cultivation of rice has been in existence for a very long time. It was one of the major commercial food crops in the 17th and 18th centuries (Mobil & Okran, 1985). The crop is very important with regards to the diets of Ghanaians, as well as its availability throughout the year. Of equal importance are maize, millet and sorghum and other cereals that are grown for food and income for both the rural and urban households in Ghana (Mabe et al., 2012). Presently, rice is one of the major cereals produced in Ghana, but its production as for other crops is affected by extremities in weather and climate such as floods, salt stress and extreme temperatures. All these extremities are expected to get worse with climate change .Kranjac-Berisavljevic et al. (2003) also state that factors such as shortage of water and the dependence of farmers on rainfall significantly influence rice production in the country. The combination of changes in the rainfall patterns and rising temperatures are expected to negatively affect the growing conditions of the rice crop due to drought, flooding, etc. thereby changing the growing seasons which could later reduce crop productivity. Sarr et al. (2007) also state that the major climate change impacts will be on rainfall, which will be changing and less reliable. This is expected to affect the onset and length of growing seasons of the crop, particularly in semi-arid areas where yields from agricultural farmlands that are mostly rain-fed could be reduced by up to 20 to 50% by 2050. The increase in temperatures is also likely to reduce the duration of the hot off-season period for irrigated rice farming, owing to increased risk of sterility due to high temperatures at flowering stage of the crop . The production of rice in Ghana is therefore expected to reduce by 36% as many rice farmers have abandoned their rice fields as a result of the effect of climate pressures in the country (Oppong-Ansah, 2011). The three northern regions of Ghana are already experiencing the highest mean temperatures and the predominance low rainfall, causing poverty across these regions. The southern parts of Ghana, like the north, are also threatened with the effects of climate change as thousands of people wail when properties worth several millions of Ghana cedis and some human lives are lost following hours of torrential rainfall each year.

Results of Biophysical Crop Simulation Models

Crop simulation models draw on controlled experiments where crops are grown in field or laboratory settings to simulate different climates and levels of carbon dioxide to estimate yield responses of a specific crop variety to certain climates and other variables. Biophysical growth models are likely to be more accurate than models based on past trends as future climate conditions are likely to differ from past conditions (Sonka, Mjelde, Lamb, Hollinger, & Dixon, 1987). Biophysical models are widely used to estimate the impact of climate change on crop yields. (Parry, Rosenzweig, Iglesias, Fischer & Livermore, 1999) have analyzed the effect of climate change on wheat, maize, soybean and rice yields during the 21st century. Under various climate scenarios, the study predicts more damaging effects of climate change on yields of these crops in India and Nigeria between 1990 and 2020 as compared to other countries. Some scenarios forecast slightly widespread yield losses across Sub-Saharan Africa vis-à-vis other regions. In analyzing climate change effect on maize yields in Botswana, Chipanshi et al. (2003) use three climate scenarios: United Kingdom Transient (UKTR), Canadian Climate Change (CCC) and Oregon State University (OSU) models to analyze the effect of climate on crops. This study predicts an increase in maize yield under OSU scenario and a decrease under the two other scenarios in both eastern and western regions but the yield losses are more severe in the western region. For sorghum, a decline in yield under CCC and UKTR scenarios is observed in both eastern and western regions but yield losses are doubled in the western region. A gain in sorghum yield is predicted in both regions under OSU scenario. In Mali, Butt et al. (2005), under CCC scenario, predict an increase in maize yields and a decrease in sorghum yields.

Biophysical models have several limitations which may influence prediction accuracy. They require daily weather data, which greatly limits the areas over which it can be applied. Furthermore, actual crop yields are likely to be lower than yields under experimental conditions in biophysical models (Rosenzweig & Parry, 1994). Lastly, the estimates of these models do not, however, include the effects of farmer adaptation to changing climate conditions, thereby over-stating damages of climate change to agricultural production (Mendelsohn & Dinar, 1999).

Empirical Literature on Climate Change and Rice Production

As for many other regions throughout the world, temperature and precipitation play a crucial role in the production potential of major crops. The effects of these factors are, however, highly country-specific because one country is distinguishable from others with regards to its sensitivity to weather conditions. Using data from farmer-managed irrigated rice fields in six important rice-producing countries, Welch, Vincent, Auffhammer, Moya, Dobermann & Dawe, 2010) concluded that rice yields plummet as nighttime temperatures are higher. Day time temperatures up to a point are found to enhance yields. They caution, however, that any gains caused by higher daytime temperatures are likely to be outweighed by losses resulting from higher nighttime temperatures as temperatures are rising faster at nights. Additionally, if daytime temperatures become too high, this will impede rice yields, inflicting more loss. Utilizing the crop model ORYZA 2000, Vaghefi, Shamsudin, Makmom & Bagheri, (2011) predicted a decline of 0.36 t/ha in rice yield under the scenario of a 2°C increases in temperature at a CO_2 concentration of 383 ppm. If the level of CO_2 concentration rises to 574ppm, the loss is 0.69 t/ha.

Mathauda, Mavi, Bhangoo, and Daliwal (2000) investigated the effects of temperature change on rice yield in the Punjab region in India by using the Ceres Rice simulation model between 1970 and 1990. They stratified the weather scenarios by five different conditions which are normal weather, slightly warm (0.5 increase), greater warm, and extreme warm condition (2℃ increase) in the simulation model. The model predicted that temperature increase decreases rice yield by 3.2% in slightly warm, 8.2% in greater warm, and 8.4% in extreme warm condition compared to normal condition scenario. The result also showed that an increase in temperature negatively affects not only rice production but also other rice attributions such as biomass, crop duration and straw yield.

Torvanger, Twena, and Vevatne (2004) analyzed climate change in Norway for the period 1958-2001. The study employed time series data with a biophysical statistical model to examine the dynamic linkages between yields of potatoes, barley, oats, wheat and climate change variables such as temperature and precipitation. The study found that there is a positive impact on yields from temperature in 18% of the crops. The effect is found to be strongest for potatoes. Regionally, the study revealed that temperature is likely to be a more important limiting factor for crop growth in Northern Norway than other regions. The effect of precipitation is found to be negative in about 20% of the cases. Peng et al. (2004) evaluate the impact of temperature on rice yields using weather and agronomic data from an experimental plot in the Philippines from 1979 to 2003. They observe an increase of 0.35°C in mean annual maximum temperature and a 1.13°C increase in mean annual minimum temperature. Their statistical analysis indicates that a 1°C increase in the minimum temperature during the growing season entails a 10% yield decrease. The maximum temperature does not appear to have a significant impact.

Basak, Titumir, Biswas and Mohinuzzaman (2013) analysed climate change impacts on rice production in Bangladesh by using a simulation model. The model specifically focused on Boro rice production which amounts to 58% of the total rice production during 2008 in Bangladesh to estimate the effects of future climate change, soil and hydrologic characteristics of the locations, typical crop management practices, and traditionally controlled in the simulation model called DASAT (Decision Support System for Agrotechnology Transfer). The simulation results show that rice production varies in different locations for different climate conditions and hydrological properties of soil although same Boro rice was used in all areas. The model also indicates that rice production decreased drastically from 2.6% to 13.6% and from 0.11% to 28.7% when the maximum temperature was increased by $2^{\circ}C$ and $4^{\circ}C$. Although the simulation model shows that a drop in minimum temperature also reduces the rice yield, it suggests that increases in temperature cause more damage in production. The model also found some positive effects of CO_2 concentration on rice yield but the impact was little compared to that of temperature change.

Ayinde, Ojehomon, Daramola, & Falaki (2013) analysed the trend of climate factors in Niger state, Nigeria, as one of the major states contributing to the total rice output of the country. This study also describes the trend in rice production of Niger state and determines the factors affecting the output of rice in the state. Secondary data from 1981-2010 are used. The analytical tools used are descriptive analysis, unit root and co-integration. The result of the research reveals that there is variation in the trend of the climate factors and also variation in rice output of Niger state. The finding also shows that humidity and minimum temperature are the climate factors that affect rice production of Niger state, such that 1% increase in humidity causes 17% reduction in rice production in Niger state while 1% increase in minimum temperature causes 52.3% increase in rice production. Thus, humidity has a negative effect and minimum temperature has a positive effect. Franklin, Rusche and McMahon (2014) analysed the empirical evidence of climate change and its effects on rice production in the Northern Region of Ghana. The study makes use of paired *t*-test to establish that climate change is evident in the study area. The climate conditions in the area are found to have become warmer over the past 40 years. Yield response regression model is used to determine the effects of temperature and rainfall on rice yield. The results indicate that if an average annual temperature increases by 1ºC, rice yield will decrease by 0.15mt/ha.

Conceptual Framework Climate-Agriculture Relationship

The determination of climate-agriculture relationship can be done by studying agricultural data and climate variables data for a number of places within a given area, for as long a period as consistent records of both agriculture and climate allow, and deducing agro-climatological relationship from analysis of the data (Olaniyan, 1981). Olaniyan assumes that data will not be tied to its historical mean. However, it is expected that data overtime will be tied together and will move up and down independent of the behaviour of each other. This results in co-integration. The presence of co-integration implies the existence of a long-term relationship between the endogenous and the exogenous variables (Ayinde et al., 2013). The existence of co-integration can be handled by the Error Correction Model (ECM). The study employed the ECM within the context of co-integration theory to analyze the data. The estimation procedure is used to overcome the problems of spurious correlation often associated with non-stationary time-series data. Further, the procedure can generate long-run relationships (Johansen, 1992). In using ECM, the first step is to assess the order of both the dependent and independent variables in the model. The order of integration ascertains the number of times a variable will be differentiated to become stationary. Dickey-Fuller statistics (DF) and Augmented Dickey-Fuller statistics (ADF) will be used in this study to test the stationarity of individual series (Dickey & Fuller 1981).

Empirical Economic Impact Studies on Climate Change

For the past 30 years, there have been many kinds of research on climate change. Most researchers have looked at the impact of climate change on agricultural production. Some researchers have tried to develop an Integrated Assessment Model (IAMs) for the assessment of the impact of climate change. According to Ringuis (2002), the other group of researchers looked at the development of local and regional quantitative indicators for assessing the impact of climate change. Manne, Mendelsohn, & Richels, (1995) categorised climate change impacts into two, namely: market damages and non-market damages (ecological damages). To Manne et al. (1995), the market damages affect the agricultural, forestry, fishery, energy, transport, tourism and water sectors. Air pollution, drought, migration, hurricanes etc. results from global warming through non-market damages. There are controversies on the number of methodologies (approaches) available for assessing the impact of climate changes on agriculture. Jaeger, Amos, Conklin, Langpap, Moore & Plantinga. (2019) indicated that there are two approaches and these are the Production Function Approach and the Ricardian Model Approach. However, Schlenker, Hanemann, & Fisher (2006) and Ofori-Boateng and Insha (2011) grouped climate change impact assessment approaches into three broad categories. These are Computational General Equilibrium (CGE) model, Agronomic Simulation Model (agro-economic analysis) and Ricardian Cross-sectional Hedonic Model.

Computational General Equilibrium (CGE) Model

Darwin et al. (1995) developed the Computational General Equilibrium (CGE) model to analyze the potential impact of climate change on agriculture, bearing in mind the interactions with non-agricultural sectors and other global regions. The assumption underlying this model is that the impact of climate change is exogenous (Bosello & Zhang, 2005). The strength of this model is that structural changes and farmer responses are implicit in the analysis, freeing the analyst from the burden of estimating the effects of climate change on particular region-specific crops and farmer responses (Darwin et al., 1995). Secondly, the model assumes spatial adaptation as initial responses to changes in climate and to the availability of spatially disaggregate data on present agricultural production, land values and climate. Despite the above strengths, the model is bedevilled with some weakness. One of the weaknesses of the spatial-analogue approach is that it assumes a long-run equilibrium that ignores short and medium-run adjustment costs.

The CGE model ignores likely changes in input prices and output that results from changes in production at the global level and affects farm-level decisions (Bosello & Zhang, 2005). Lastly, the approach also assumes that farmers will inevitably know when and how to respond to changes in climate variables. This model is also called the Production Function or Yield Response model. It is based on the assumption that crop yields are functions of exogenous environmental or climate factors such as rainfall, temperature, wind speed etc. (Cassman, Grassini, & van Wart, 2010). It uses a controlled physiological changes approach of crop growth to stimulate yields based on uncontrollable climate factors. As noted by Environmental Economist, climate factors are important inputs in production but they are usually unaccounted for. This model deals with this omission. Despite its advantage, it has certain disadvantages. However, the effect of climate change on yield has made many farmers adopt strategies that are intended to mitigate the negative impact of climate change on crop yield. The adaptive strategies can increase production thereby leading to the insignificant negative impact of climate change on crop yield. Agronomic-Simulation Model (production function model) is deficient in accounting for these adjustments on the part of farmers (Dinar, Mendelsohn, Evenson, Parikh, Sanghi, Kumar, & Lonergan, 1998). Another drawback of this model is the uncertainty of the functional form to give the best coefficient of determination. It cannot also link the agricultural sector with other sectors in the economy.

Ricardian Cross-Sectional Hedonic Models

This model can simply be called the Ricardian model. It was named after a classical economist called David Ricardo (1772-1823). As the name of the model implies, it uses cross-sectional data to regress net revenue or land value on the explanatory variables (Kabubo-Mariara, 2008). David Ricardo in his time made a crucial observation that the rent of land would reflect its productivity in a perfectly competitive market. The perfectly competitive assumption ensures that excess profit is zero. A Ricardian model is a hedonic approach which tries to price land and regress it on exogenous inputs (purchased inputs, climate, socio-economic and soil variables). Schlenker et al. (2006) noted that the model operates under the assumption that land value is equal to the stream of the discounted value of future rent. The basic concept of the model is that land productivity is a function of climate variables like rainfall, relative humidity and temperature (Kurukulasuriya & Mendelson, 2007). As such, variation in climate and other inputs affect net revenue or land value. It determines the impact of climate change on crop yield by noting that a farmer maximizes net revenue by choosing controllable inputs and those that are uncontrollable (environmental factors). In stating empirically the Ricardian model (climate response function), temperature and rainfall enter as both linear and non-linear factors. The Ricardian Model has a number of merits, in estimating the effect of climate variables on net revenues; the model takes the individual farmer's adaptation strategies into account. The adjustment that a farmer makes can minimize the effects that climate change has on productivity.

Kurukulasuriya and Mendelson (2007) indicated that the Ricardian model can deal with over-estimation of the damage that other models are likely to cause. This is an advantage over the two models mentioned above. However, the model has certain demerits. The model has a limitation of not being able to consider price changes in the advent of climate change (Horowitz &Quiggin, 1999). The assumption underlying the Ricardian model is that price changes are netted out. Thus, an increase in price in some areas due to a reduction in crop production neutralizes the effects of a decrease in prices due to expansion in crop production. This is not entirely true. The model usually underestimates damages or overestimates benefits of land productivity by assuming that prices are constant. Also, another limitation of this model is its inability to quantify the effects of variables which are constant across space (Kurukulasuriya & Mendelson, 2007). Thirdly the model assumes that farmers can easily adjust to climate change by adaptation. It notes that adaptation to climate change is less expensive and hence farmers adjust rapidly. It was observed by many researchers that adaptations are expensive and farmers slowly adjust to climate change. Another limitation is that it does not consider past and future agricultural policies. Additionally, the explicit inclusion of irrigation in the Ricardian model's analysis is a limitation. Furthermore, it does not apply to the situation when farmers switched from one production industry to another. This is because it does not quantify the transition cost. Even though the model has a lot of criticism, Kurukulasuriya and Mendelson (2007), Kabubo-Mariara (2010) used it to assess the impact of climate change on crops and animal production.

Chapter Summary

The literature has revealed the extent to which climate changes pose a challenge to food and water security, public health, natural resources, and biodiversity. It is established that the effect of climate change is a reality in most parts of the world. It is consistent in the literature that there is an increase in temperature and decreases in rainfall by an amount of $1^{\circ}C$ per decade and about $2.5^{\circ}C$ per decade, respectively. Records further indicate that temperatures are likely to continue rising in the future. It is identified that in Ghana, there is evidence of changes in climate which are seen in rising temperatures, declining and increasing variability of rainfall, rising sea levels and high incidence of weather extremes such as floods and droughts. There are studies on the impact of changes in weather conditions on yield and attributions of rice and other agricultural products. Simulation studies have mainly been used in studying the effect of climate changes on agriculture. The results show that the effect of the changes depends on the nature of the weather condition. The results suggest that since climate conditions are not the same over different countries, the extent of the effect of these climate conditions would not be the same over all countries. It is evident, however, that the effect of increases in temperature has an important and consistent impact on yield under various conditions.

The literature also contains studies, though few, on the determination of the effect of the yield of different types of rice and other agricultural products which incorporates other climate conditions. It is not reported clearly how the two sets of variables are examined in a multivariate fashion for example is the Vector

Auto-regressive models. This model is able to examine the level of influence climate impose on the yield of rice over short and long terms period.

CHAPTER THREE

RESEARCH METHODS

Introduction

In this chapter, we review the methodology employed in the analysis of the data under study. It will describe the data and examine the vector autoregressive model (VAR). It then shows an inclusion in the VAR of other influencing variables that are thought to affect the original set of variables in the classical VAR technique.

Study Area

The study is conducted in Nyankpala, a town under the Tolon District of the Northern Region. The region has a land size of 70,384km^2 , representing 31% of the total land size of the country. The region has an estimated population of 3.706 million as at 2010 population census of the Ghana Statistical Service with the main occupation of the inhabitants being farming. This study seeks to establish the relationship between climate conditions and the yields of rice varieties.(Figure1) is a map clearly showing the communities and landmarks of the Northern Region of Ghana.

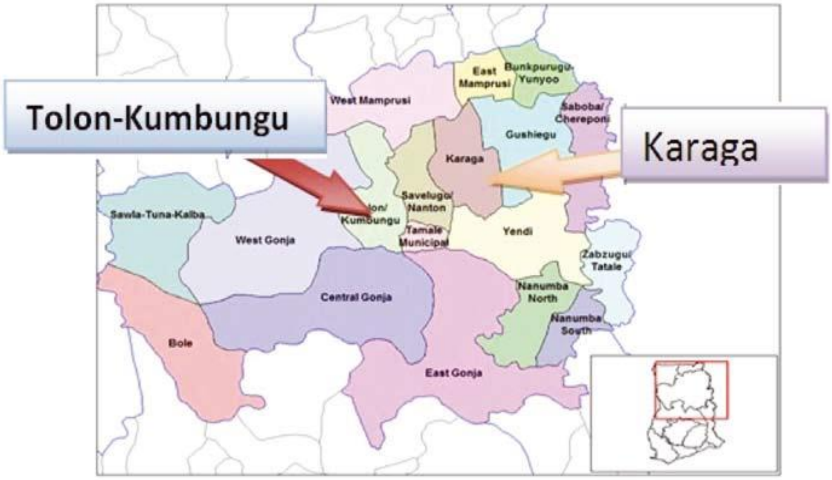


Figure 1: Map of Northern Region of Ghana indicating the District of Tolon

Nature of Data

The data is obtained from the Savanna Agriculture Research Institute (SARI), an agricultural research station which is a branch of the Centre for Scientific and Industrial Research (CSIR) in the Tolon District, specifically located in Nyankpala. The data include climate data from period of 1957 to 2016. The variables of the climate data include rainfall, number of rain days, total evaporations, mean wind speed, mean sunshine, and mean temperature. This data is observed monthly, so it comprises of a total of 720 months over the 60 years. The second part of the data is the rice yield of four different varieties of both lowland and upland rice. The varieties are Mandii, Oryza Sativa, Kpukpula and Bazulgu.

Consider p time series variables $\{y_{1t}\}, \{y_{2t}\}, \cdots, \{y_{pt}\}$. A multivariate time series is the $(p \times 1)$ vector time series $\{\mathbf{Y}_t\}$ where the i^{th} row of $\{\mathbf{Y}_t\}$ is $\{y_{it}\}$, $i = 1, 2, \ldots, p.$. That is for any time t, $\mathbf{Y_t} = (y_{1t}, \ldots, y_{pt})'$. We therefore define another set of time series $\mathbf{C}_t = (C_{1t,}C_{2t},\cdots,C_{qt})$ of q variables. The focus will be to determine $\{\mathbf{Y}_t\}$ interms of its own past values in addition to those of $\{\mathbf{C}_t\}$. The purpose of the technique is to model and explain the interactions and co-movements among a group of time series variables. In this study, the two sets of variables are the yield of varieties of rice and climate variables.

Stationary and Ergodic Multivariate Time Series

A multivariate time series $\{\mathbf{Y}_t\}$ is a covariance stationary and ergodic if all of its component-time series are stationary and ergodic. This means there is no change in statistical properties of the random process. Let

$$E(Y_t) = \mathbf{u} = (u_{1,\dots,}u_p)' \tag{1}$$

The variance-covariance (VC) matrix is given by

$$\mathrm{V}(Y_t) = \mathbf{\Gamma}_o = E[(Y_t - u)(Y_t - u)'] \tag{2}$$

with the $(p \times p)$ structure given as

$$\mathbf{\Gamma}_o = \begin{pmatrix} \mathrm{var}(y_{1t,}) & \mathrm{cov}(y_{1t,}y_{2t}) & \cdots & \mathrm{cov}(y_{1t,}y_{pt}) \\ \mathrm{cov}(y_{2t,}y_{1t}) & \mathrm{var}\,(y_{2t}) & \cdots & \mathrm{cov}(y_{2t,}y_{pt}) \\ \vdots & \vdots & \ddots & \vdots \\ \mathrm{cov}(y_{pt,}y_{1t}) & \mathrm{cov}(y_{pt,}y_{2t}) & \cdots & \mathrm{var}(y_{pt}) \end{pmatrix} \tag{3}$$

The matrix in Equation (3) is the VC matrix at lag zero. The corresponding correlation matrix is derived as

$$\mathbf{R}_o = \mathbf{D}^{-1}\mathbf{\Gamma}_o\mathbf{D}^{-1}, \tag{4}$$

where D is a $(p \times p)$ diagonal matrix with j^{th} diagonal element given by the univariate standard deviation of the jth variable and given by $(\gamma_{jj}^{o})^{\frac{1}{2}} = (\mathrm{var}(y_{jt}))^{\frac{1}{2}}$

the parameters u, Γ_0, R_0 are estimated from data $(Y_1 \cdots\cdots Y_T)$ using the sample moments

$$\bar{Y} = \frac{1}{T}\sum_{t=1}^{T} Y_t \to E(Y) = \mu \tag{5}$$

That is $E(Y) = \mu$

$$\hat{\Gamma}_O = \frac{1}{T}\sum_{t=1}^{T}(Y_t - \bar{Y})(Y_t - \bar{Y})' \to \text{var}(Y_t) = \Gamma_o \tag{6}$$

$$\hat{R}_0 = \hat{D}^{-1}\hat{\Gamma}_o D^{-1} \tag{7}$$

The ergodic theorem justifies the convergence of the sample moments to their population counterparts.

Cross Covariance and Correlation Matrices

Given that a multivariate time series $\{\mathbf{Y}_t\}$ with components each having auto-covariance and auto-correlations, there are also cross lead-lag covariance and correlation between all possible pairs of components. The auto-covariance and auto-correlations of $\{y_{jt}\}$ for $j = \{1,2,\cdots,p\}$ are defined for lag k as

$$\gamma_{jj}^{k} = \text{cov}(y_{jt}, y_{jt-k}) \tag{8}$$

$$\rho_{jj}^{k} = corr(y_{jt}, y_{jt-k}) = \frac{\gamma_{jj}^{k}}{\gamma_{jj}^{o}}, \tag{9}$$

and these are symmetric in k: $\gamma_{jj}^{k} = \gamma_{jj}^{-k}, \rho_{jj}^{k} = \rho_{jj}^{-k}$

the cross lag covariance and cross lag correlations between y_{it} and y_{jt} are defined mathematically as

$$\gamma_{ij}^{k} = \text{cov}(y_{it}, y_{jt-k}) \tag{10}$$

$$\rho_{ij}^{k} = corr(y_{jt}, y_{jt-k}) = \frac{\gamma_{ij}^{k}}{\sqrt{\gamma_{ii}^{o}\gamma_{jj}^{o}}} \tag{11}$$

However, these are not necessarily symmetric in k. In general,

$$\gamma_{ij}^{k} = \text{cov}(y_{it}, y_{jt-k}) \neq \text{cov}(y_{it}, y_{jt+k})$$

$$= \text{cov}(y_{it-k}, y_{jt}) = \gamma_{ij}^{-k} \tag{12}$$

The following are defined accordingly :

- If $\gamma_{ij}^{k} \neq 0$ for some $k > 0$, then y_{jt} is said to lead y_{it}
- if $\gamma_{ij}^{-k} \neq 0$ for some $k > 0$, then y_{it} is said to lead y_{jt}
- it is also possible that y_{it} leads y_{jt} and vice versa. In such a case, there is said to be feedback between two series.

All the lag k cross variance and correlations are summarized in the $(p \times p)$ lag k cross variance and lag k cross-correlation matrices

$$\Gamma_{k} = E[(Y_t - \mu)(Y_{t-k} - \mu)]$$

which results in the matrices

$$\mathbf{\Gamma}_{k} = \begin{pmatrix} \text{cov}(y_{1t,}y_{1t-k}) & \text{cov}(y_{1t,}y_{2t-k}) & \cdots & \text{cov}(y_{1t,}y_{pt-k}) \\ \text{cov}(y_{2t,}y_{1t-k}) & \text{cov}(y_{2t}, y_{2t-k}) & \cdots & \text{cov}(y_{2t,}y_{pt-k}) \\ \vdots & \vdots & \ddots & \vdots \\ \text{cov}(y_{pt,}y_{1t-k}) & \text{cov}(y_{pt,}y_{2t-k}) & \cdots & \text{cov}(y_{pt}, y_{pt-k}) \end{pmatrix}$$

and

$$\mathbf{R}_{k} = \mathbf{D}^{-1}\mathbf{\Gamma}_{k}\mathbf{D}^{-1}.$$

The matrices $\mathbf{\Gamma}_{k}$ and $\mathbf{R}_{k}$ are not symmetric in k but can be shown that $\mathbf{\Gamma}_{-k} = \mathbf{\Gamma}_{k}'$ and $\mathbf{R}_{-k} = \mathbf{R}_{k}'$, and $\mathbf{D}$ is a covariance matrix.

Vector Auto-Regressive Model

The vector autoregression (VAR) is an effective, flexible and simplest way of analyzing multivariate time series data. It is an extension of the univariate autoregressive model to a dynamic multivariate time series. The VAR model has shown with time to be the most useful for describing the dynamic behaviour of financial, economic and climate behaviour, and for forecasting. Forecast from the VAR model is flexible because they can be made conditional on the potential future paths for specific variables in the model. The general model for of the VAR of order k or lag k is represented as

$$y_t = \phi_o + \phi_1 y_{t-1} + \cdots + \phi_k y_{t-k} + z_t \tag{13}$$

where ϕ_0 is a p - dimensional vector, $\phi_s; (s = 1, 2, \ldots, k)$ is each $(p \times p)$ matrix and $\mathbf{z}_t$ is a system of the serially uncorrelated random vector with a zero mean and covariance matrix $\mathbf{\Sigma}$. The vector $\mathbf{z}_t$ is considered to have a multinomial normal distribution and therefore have the following assumptions:

1. $E(\mathbf{z}_t) = \mathbf{0}$
2. $E(\mathbf{z}_t \mathbf{z}_t') = \mathbf{0}$, which is a contemporaneous matrix of the error term and a $(p \times p)$ positive definite matrix.
3. $E(z_t, z_{t-k}') = \mathbf{0}$. That is, for any non-zero k, there is no correlation across time.

Reduced Structure of the VAR model

In a broad-spectrum, the coefficient matrix ϕ of the VAR model of order p measures the dynamic dependencies of y_{it}. The concurrent relationship y_{1t} y_{2t}, $\cdots$, y_{nt} is shown by the off-diagonal element of σ_{ij} the covariance matrix $\mathbf{\Sigma}$. of z_{it}. If $\sigma_{ij} = 0$, then there is no contemporaneous linear relationship between the component series. In econometric literature, VAR (1) is a reduced form of the model because it does not show clearly the contemporaneous dependence amid the component series. An explicit expression involving the concurrent relationship can be deduced from the reduced form model by a simple linear transformation. Since $\mathbf{\Sigma}$ is positive definite, there exists a lower triangular matrix $\boldsymbol{L}$ as identity matrix, and a diagonal matrix $\boldsymbol{G}$, such that $\mathbf{\Sigma} = \mathbf{LGL}'$.

Then, it follows that $\mathbf{L}^{-1}\mathbf{\Sigma}(\mathbf{L}') = \mathbf{G}$.

Let $b = (b_{1t,\cdots,}b_{kt})' = L^{-1}z_t$. Then $E(b_t) = L^{-1}E(z_t) = \mathbf{0}$, $\text{cov}(b_t) = L^{-1}\mathbf{\Sigma}(L')^{-1} = G$

Because G is a diagonal matrix, the components of b_t are uncorrelated, when we multiply L^{-1} on the left by the reduced VAR model of order one, we get;

$$L^{-1}y_{1t} = L^{-1}\phi_0 + L^{-1}\phi y_{t-1} + L^{-1}z_t = \phi_0^* + \phi^* y_{t-1} + b_t \tag{14}$$

where $\phi_0^* = L^{-1}\phi_0$ is a p-dimensional vector and $\phi^* = L^{-1}\phi$ is a $p \times p$ matrix. Because of the special matrix structure, the ith row is L^{-1} is of the form $(u_{i1}, u_{k2}, \ldots, 1)$. Therefore the ith model is,

$$y_{it} + \sum_{s=11}^{i-1} u_{is} y_{st} = \phi_s^*, 0 + \sum_{s}^{i} \phi_{si}^* y_{s,t-1} + b_{it} \tag{15}$$

with $\phi_i^*,0$ being the ith element of ϕ_0^* and ϕ_{is}^* is the (i,s) element of ϕ^*. Since b_{it} is uncorrelated with b_{st} for $1 \le s < i$. Eq. (15) shows clearly the concurrent linear dependence of y_{it} on y_{st} where $1 \le s \le i-1$. This equation is also known as the structural equation for y_{it} in econometric literature.

Stationary Conditions and Moments of VAR(1) Model

Given that the model of VAR (1) is weakly stationary. Applying the expectation of the model using $E(z_t)=0$ we have $E(y_t)=\phi_0+\phi E(y_{t-1})$.

Because $E(y_t)$ is time-invariant, we obtain $\mu \equiv E(y_t)=(I-\phi)^{-1}\phi_0$ on condition that the matrix $(I-\phi)$ is nonsingular, where I is a $k \times k$ unit matrix using $\phi_0=(I-\phi)u$, the VAR(1) would become

$$(y_t-u)=\phi(y_{t-1}-u)+z_t \;. \tag{16}$$

We let $\tilde{y}_t=y_t-u$ represent the mean-corrected time series. Based on this condition, we obtain the VAR(1) model to be

$$\tilde{y}_t=\phi\tilde{y}_{t-1}+z_t \tag{17}$$

We use Equation (17) to derive properties of the VAR (1) model. It is possible through repeated substitution of Eq. (17) to obtain the equivalent equation

$$\tilde{y}_t=z_t+\phi z_{t-1}+\phi^2 z_{t-2}+\phi^3 z_{t-3}+\cdots\cdots \tag{18}$$

Equation (18) exhibits several characteristics of the VAR (1) model and stated as follows:

1. Since z_t is serially uncorrelated, implies that the $\text{cov}(z_t, y_{t-\ell}) = \mathbf{0}$. z_t is not correlated with $y_{t-\ell}\ \forall\ \ell > 0$. Because of this, z_t is known as the shock of the series at time t.
2. post multiplication of z_t' taking expectations, and the fact no serial correlation in the z_t process we get $\text{cov}(y_t, z_t) = \mathbf{\Sigma}$.
3. For a VAR(1) model, y_t is dependent on previous innovations z_{t-j} with coefficient matrix ϕ^j.

In the third note, if such dependence is to make sense, then ϕ^j must approach 0 as $j \to \infty$. This implies that the k eigenvalues of ϕ must be less than 1 in modulus which is the necessary and sufficient condition for weak stationarity of y_t, provided that there exists a covariance matrix of z_t. From this, the stationary conditions reduce to that of the univariate AR (1) process in which $|\emptyset| < 1$

Also, since $|\lambda I - \emptyset| = \lambda^k \left|I - \emptyset\frac{1}{\lambda}\right|$, the eigenvalues of ϕ are the inverse of the roots of the determinant $|I - \emptyset B|$, thus an equivalent and necessary conditions for stationarity of y_t is that all roots of the determinant of $|\emptyset B|$ are more than one in modulus ; this implies all roots lie outside the unit circle in the complex plane.

Vector AR Models

In Equation (13), the VAR of order k is

$$y_t = \phi_o + \phi_1 y_{t-1} + \cdots + \phi_k y_{t-k} + z_t$$

When the backshift operator B is applied to the VAR(k) model, it becomes $(I - \phi_1 B - \cdots - \phi_k B^k) y_t = \phi_0 + z_t$, where I is a $p \times p$ identity matrix. This can be written further in a compressed form as $\phi(B) y_t = \phi_0 + z_t$, where $\phi(B) = (I - \phi_1 B - \cdots - \phi_k B^k)$ is a matrix polynomial. Given that y_t is less stationery, we get $\mu = E(y_t) = (I - \phi_1 - \cdots - \phi_P)^{-1} \phi_0 = [\phi(1)]^{-1} \phi_0$, on condition that the inverse exist. We assume $\tilde{y}_t = y_t - u$. The VAR(k) model becomes

$$\tilde{y}_t = \phi_1 \tilde{y}_{t-1} + \cdots \phi_p \tilde{y}_{t-p} + z_t \tag{19}$$

Applying the same method as in the VAR(1) model, we find that

1. $\text{cov}(y_t, z_t) = \Sigma$
2. $\text{cov}(y_{t-\ell}, z_t) = \mathbf{0}$
3. $\Gamma_\ell = \phi_1 \Gamma_{\ell-1} + \cdots + \phi_p \Gamma_{\ell-p}$ for $\ell > 0$

A third property is also known to be the moment equation of VAR(k) model. This is a multivariate version of the Yule-Walker equation of a univariate AR(k).

An easy approach of comprehending the axioms of the VAR(k) is in Equation (1) is to utilize the results of the VAR(1) model in Equation (1). This can be done by transforming the VAR(k) model y_t into a kp - dimensional VAR(1) model. Particularly let $x_t = (\tilde{y}'_{t-p+1,} \tilde{y}'_{t-p+2} \cdots, \tilde{y}')'$ and also

$b_t = (0,\cdots,0,z_t')'$ become two kp- dimensional process, b_t has a zero mean and the covariance matrix b_t is a $kp \times kp$ matrix containing zero entries except for the lower right corner, which is $\boldsymbol{\Sigma}$. The VAR(k) model can now be written as

$$y_t = \phi^* x_{t-1} + b_t \tag{20}$$

where ϕ^* is a $kp \times kp$ matrix given by

$$\boldsymbol{\varphi}^* = \begin{pmatrix} \mathbf{0} & \mathbf{I} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{I} & \mathbf{0} & \cdots & \mathbf{0} \\ \vdots & \vdots & \vdots & & & \vdots \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{I} \\ \boldsymbol{\varphi}_{\mathbf{k}} & \boldsymbol{\varphi}_{\mathbf{k-1}} & \boldsymbol{\varphi}_{\mathbf{k-2}} & \boldsymbol{\varphi}_{\mathbf{k-3}} & \cdots & \boldsymbol{\varphi}_{\mathbf{I}} \end{pmatrix} \tag{21}$$

where $\mathbf{0}$ and $\boldsymbol{I}$ are the $p \times p$ zero matrices and identity matrix, respectively. In the literature, $\boldsymbol{\varphi}^*$ is known as the companion matrix of the matrix polynomial $\phi(B)$.

Building the VAR() Model

The theory of the partial autocorrelation function of a univariate time series can be generalized to specify the order k of vector series. Below is how this is generated.

$$\begin{aligned} y_t &= \phi_0 + \phi_1 y_{t-1} + z_t \\ y_t &= \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + z_t \\ &\vdots \\ y_t &= \phi_0 + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + z_t \end{aligned}$$

The use of ordinary least squares can estimate the parameters of the model. This method is called the multivariate linear regression estimation in multivariate statistical analysis. This can be verified in an article by Johnson and Wichern (1998). For the *i*th equation, we let $\hat{\phi}_j^{(i)}$ be the OLS estimate for ϕ_j and $\hat{\phi}_0^{(i)}$ be the estimate for ϕ_0, where the superscripts (i) are used to represent the estimates are that of a VAR(*i*) model. The error estimate is;

$$\hat{z}^{(i)}{}_t = y_t - \hat{\phi}_0^{(i)} - \hat{\phi}_1^{(i)} y_{t-1} - \cdots - \hat{\phi} i^{(i)} y_{t-i}$$

Given that $i = 0$, the residual is defined as $\hat{y}_t^{(0)} = y_t - \bar{y}$ where $\bar{y}$ is the sample mean of y_t. Therefore, the residual covariance matrix is given as

$$\hat{\mathbf{C}}_{\mathbf{i}} = \frac{1}{T - 2i - 1} \sum_{t=i+1}^{T} \hat{z}_t^{(i)} (\hat{z}_t^{(i)})', i \geq 0$$

For the necessary condition for the order of k, test the hypothesis $H_0 : \phi_\ell = 0$ against $H_1 : \phi_\ell \neq 0$ given $\ell = 1, 2, 3, \ldots$ This hypothesis can be tested using Equation (12) with a test statistic

$$M(1) = -(T - k - \frac{5}{2}) In\left(\frac{|\hat{\mathbf{C}}_{\mathbf{1}}|}{|\hat{\mathbf{C}}_{\mathbf{0}}|} \right),$$

where $\hat{\mathbf{C}}_{\mathbf{1}}$ and $\hat{\mathbf{C}}_{\mathbf{0}}$ are Covariance matrices of residuals.

Under some conditions of orderliness, the test statistic M(1) is asymptotically a chi-squared distribution with k^2 degrees of freedom (Tiao & Box, 1981).

Generally the use of the i^{th} and $(i-1)th$ equations in Equation (12) to investigate $H_0 : \phi_i = 0$ and $H_1 : \phi_i \neq 0$, that is to say, testing a VAR(*i*) model against VAR (*i*-1) model. It follows the test statistic

$$M(i) = -(T - k - i - \frac{3}{2})In\left(\frac{|\hat{\mathbf{C}}_{\mathbf{I}}|}{|\hat{\mathbf{C}}_{\mathbf{i-1}}|}\right)$$

and asymptotically, M(I) is a chi-squared distribution with k^2 degrees of freedom.

The VAR (k) Model with Exogenous Variables

In the previous section, we presented the VAR model in the form

$$y_t = \phi_o + \phi_1 y_{t-1} + \cdots + \phi_k y_{t-k} + z_t$$

for a multivariate time series $\{Y_t\} = \{y_{1t}, y_{2t}, \cdots, y_{pt}\}$. Suppose that the variables are influenced by another set of multivariate times series of climate factors $\{C_t\} = \{c_{1t}, c_{2t}, \cdots, c_{qt}\}$. Then an incorporated VAR model which would be denoted as IVAR (k) is an extension of the VAR to incorporate climate multivariate time series data set is an extension of equation (13) and will be written as

$$\begin{aligned} y_t &= \phi_o + \phi_1 y_{t-1} + \cdots + \phi_j y_{t-k} + \\ &\quad w_1 c_{t-1} + w_2 c_{t-2} + \cdots + w_q c_{t-k} + z_t \end{aligned} \tag{22}$$

In Equation (22), ϕ_0 and ϕ_j are as defined already. The coefficient w_j is the coefficient matrix of dimension, $p \times q$. Similar to the matrix ϕ_j, the t^{th} row of w_j are the coefficients at lag j for each of the q influencing factor series. To present a more concise form that distinguishes clearly between the two series involved in Equation (21), we could present a formulation that shows clearly two main components series. The new formulation would be stated as;

$$y_t = \phi_o + (\phi_1 \mid \phi_2 \mid \cdots \mid \phi_p) y_{tL} + (w_1 \mid w_2 \mid \cdots \mid w_p) C_{tl} \tag{23}$$

Multivariate Portmanteau Test

According to Hosking (1980, 1981) and Li and Mcleod (1981) the multivariate generalization of the Ljung-Box statistic $Q(m)$ which is a univariate test is well known. Hypothesis for this kind of test for the multivariate time series data may be given by

H_o: $\rho_1 = \rho_2 = \cdots = \rho_m = 0$

H_a: $\rho_i \neq 0$ for some $i \{= 1, 2, \ldots, m\}$

The test statistic is used to check whether there exists autocorrelation between y_{jt} in the vector series. The test statistic for the test is

$$Q_{K(m)} = T^2 \sum_{\ell=1}^{m} \frac{1}{T-\ell} tr(\hat{\Gamma}_\ell' \hat{\Gamma}_0^{-1} \hat{\Gamma}_\ell \hat{\Gamma}_0^{-1}) \tag{24}$$

where T represents sample size, k defines the dimension of y_t, $tr(\phi)$ is the trace of matrix ϕ which represents the summation of all diagonal elements of ϕ under H_o. The test statistic follows a chi-squared distribution with k^2m degrees of freedom.

Granger Causality

For the purpose of this study, after developing the VAR model, we seek to make some estimate forecast of response variables. The theoretical notations behind these predictions are as a result of Granger (1960). The test results would be displayed in tables for further interpretation.

1. For some response variable, say Y_1, to be useful in predicting another variable, say Y_2, we can conclude that Y_1 is said to have granger-caused Y_2.
2. Previously, if Y_1 failed to granger-cause Y_2 if $\forall\ s > 0$, the MSE of a prediction of $Y_{2,\,(t+s)}$ given $(Y_{2t},\ Y_{2,(t-1)}, \dots)$ is the same as the MSE of the forecast.

Impulse Response Function

This is one of the model check diagnosis of the VAR model. It is the response to a shock from the response variable onto itself and onto other response variables over time, as a result of a one-unit standard deviation from any of the variables being the source of the shock. For the purpose of this study, after developing the IVAR model, we would show the impulse response graphs which would indicate how the dynamic system of the IVAR model would respond to various shocks over time.

Chapter Summary

The study is carried out in Nyankpala under the Tolon district of the Northern region of Ghana. It has a total population of about 3.706 million as at 2010 population census. The main occupation of the inhabitants is farming. Data collected for the study is from the centre for scientific and industrial research; an agric research station in Nyankpala. Data collected includes climate conditions and yield of rice varieties specifically from 1957 to 2016. Thus, such a dataset comprises a time series multivariate dataset that may be partitioned into two separate multivariate dataset, one on the rice varieties and the other on climate conditions for the same set of observations. The chapter has also reviewed several techniques that are considered suitable for the analysis of such data. The techniques include the vector autoregressive model (VAR) and underlying conditions. The VAR which involves an initial set of random vector is incoprated with another set of vector variables of climate conditions. It is anticipated that the inclusion of the climate condition random vector could improve the model for determining the yield of each of the rice varieties.

CHAPTER FOUR

RESULTS AND DISCUSSION

Introduction

This chapter uses multivariate times series statistical techniques to analyze the data for the research. The data is composed of two major component variable sets. The first is the yield of four varieties of rice: namely, Mandii, O.Sativa, Kpukpula and Bazulgu. The second set of variables consists of five climate conditions: namely, rainfall, temperature, total evaporation, wind speed and sunshine, in hours. The data is composed of a total of 60 observations of each variable taken from 1957 to 2016. The nature of the data requires the application of multiple software for analysis. The software utilised includes Excel, Minitab, Gretl and R studio.The model would be developed in two stages: the first is to develop the model from only the rice varieties; the second is to develop the model which would include the climate conditions. The aim is to determine by how much the rice production would be influenced by climate conditions.

Descriptive Statistics

Table 1 shows simple descriptive statistics from the data on all the nine-time series variables. The table shows that in certain years, there is no production for all four rice varieties. The records show that this is due to severe drought in those years (in 1982 and 1983). It is not surprising therefore that there are no evapo-transpirationvalues recorded in those years. Figure 2 shows those years in which values are at the extremes.

Table 1: Descriptive Statistics of Variables

Variable	Mean	SD	Minimum	Maximum
Mandii	24479	14063	0.00	62416
Bazulgu	21727	14138	0.00	84612
Sativa	15673	7107	0.00	29460
Kpukpula	15359	6637	0.00	29460
Rain	988.2	315.9	0.00	1560.00
Temp	33.925	4.533	22.30	47.80
Evapo-transpiration	141.81	34.42	0.00	190.10
Wind	3.638	0.931	2.00	5.70
Sunshine	6.528	1.290	3.70	9.40

Source: Researcher's Computation (2020)

Original Series of Variables

For the purpose of this research, in which the data as a multivariate time series, we need to determine the stationarity for each variable, to achieve a constant variance and zero-mean data. We first consider the plot of the dependent variables on a single graph as well as that of the independent variables. The plot of the yield for the four rice varieties is shown in Figure 2.

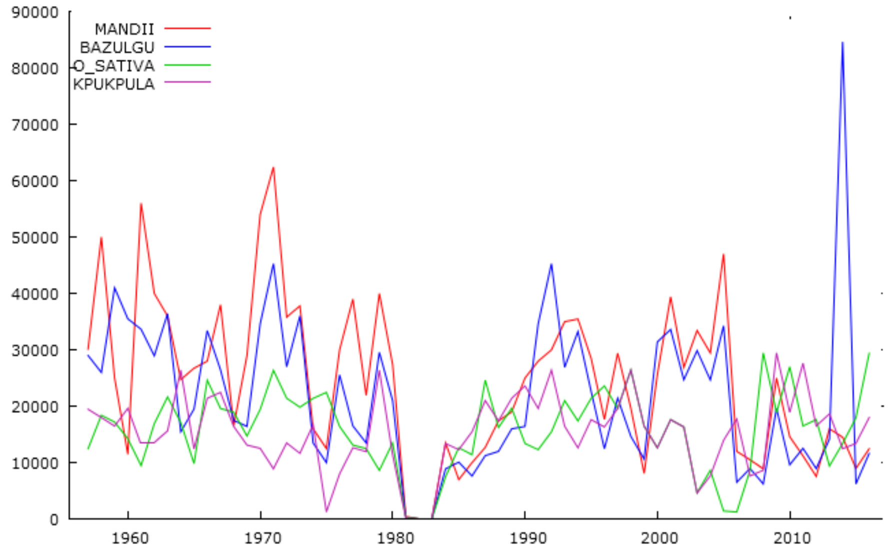


Figure 2: Time series plot of the yield of four rice varieties

From Figure 2, it can be seen that each variety of rice seems to have a downward trend from 1957 to 1981. Then, there is a steady increase in trend between the periods of 1981 to1995. The trend again from 1995 experiences an undulating behaviour till 2016. It would be necessary to plot the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the series to determine if there exists a unit root in the data. Figures 3 to 6 show the graphs of the ACF and PACF of the four rice varieties.

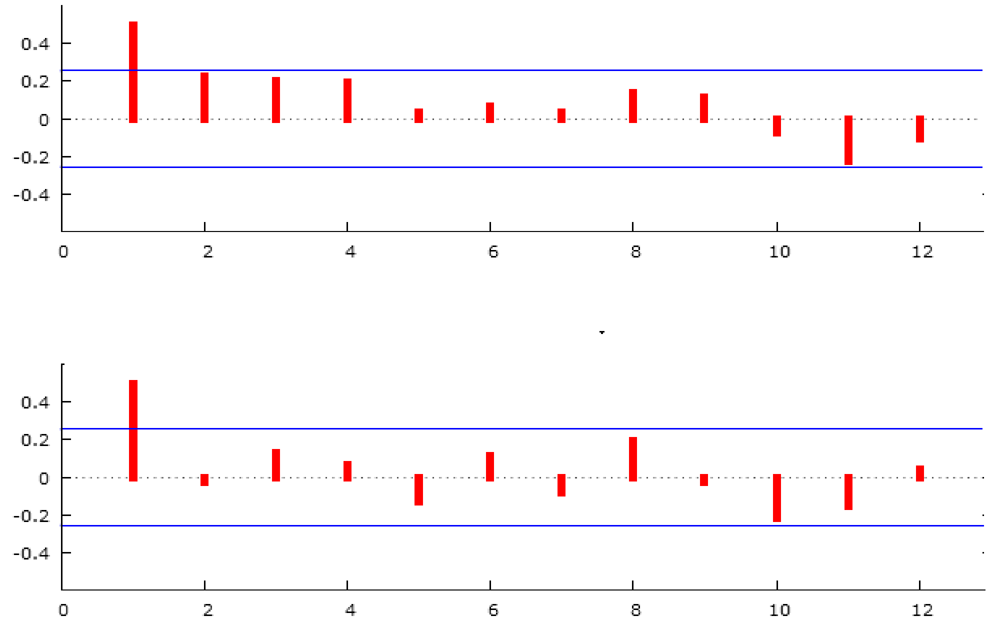


Figure 3: ACF and PACF of Mandii up to lag 12

From Figure 3, the first is the ACF and the second is the PACF of Mandii, It is seen that the ACF is statistically significant at lag 1. A slow decline in the bars suggests a long memory of the process, and indicates some amount of correlation at some number of lag orders, in this case, lag 4. The PACF, on the other hand, is also significant only at lag 1. It describes the amount of correlation between Mandii and lags of itself which is not explained by autocorrelation at lower lag order. A PACF which crosses the blue line (i.e., the confidence interval band) and greater than 0.5 is a hint of a possible unit root in the data and therefore would suggest non-stationarity in the variable Mandii. Both the ACF and PACF show that the series could be non-stationary and that the model for Mandii could be dominated by an AR(1) component.

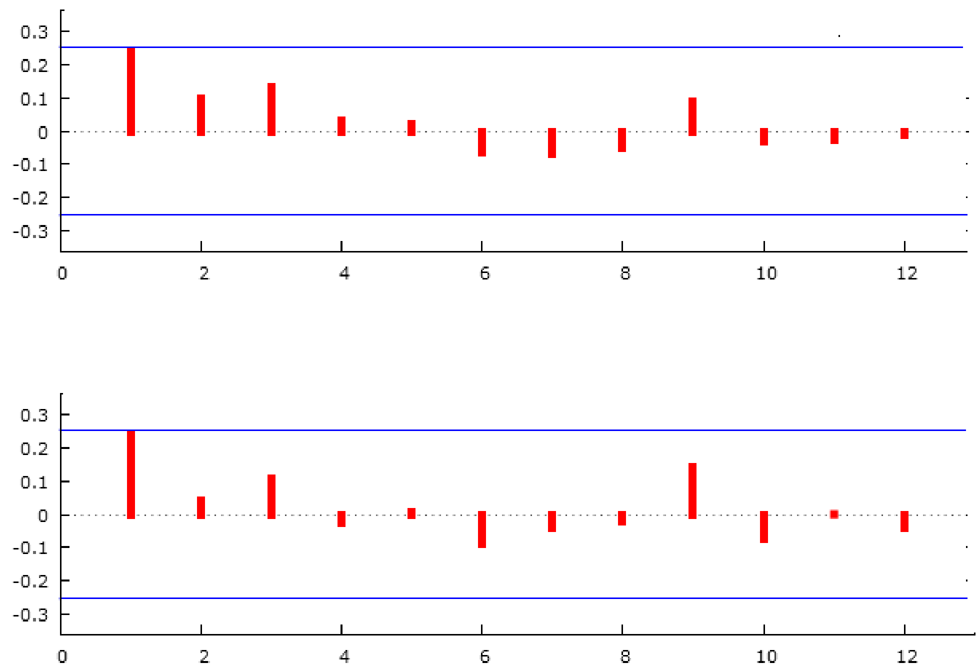


Figure 4: ACF and PACF of Bazulgu up to lag 12

Figure 4 is the ACF and PACF plot for Bazulgu. The ACF is barely statistically significant at lag 1 only. The pattern of both the ACF and PACF appear the same and almost all lie within the 95% confidence both, suggesting that the data could be stationary. This would be further confirmed in the augmented Dickey-Fuller test.

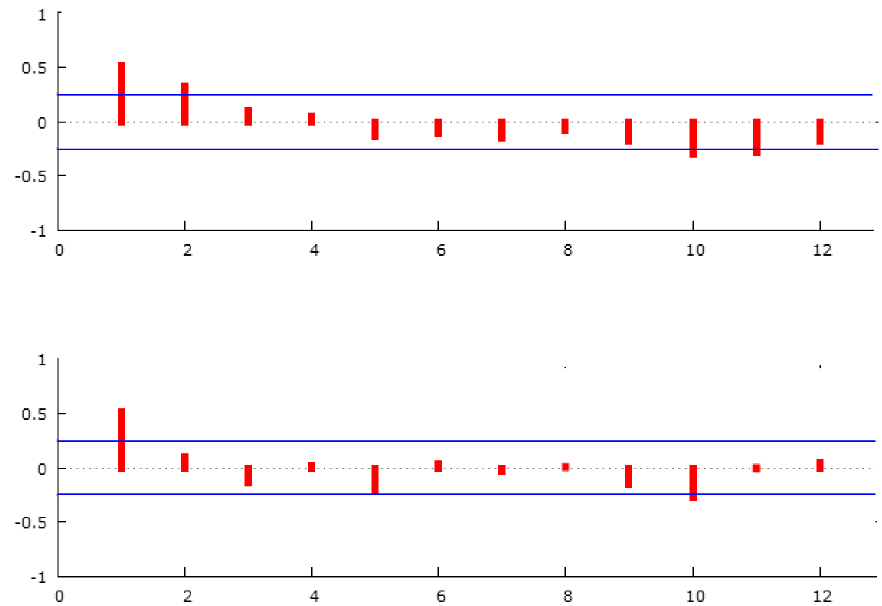
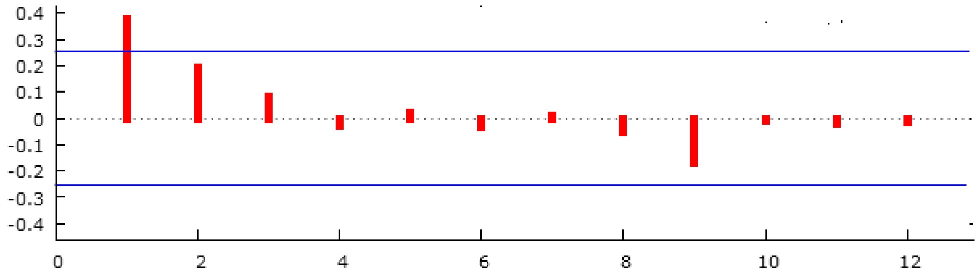


Figure 5: ACF and PACF of Sativa up to lag 12

Figure 5 is the ACF and PACF of O.Sativa. The graph shows that the autocorrelation for O. Sativa are statistically significant at 1% at lag 1 and also statistically significant at lag 2 and 10 and 11. A slow decline in the bars also suggests a long memory of the process. The PACF, on the other hand, is also significant at lag 1 and which also suggests that there could exist unit root in the series.



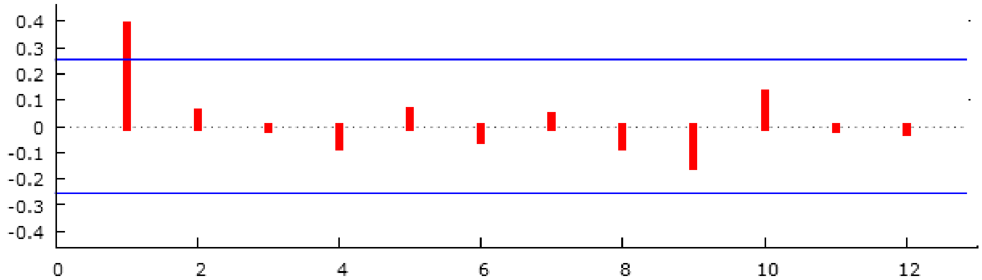


Figure 6: ACF and PACF of Kpukpula up to lag 12

Figure 6 is the ACF and PACF graph for Kpukpula. It suggests that the ACF is statistically significant at lag 1. The PACF on the other hand, which has the highest bar even though crossed the bands, but less than 0.5 suggest that the data may be stationary and therefore we would not expect the existence of unit root in the data for Kpukpula. Next, the researcher confirms stationarity status of the rice data and also the climate dataset using the augmented Dickey-Fuller test at 5%. The *ps* with constant and with constant and trend after testing for stationarity among the rice data set are presented in Table 2

Table 2: Test of Stationarity of Rice Varieties

Variable	P with contant	P with constant and trend	Conclusion
Mandii	0.2974	0.4075	Not Stationary
Bazulgu	4.798×10^{-6}	2.974×10^{-5}	Stationary
O-Sativa	0.02046	0.1328	Not Stationary
Kpukpula	8.603×10^{-5}	6.11×10^{-4}	Stationary

Source: Researcher's Computation (2020)

From table 2, it can be seen that Mandii and O. Sativa are not stationary as the associated *p*s are greater than 0.05. To attain stationarity, we need to perform the first difference in these variables. Figure 7 shows the plot after the first difference of Mandii and O.Sativa with the other stationary variables.

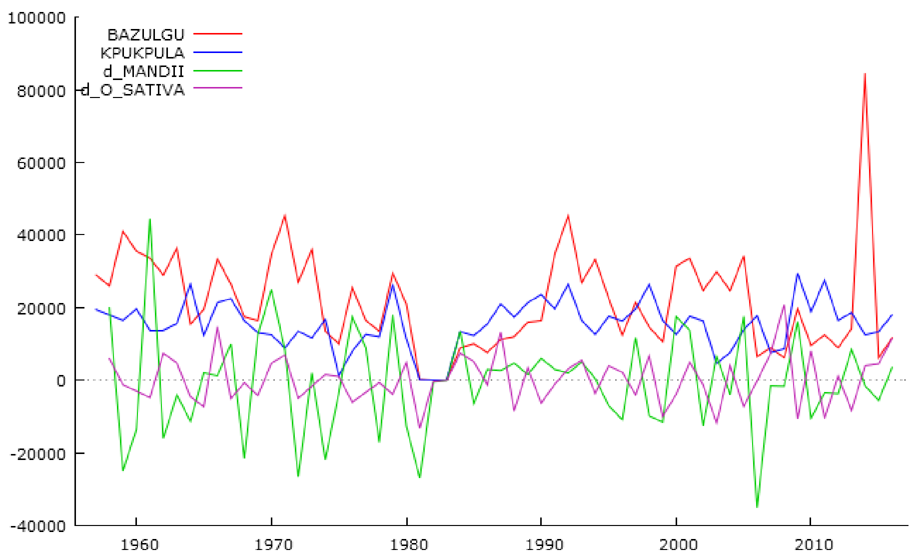


Figure 7: Time series plot of Mandii and O.sativa after first difference

From Figure 7, it can be seen clearly that the individual graphs have a constant trend over time, and hence, constant mean as well. This suggests that the response variables are now all stationary. The results of the ADF test to confirm stationarity of the first differenced variables is shown in Table 3.

Table 3: ADF Test After First Difference of Mandii and O.Sativa

Variable	P with constant	P with constant and trend	Conclusion
Mandii	8.504×10^{-5}	0.0008447	Stationary
O-Sativa	0.04493	0.1685	Not Stationary

Source: Researcher's Computation (2020)

From the Table 3 , it can be seen that stationarity is obtained in the variable Mandii but not in O.Sativa. We, therefore, need to further difference O.Sativa to achieve absolute stationarity. Results of the ADF test for O.Sativa after second difference is presented in Table 4

Table 4: ADF Test for Stationarity for O.Sativa

Variable	P with constant	P with constant and trend	Conclusion
O.Sativa	3.81×10^{-7}	5.3×10^{-6}	Stationary

Source: Researcher's Computation (2020)

Table 4 exhibits stationarity in the data after a second difference of the variable O. Sativa at 5% significant level. Again we would also plot the original series of the climate conditions which represent our 'independent' variables. This procedure is a preliminary test to show whether there exists a unit root in the data The graph in Figure 8 shows the original series plot of the climate conditions of the data from a period of 1957 to 2016.

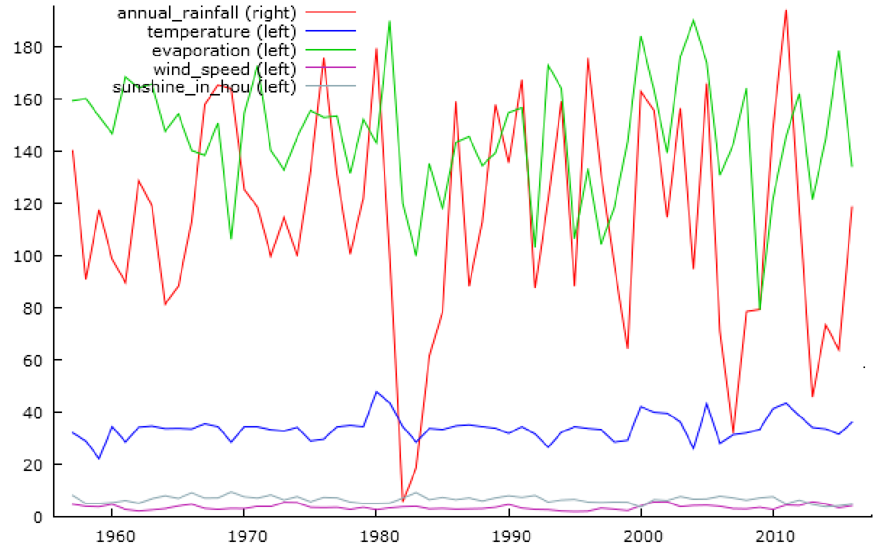


Figure 8: Time series plot of climate conditions

From the graph above, the individual series shows a constant trend except that of rainfall that is slightly undulating or has a sinusoidal movement over time. Wind speed and sunshine show a very close movement over time from 1957 to 2016. Their movement of the two series could also indicate a sign of multicollinearity. Table 5 shows the results of the ADF test, using a maximum lag up to 10 at 5% which is a confirmatory procedure for stationarity of the independent variables.

Table 5: ADF Test Results for Climate Conditions

Variable	*p* with constant	*p* with constant and trend	Conclusion
Annual Rainfall	2.12×10^{-5}	0.0001	Stationary
Temperature	6.65×10^{-6}	2.618×10^{-5}	Stationary
Evaporation	0.0004255	0.003933	Stationary
Wind Speed	0.001561	0.007337	Stationary
Sunshine	0.01682	0.0003483	Stationary

Source: Researcher's Computation (2020)

The above results of the ADF test confirm that the independent variables are stationary and therefore we can be assured that it has constant mean and variance and suitable to fit the vector autoregression model.

Cross Correlogram of The Response Variables

Is the analysis of correlation Statistics of data at different time lags apart of a bivariate sense, for our research, we consider a maximum of lag 12 for the pairwise correlogram of the response variable. The reason for this procedure is to investigate the measure of correlation that exists between pairwise variables or the extent of multicollinearity between the variables.

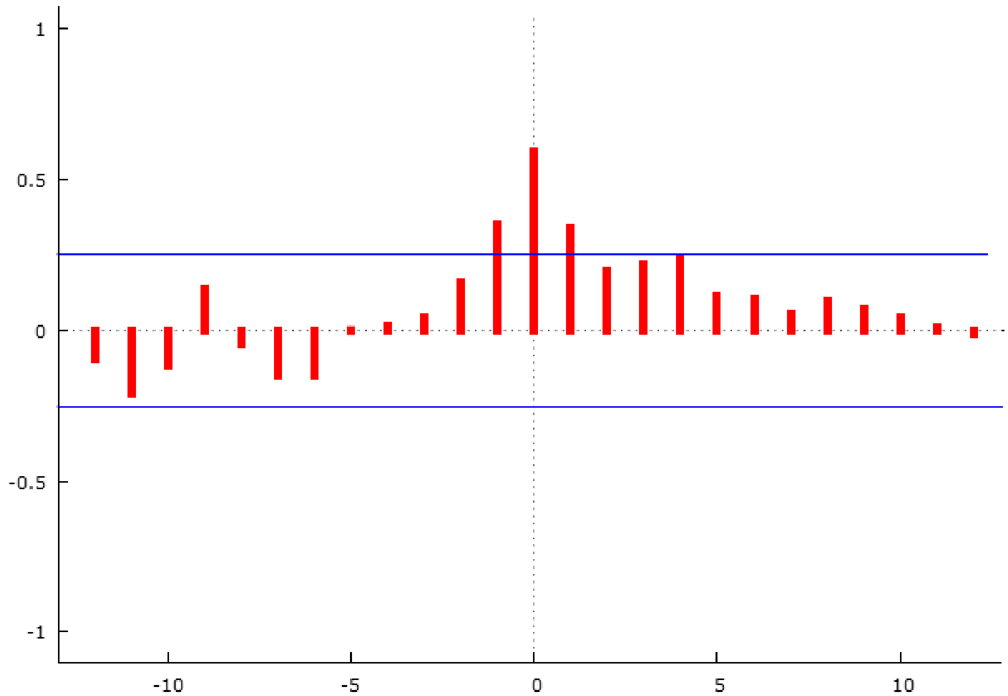


Figure 9 : Cross correlogram of Mandii and Bazulgu

From the above, we can observe that the highest correlation between the two yields of rice occurred at lag 0 at 1% level of significance, or when the two are considered simultaneously, the peak of their correlation is 0.5952 at lag 0. Also, the next highest correlation between the two yields of rice is observed when they are considered one time apart. We can also observe that apart from correlation values at lag 0 and lag 1, the correlation at different lags are not statistically significant except correlation values of at lag 3 and 4 which are statistically significant at 10%. This could also mean that, when the yield of one variable increases over time, the yield of the other is also likely to increase over that same time apart. We would also consider the cross correlogram of Mandii and O. Sativa

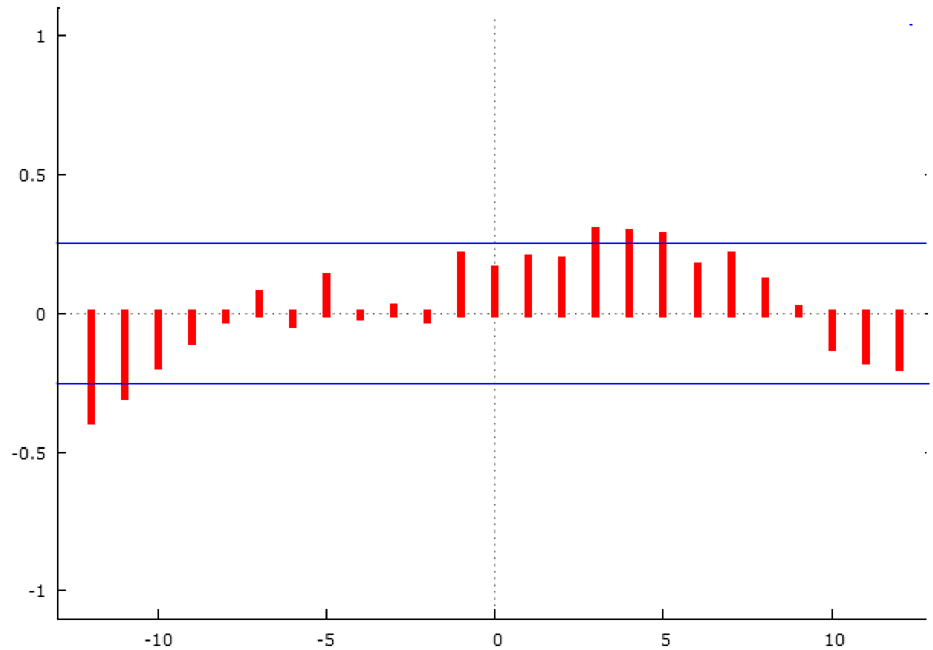


Figure 10: Cross correlogram of Mandii and Sativa

From the above cross correlogram between the two yields of rice, it can be observed that the correlation values are significant at lags 3, 4 and 5. The correlation at different time lags apart from lags 3,4 and 5 are not significant. The correlation of the above indicates that the yields of the two varieties are independent of one another, meaning that, when the yield of one variety is high, we would not expect the same for the other over time. We would also consider the cross correlogram for Mandii and Kpukpula

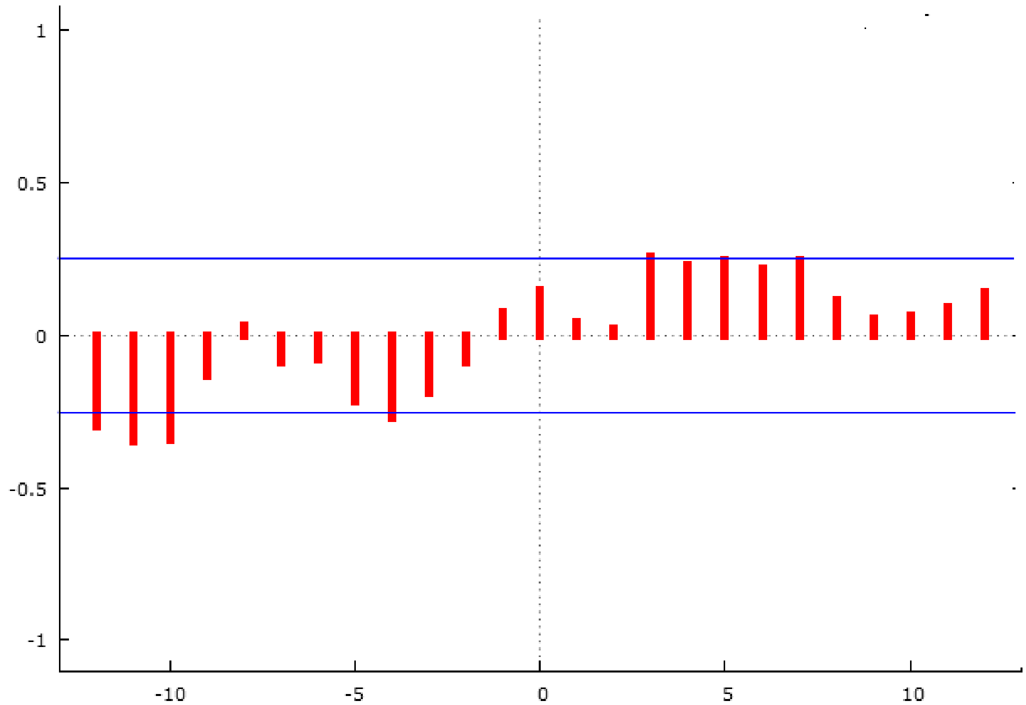


Figure 11 : Cross correlogram of Mandii and Bazulgu up to lag 10

The cross correlogram of the above indicates that the correlation between them is statistically significant at 10% from lag 4 up to lag 6 and 5% at lag 3.

We could also suggest that at a 10% level of significance, there is a high likelihood that the yield increase of one variety would be independent of the yield of the other. This, therefore, suggests that the yields of the varieties are not conditional but independent of each other over some time.

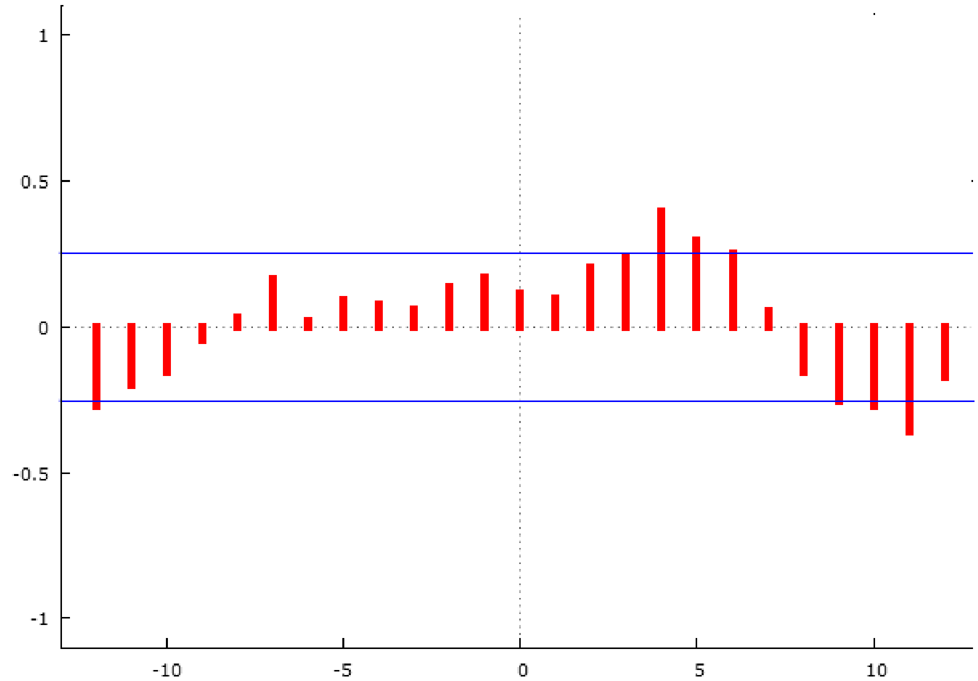


Figure 12: Cross correlogram of Bazulgu and O. Sativa up to lag 10

The cross correlogram indicates that when the yield is considered at the same time at lag 0, they have very insignificant correlations. However, we observe the highest cross-correlations at lag 3 which is statistically significant at 1%. We can also suggest that, at higher lag orders, the yields when considered at the same time, are negatively correlated which could imply that, when at a particular time lag, when there is an increase in the yield of one rice variety, we expect a decrease in the yield on the other.

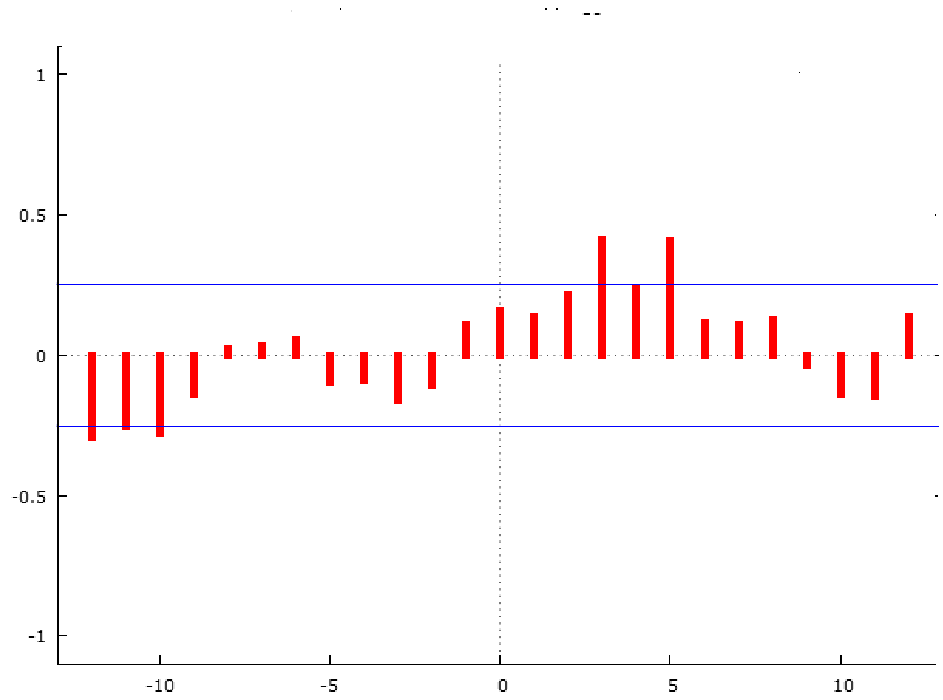


Figure 13: Cross correlogram of Bazulgu and Kpukpula up to lag 10

The cross correlogram indicates the highest cross-correlation at lag 3 with a cross-correlation value of 0.4102. The next highest cross-correlation values are at lag 5 with a value of 0.4064. This could suggest that, there is a 41% chance that the two varieties when considered at the same time, would yield almost equally at lag 3. This can be through at 40% at lag 5.

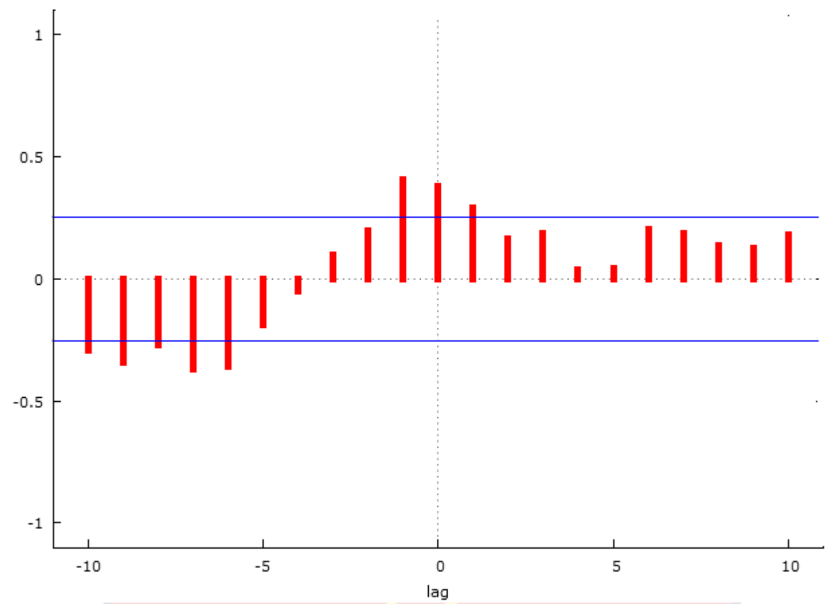


Figure 14 : Cross Correlogram of Sativa and Kpukpula up to lag 10

The cross correlogram indicates that it has significant correlation values at lag 0, as well as one time period apart. This could also mean that the yields of the varieties have some level of multicollinearity over time but is not too strong.

VAR Model Fitting

The models for only the four varieties are considered first. The Vector Auto Regression model for the study would be concerned with the VAR model with only varieties of rice and also another VAR model which would include the climate conditions. Based on the output on each model we would justify why one would be used instead of the other. Table 6 presents lag order selection procedure for the first model.

Table 6: Lag Order Selection for the VAR model of Rice Varieties Only

Variety	R- Square at lag 1	Std error at lag 1	P at lag1	Conclusion
Mandii	0.3147	12270	P =1	Fail to reject Ho
Bazulgu	0.1366	13830	P =1	Fail to reject Ho
Sativa	0.3018	6255	P =1	Fail to reject Ho
Kpukpula	0.2466	6058	P =1	Fail to reject Ho
	R- Square at lag 2	Std error at lag 2	P at lag 2	
Mandii	0.3147	12400	P =1	Fail to reject Ho
Bazulgu	0.1786	14160	P =1	Fail to reject Ho
Sativa	0.3768	6202	P =1	Fail to reject Ho
Kpukpula	0.3159	6058	P =1	Fail to reject Ho
	R- Square at lag 3	Std error at lag 3	P at lag 3	
Mandii	0.4357	12000	P =0.9999	Fail to reject Ho
Bazulgu	0.3122	13460	P =0.9999	Fail to reject Ho
Sativa	0.4328	6248	P =0.9999	Fail to reject Ho
Kpukpula	0.3192	6382	P =0.9999	Fail to reject Ho
	R- Square at lag 4	Std error at lag 4	P at lag 4	
Mandii	0.4627	12360	P =0.9997	Fail to reject Ho
Bazulgu	0.3542	13750	P =0.9997	Fail to reject Ho
Sativa	0.4987	6247	P =0.9997	Fail to reject Ho
Kpukpula	0.446	6100	P =0.9997	Fail to reject Ho

Source: Researcher's Computation (2020)

Table 6 shows the criteria for the lag selection process. The VAR model is tested for significance of residuals using the portmanteau test at 5% level of significance at various lags. The hypothesis of interest is stated as

H_o: autocorrelation of the residual time series are zero

H_a: autocorrelation of the residual time series are not zero

When $p < 0.05$, we reject the null hypothesis. From the test results at various lags, the aim is to determine the optimum lag for the VAR model, and the first column represents the R- Square of each VAR that was derived at various lags for the various varieties of rice. The second column represents the standard error associated with each model at a particular lag order. For convenience and optimality of our model, it is observed that the results of the R squares improve significantly as the lag order increases, with *p*s more than 0.05 until lag order 4. The lag order selection from the results indicates that lag order three would be optimum since there is no significant difference between the R-square values in the fourth lag order and that of lag three. The residuals or standard errors are a bit less for lag order 3 as compared to that of the lag order 4. Therefore, our VAR model is most suitable at lag order three.

$$\begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \\ y_{4t} \end{pmatrix} = \begin{pmatrix} 11530 \\ 5052 \\ 4577 \\ 7450 \end{pmatrix} + \begin{pmatrix} 0.4397^{*} & -0.0000 & 0.2945 & -0.1260 \\ -0.0606 & 0.3467 & -0.3000 & -0.0233 \\ 0.5999^{***} & 0.0792 & 0.0391 & 0.1291 \\ 0.2387 & 0.0469 & 0.0265 & 0.4138^{*} \end{pmatrix} \mathbf{y}_{t-1}$$

$$+ \begin{pmatrix} -0.1786 & 0.0793 & -0.2012 & -0.2451 \\ -0.0636 & 0.0762 & 0.1323 & 0.1080 \\ 0.0613 & -0.2214^{*} & 0.0487 & -0.0405 \\ 0.0551 & -0.0651 & -0.0815 & -0.0685 \end{pmatrix} \mathbf{y}_{t-2}$$

$$+ \begin{pmatrix} 0.0231 & 0.0302 & 0.3865 & 0.5241 \\ 0.0367 & -0.1867 & 0.0741 & 0.8980^{**} \\ -0.1879 & -0.0260 & 0.1833 & 0.0452 \\ -0.0078 & -0.0243 & 0.0162 & -0.0600 \end{pmatrix} \mathbf{y}_{t-3} + \begin{pmatrix} 12000 \\ 13460 \\ 6248 \\ 6382 \end{pmatrix}$$

Interpretation of the Model

From the results of these models, starting with vector equation model of Mandii, it has an R-square value of 43.57% from Table 6 which indicates that it can explain 43.57% of the total variation in the system. Vector Equation of Bazulgu shows that the R-square value is 31.22% which represents the total variation it can explain. The model also indicates that the coefficient of Variety Kpukpula is significant at 5% at lag 3. The coefficients with the asterisks show that they are significant. This can be verified from the VAR estimate results found on the appendix of the study. The model equation representing Sativa depicts that it has a 43.28% total variation accounted for. It also shows that the coefficient of Sativa is significant at 5% at lag 1.

The Incoporated Model with Exogeneous Variables

The last VAR model equation shows 31.92% of total variation it can explain. The coefficient of Sativa is significant at 5% at lag order 1. From above, we can observe that for each model, the coefficient of determination was stated and it indicates that there exists more than 50% of total variations unexplained in each model. The purpose of the study is the determination of the extent of the influence of climate conditions on the yield of rice varieties. For this reason, we would carry out another model of the vector auto-regression, which would include climate conditions. We hope that it becomes an improvement of the first model which would at least be able to account for 50% of the total variation in each model, therefore would be a better model to the previous.

Table 7: Portmanteau Test of Variables for Serial Correlation

Variety	R^2 at lag 1	Std error at lag 1	Portmanteau Test
Mandii	0.4297	11760	Chi-squared= 1238.4, df = 1539,
Bazulgu	0.3081	13010	p = 1
Sativa	0.368	6253	
Kpukpula	0.3031	6122	
	R^2 at lag 2	Std error at lag 2	
Mandii	0.5262	11690	Chi-squared = 1248.4, df = 1458,
Bazulgu	0.4277	13280	p = 1
Sativa	0.5021	6230	
Kpukpula	0.462	6037	
	R^2 at lag 3	Std error at lag 3	
Mandii	0.6302	12040	Chi-squared = 1251.5, df = 1377,
Bazulgu	0.6676	11600	p = 0.993
Sativa	0.6371	6194	
Kpukpula	0.5339	6544	
	R^2 at lag 4	Std error at lag 4	
Mandii	0.8254	10240	Chi-squared = 1402.7, df = 1296,
Bazulgu	0.7603	12170	p = 0.02
Sativa	0.8145	5522	
Kpukpula	0.7643	5782	

Source: Researcher's Computation (2020)

The results of the R-Squares shows a gradual increase or improvement as the lags increases for each model. On the other hand, apart from the standard errors of Sativa which reduce steadily as the lag order increases consecutively for each model, the errors of the remaining varieties are inconsistent. From the test, we can observe that, at lag order 4, the $p< 0.05$, and therefore suggest that we cannot fit the VAR model for lag order 4 since it would suggest that the white noise of the series are not equal to zero. From the test results even though the p of the model for lag order 1 and 2 are unity, meaning the highest p we can get, we would settle on lag order 3 which has considerably higher values of R-squares and can account for some significant level of variations in the model. The IVAR model shown represents coefficients of the response variables as well as the climate conditions at various lags.

$$
\begin{aligned}
\begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \\ y_{4t} \end{pmatrix} = \begin{pmatrix} 30830 \\ 40130 \\ 16270 \\ 18600 \end{pmatrix} &+ \begin{pmatrix} 0.096 & 0.1974 & 0.2478 & -0.2209 \\ -0.1821 & 0.3713 & -0.0982 & 0.0246 \\ 0.2852 & 0.2091 & -0.0548 & -0.1117 \\ 0.1122 & -0.0081 & 0.0167 & 0.1626 \end{pmatrix} \mathbf{y}_{t-1} \\
&+ \begin{pmatrix} -0.2124 & 0.1298 & -0.1802 & -0.1528 \\ -0.1653 & 0.2595 & 0.1084 & 0.4546 \\ 0.2001 & -0.1354 & 0.0835 & 0.0406 \\ 0.0818 & -0.0593 & -0.0343 & -0.0514 \end{pmatrix} \mathbf{y}_{t-2} \\
&+ \begin{pmatrix} -0.0856 & 0.0751 & 0.2766 & 0.3145 \\ -0.1502 & -0.1722 & 0.0488 & 0.9680^{*} \\ -0.0187 & 0.0293 & 0.1349 & 0.4073 \\ 0.0141 & -0.0159 & -0.1008 & 0.0141 \end{pmatrix} \mathbf{y}_{t-3} \\
&+ \begin{pmatrix} 5.657 & -417.4 & 57.91 & 2861 & 4085 \\ -3.9290 & -792.4 & 9.800 & 5806^{*} & 929.1 \\ -6.967 & -218.2 & -31.39 & -995.8 & -1693 \\ 3.683 & -357.8 & 24.63 & -306.6 & 10.6 \end{pmatrix} \mathbf{C}_{t-1} \\
&+ \begin{pmatrix} 2.865 & -603.9 & -1.506 & -4294 & 1598 \\ -9.069 & -549.9 & 57.44 & -1585 & 2434 \\ 1.804 & -264.1 & -7.079 & 1239 & 1635 \\ -7.055 & -13.13 & 49.03 & -1372 & 679.3 \end{pmatrix} \mathbf{C}_{t-2} \\
&+ \begin{pmatrix} 12.97 & -552.2 & -51.94 & 2456 & -3155 \\ 14.64 & -359.2 & -100.4 & 2873 & -4210 \\ -12.68^{*} & 85.53 & 77.44 & -2051 & 2026 \\ -3.970 & -145 & 56.70 & -1248 & 669.1 \end{pmatrix} \mathbf{C}_{t-3} + \begin{pmatrix} 12040 \\ 11600 \\ 6194 \\ 6544 \end{pmatrix}
\end{aligned}
$$

Interpretation of the IVAR Model with Climate Conditions

The output of the model (refer to appendix) indicates that the first equation, which represents Mandii have R- square value of value of 0.6302. This implies that, the equation Mandii can account for 63.02% total variation for Mandii as compared to equation Mandii when the VAR model was developed with on only the four rice varieties (refer to appendix) also at a third lag order, which could only account for 43.57% of the total variation. But the model for the equation for Mandii, suggest that its yield is dependent on the past yield values of itself at various time lags from 1 up to lag 3, it is also dependent on other rice varieties at various time lags from 1 to 3, as well as the climate conditions. The model indicates that with the coefficients and concerning the model output, none of the coefficients is significant at 5%. This could mean that the other rice varieties at various lags cannot be used to determine the present yield of Mandii, not even its own yield at various lags up to 3. This also could mean that, if the yield of Mandii in a particular year, say last year is high, would not mean its yield in the coming farming season would be high. There is no interdependence among the variables of equation Mandii.

The second equation which represents the yield variety of Bazulgu have R- square value of 0.6676. This indicates that the equation Bazulgu can account for 66.76% total variation in its equation. When the VAR model was run on only varieties of the rice yield, equation Bazulgu had an R- square of 31.2% which represent the amount of explained variations in its model. The above indicates that including the climate conditions could be a better approach to determining future value yields of Bazulgu rice variety. The coefficients of the model with the climate conditions indicate that wind is significant at lag 1 with a p of 0.0418 as well as the rice variety Kpukpula at lag 3 at 5% level of significance. This could also suggest that the present yield of Bazulgu could be determined if, for the past three years, we know the yield of Kpukpula and given that Bazulgu would be cultivated at the same location of Kpukpula three years ago.

We can also say that there is some level of dependence that exists between the present yield of Bazulgu, the yield of Kpukpula at lag 3 and wind speed at lag 1. The output of the model (refer to appendix) indicates that the third, equation, which represents Sativa have R-square value of 0.6371. This implies that the equation Sativa can explain 63.71% total variation for Sativa which can be used as a measure of an improved version of the Sativa equation when only the varieties of the rice were used to develop the VAR model which resulted in an R – square value of 0.4328 which meant that it could account for 43.28% of the total variation in the equation in that equation. The equation Sativa in the VAR model with associated climate conditions have the coefficient of rain at lag 3 being significant at 5% with a corresponding p of 0.0332. Meanwhile the other variables in the equation Sativa do not have significant coefficients and therefore could mean that the yield of Sativa would not depend on the other rice varieties even if their past yields are known. This also includes climate conditions but rainfall at lag 3. This suggests that the yield of Sativa could be known at a particular time in the future if the rainfall pattern is known for the past 3 years.

The last equation of the model which is Kpukpula have R- square value of value of 0.5339 and means that it can account for 53.39% as far as the relationship between its yield and the other variables are concerned. The equation of this variety of rice indicates that its coefficient of determination is an improvement of the other equation of that same variety when the VAR model was derived from data that included only the four varieties of rice at their respective lags up to 3 with corresponding R-square value of 0.3192 or 31.92%. Even though the VAR model that was developed from data which included climate conditions have better R-squares than the VAR model with only of the coefficients of the rice varieties, their yields are still not influenced greatly by the other climate conditions.

Table 8: Summary of Both Models

	VAR(3)		**IVAR(3)**		
Rice Variety	**R-Sq(%)**	**ResStd Error**	**R-Sq(%)**	**ResStd Error**	**% change in model**
Mandii	43.57	12000	63.02	12040	44.64
Bazulgu	31.22	13460	66.76	11600	113.83
Sativa	43.28	6248	63.71	6194	47.20
Kpukpula	31.92	6382	53.39	6544	67.26

Source: Researcher's Computation (2020)

Even though the inclusion of climate conditions has improved R- Squares of the model of each rice variety, the corresponding errors again though have fairly reduced but for the model Kpukpula which shows an increase in its standard errors.

Best Subsets VAR Model Selection with Climate Conditions

The tables below indicates the best model selection based on climate condition combination, from one climate condition combination model to four climate combination model. These are summary of the model results.

Each table is subdivided into two categories of climate conditions. The first category is the best subset for a particular climate number combination. Tables 9,10,11 and 12 presents details of subset models for the climate combination.

Table 9: Summary of One –Variable Best Subset Models

Climate	Variety	R-Squared	Residual Standard Error
Temperature	Mandii	0.5105	11590
	Bazulgu	0.4528	12450
	O.Sativa	0.4799	6204
	Kpukpula	0.4024	6199
Sunshine	Mandii	0.5052	11650
	Bazulgu	0.4156	12870
	O.Sativa	0.4790	6209
	Kpukpula	0.3312	6558

Source: Reseacher's Computation(2020)

The first part of Table 9 shows quite better variations in particular for model mandii and also have considerably smaller standarded errors and this observations is similar to the remaining tables 10,11 and 12

Table 10 : Summary Two -Variable Best Subset Models

Climate	Variety	R-Squared	Residual Standard Error
Temperature and Sunshine	Mandii	0.5717	11270
	Bazulgu	0.5311	11990
	O.Sativa	0.5086	6270
	Kpukpula	0.4077	6417
Wind and Sunshine	Mandii	0.5393	11690
	Bazulgu	0.4842	12870
	O.Sativa	0.5016	6314
	Kpukpula	0.3816	6557

Source: Reseacher's Computation(2020)

Table 11: Summary of Three -Variable Best Subset Models

Climate	Variety	R-Squared	Residual Standard Error
Rain, Temperature And Sunshine	Mandii	0.5960	11420
	Bazulgu	0.5484	12270
	O.Sativa	0.5619	6176
	Kpukpula	0.4433	6490
Temperature, Wind and Sunshine	Mandii	0.5891	11510
	Bazulgu	0.6184	12870
	O.Sativa	0.5303	6395
	Kpukpula	0.4306	6564

Source: Reseacher's Computation(2020)

Table 12: Summary of Four -Variable Best Subset Models

Climate	Variety	R-Squared	Residual Standard Error
Rain, Temperature Wind and Sunshine	Mandii	0.5960	11420
	Bazulgu	0.5484	12270
	O.Sativa	0.5619	6176
	Kpukpula	0.4433	6490
Temperature, Evapotranspiration, Wind and Sunshine	Mandii	0.5891	11510
	Bazulgu	0.6184	12870
	O.Sativa	0.5303	6395
	Kpukpula	0.4306	6564

Source: Reseacher's Computation (2020)

The following can be deducted from the results presented on the IVAR (3) model reduction arising from different climate condition combination.

1. Best subset model for each of the varieties R-square in Table 12 is the highest among all models with a different combinations of climate conditions (Rain,Temperature,Wind and Sunshine)
2. Bazulgu generally accounts for the highest variation. Thus it is more effective to model for this variety as a result of higher consistency in the yield of that variety. This observation is made from figure of the study.
3. In contrast, models for Kpukpula in most times account for the least variation among all possible combination of climate conditions.

4. For Kpukpula, R- Squares does not improve much with the inclusion of a higher number of climate conditions.

   It can be inferred therefore that that the best climate combination that gives the best model is : Rain, Temperature, Wind and Sunshine.The model is presented as

$$\begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \\ y_{4t} \end{pmatrix} = \begin{pmatrix} 3736 \\ 40540 \\ 15220 \\ 2914 \end{pmatrix} + \begin{pmatrix} 0.819 & 0.1293 & 0.2274 & -0.3393 \\ 0.464^{*} & -0.2553 & -0.1379 & -0.06323 \\ 0.129 & 0.015 & 0.178 & -0.325 \\ -0.0139 & 0.042 & -0.223 & 0.16 \end{pmatrix} \mathbf{y}_{t-1}$$

$$+ \begin{pmatrix} -0.1985 & 0.1314 & -0.1969 & -0.0809 \\ 0.2656 & -0.1882 & 0.1713 & 0.4529 \\ -0.142 & 0.09 & 0.1777 & -0.000 \\ -0.043 & -0.034 & -0.098 & 0.08402 \end{pmatrix} \mathbf{y}_{t-2}$$

$$+ \begin{pmatrix} -0.0598 & 0.0061 & 0.234 & 0.4609 \\ -0.1846 & -0.1756 & -0.0188 & 1.114^{**} \\ 0.0196 & 0.082 & 0.011 & 0.2708 \\ -0.0099 & -0.01302 & 0.048 & 0.006 \end{pmatrix} \mathbf{y}_{t-3}$$

$$+ \begin{pmatrix} 0.6574 & -470.8 & 2868 & 2810 \\ -6.543 & -777. & 5742^{*} & -420.6 \\ -6.299 & -1697 & -796.3 & -318.5 \\ 5.063 & -260.9 & 476.1 & 756.1 \end{pmatrix} \mathbf{C}_{t-1}$$

$$+ \begin{pmatrix} 5.190 & -697.2 & -3585 & 1957 \\ -3.123 & -662.5 & -9492 & 2298 \\ -1.294 & -1.779 & 5165 & 1303 \\ -5.913 & -40.06 & -1775 & -44.8 \end{pmatrix} \mathbf{C}_{t-2}$$

$$+ \begin{pmatrix} 7.558 & -545.6 & 2131 & -2370 \\ 7.312 & -2784 & -2370 & -2774 \\ -5.864 & 10.92 & -1449 & 965.2 \\ 1.086 & -331.6 & -206.7 & 63.60 \end{pmatrix} \mathbf{C}_{t-3} + \begin{pmatrix} 11640 \\ 11470 \\ 6330 \\ 6612 \end{pmatrix}$$

Model Validation

Model validation and verification is an important step in model building and formulation. This technique is needed by stakeholders and industry to minimize cost, time and risk associated with full-scale testing of products. Model validation and verification are the fundamental processes for quantifying and building credibility in numerical models (Salamanca, Krpo, Martilli, & Clappier, 2010).The study used out of a sample of the original data set of 50 years to formulate another model and then was used to predict the remaining 10 years compared to the original data in the form of graphs. Details of forecast yields and actual yields are presented in Appendix B. Table 13 presents the results of out of sample model generated from the experimental data.

Table 13: Summary Results of Out of Sample VAR model

Rice Variety	R-Square	Std Error
Mandii	0.6270	13870
Bazulgu	0.7468	9335
O.Sativa	0.7997	5077
Kpukpula	0.7843	4478

Source: Researcher's Computation (2020)

Table 13 is a summary of out of sample VAR model which included a set of time series of climate conditions . An order lag-3 was suitable for the formulation of the model. The results indicates that the model performs better than the model developed using all the data set of 60 years. It can be inferred that there is none consistency in recent data on climate conditions or there are variations in the yield among the varieties of rice. Modeling O. Sativa would account for almost 80% of total variation in the model associated with small standard error, even though it is not the least standard error. From this we can infer that there would be little variations between actual and estimated yield. Mandii on the other hand have the highest standard error and accounts for 62.7% of total variation in the model of Mandii. It can also be deducted from this that, there could be a great variation between the actual and estimated yield for Mandii.

The graphs in Figure 15,16,17 and 18 shows the level of variations between actual and estimated yield of the rice variaties.

Figure 15: Plot of actual and estimated yield for Mandii

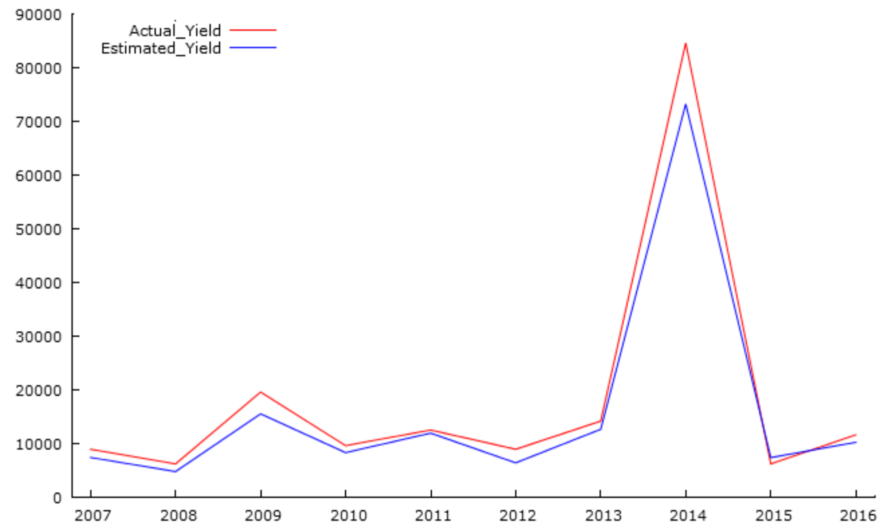


Figure 16 : Plot of actual and estimated yield for Bazulgu

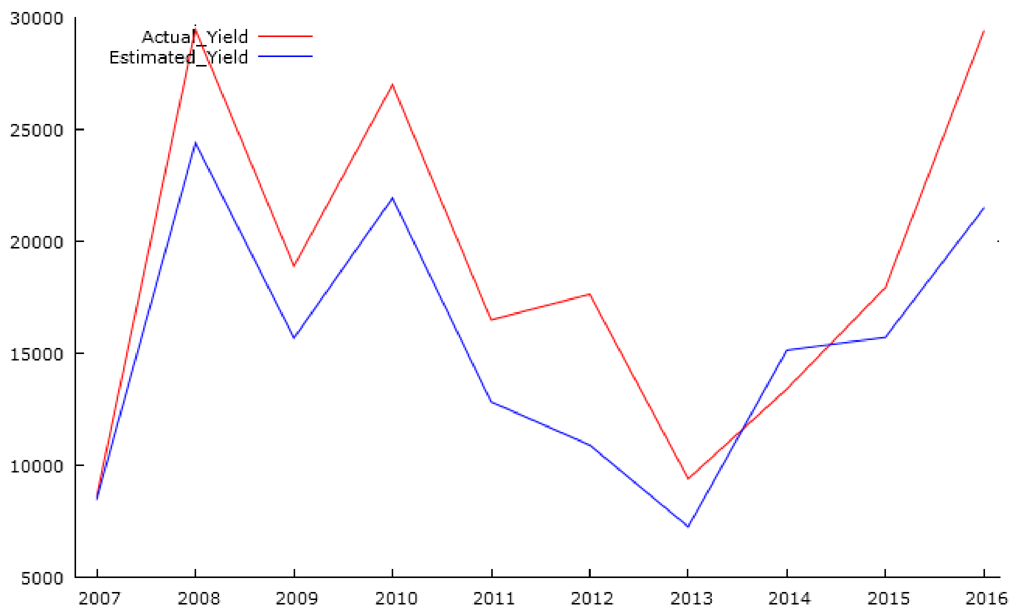


Figure 17 : Plot of actual and estimated yield for O. Sativa

Figure 18 : Plot of actual and estimated yield for Kpukpula

Model Diagnosis

For the above model, a series of the test would be carried out to determine the efficacy of the model apart from carrying out the portmanteau test used in selecting the lag order. Such diagnosis would include normality test, heteroscedasticity, granger causality, impulse response function and variance decomposition.

Normality Test

Is a test carried out to determine whether the data set used for the VAR model estimation is normally distributed and follows the assumption of normality. For this test, we are interested in finding out whether there is enough evidence that shows the variables within the data are normally distributed or not.

The hypothesis of the normality Test

H_o: The variables in the data are normally distributed

H_a: The variables in the data are not normally distributed

Table 14: Jarque Bera Test for Normality (Multivariate only)

Parameter	Chi-square	D.F	P
Skewness	1.1588	6	0.9798
Kurtosis	2.2179	6	0.8986

Source: Reseacher's Computation (2020)

For normality test, we expect that p is greater than 0.05 and would be evidence to indicate that the variables in the data are normally distributed. From the results, we can see that the p values for each parameter is greater than 0.05 and therefore suggest that the variables in the data are normally distributed.

Heteroscedasticity

Heteroscedasticity is a phenomenon in which the error of variance is not constant across a range of variable that predicts it. For our VAR model, we expect not to experience a situation of heteroscedasticity which would suggest that the model is healthy and reliable for predicting the individual response variables

Table 15: Test of Heteroscedasticity

Chi-squared	D.F	P
2115	20250	1.000

Source: Reseacher's Computation(2020)

The test results indicate that since the p is greater than 0.05, and further shows that it is not significant, hence we fail to reject the null hypothesis and conclude that the VAR model does not show any form of heteroscedasticity.

Granger Causality

Granger Causality is a statistical concept or hypothesis for determining whether one-time series is useful in forecasting the other series. Is also a way to find out causality of two variables in a time series. For the research, the researcher is interested in investigating whether response variables show some level of granger causality property with them over time. The hypothesis is that:

H_o: There is no Granger causality between the variables

H_a: There is granger causality between the variables

The results indicates that almost all the variables do not Granger cause each other taken two at a time at 5%. Table 16 presents the results of Granger casaulity among the rice varieties.

Table 16: Test Results of Granger Causality

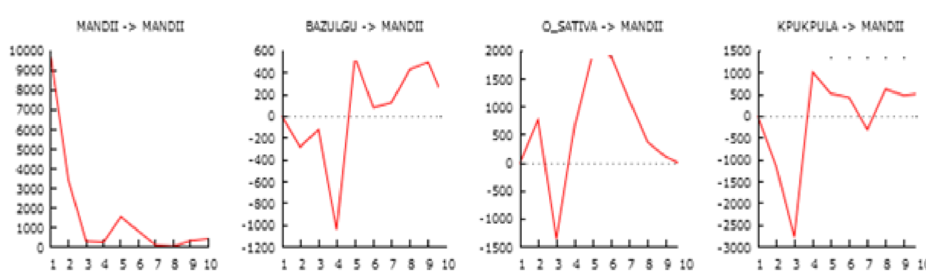
Null Hypothesis	**F- Stat**	**P**	**Decision**
Mandii do not granger cause Bazulgu	1.0747	0.3635	Fail to reject H_o
Bazulgu do not granger cause Mandii	0.36858	0.7758	Fail to reject H_o
Mandii do not granger cause Sativa	2.1143	0.1033	Fail to reject H_o
Sativa do not granger cause Mandii	1.6152	0.1908	Fail to reject H_o
Mandii do not granger cause Kpukpula	0.734	0.5343	Fail to reject H_o
Kpukpula do not granger cause Mandii	2.1771	0.0955	Fail to reject H_o
Bazulgu do not granger cause Sativa	0.50773	0.6779	Fail to reject H_o
Sativa do not granger cause Bazulgu	0.87472	0.457	Fail to reject H_o
Bazulgu do not granger cause Kpukpula	0.80935	0.4917	Fail to reject H_o
Kpukpula granger cause Bazulgu	3.0836	0.0309	Reject H_o
Sativa do not granger cause Kpukpula	2.3233	0.0797	Fail to reject H_o
Kpukpula do not granger cause Sativa	0.40366	0.7507	Fail to reject H_o

Source: Reseacher's Computation(2020)

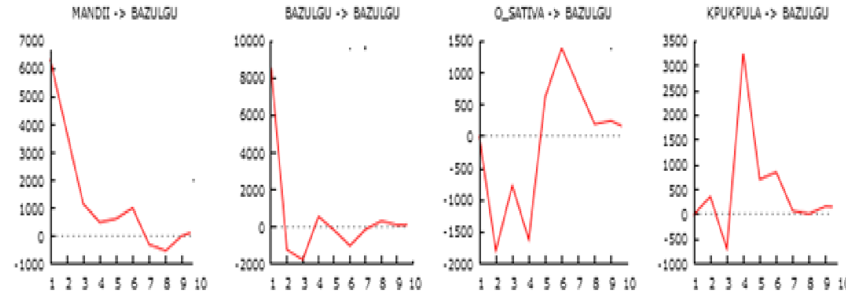
It can be deduced from table 16 that, all the test results at 5% level of significance of the response variables. It goes a long way to buttress conclusions made initially about the cross-correlation of the response variables. Meaning that even if we know the yields of a particular rice variety up to three years, would not be sufficient enough to predict the production of another rice variety.

Impulse Response Functions (IRFs)

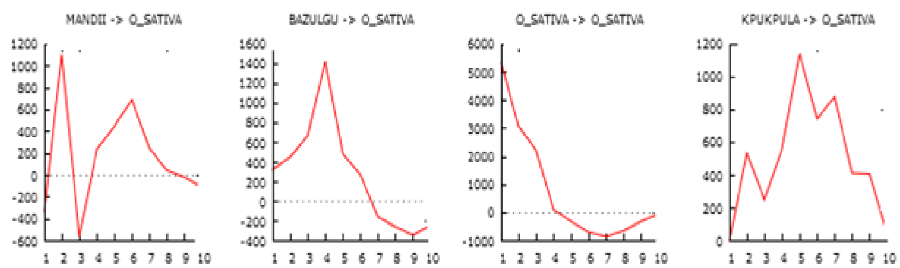
IRFs describe the way a variable retorts to a shock in another variable over time. It also informs us about the effect of a single standard deviation shock to one of the inventions. The impulse response function forecasts the feedback of a variable is yet to come. IRF is mostly applied in vector autoregression and vector error correction models. For our research, we would be interested in the shock the response variables have on one another over time as well as on themselves over time. The graphs showing the IRFs of rice yield varieties for ten time points are presented in figure 19 as:



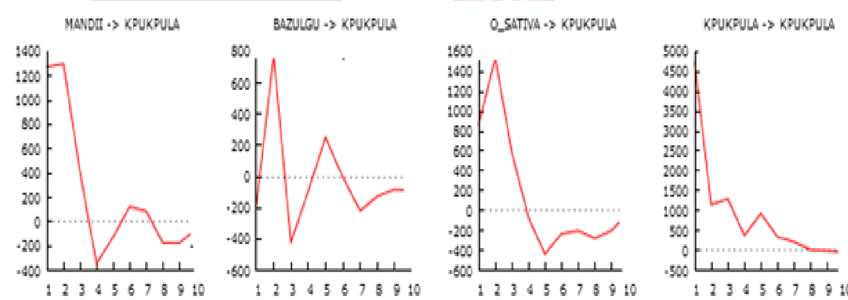
(a) Shocks from Mandii on Mandii and other rice varieties



(b) Shocks from Bazulgu on Bazulgu and other rice varieties

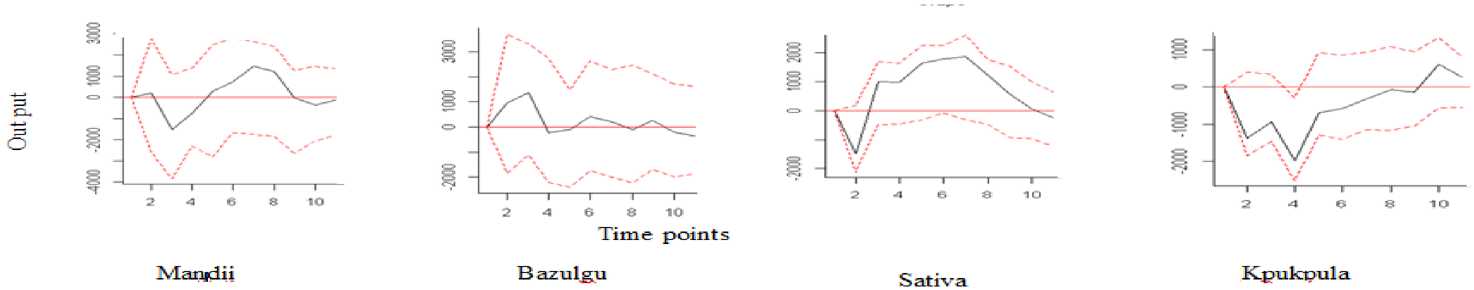


(c) Shocks from O.Sativa on O.Sativa and other rice varieties

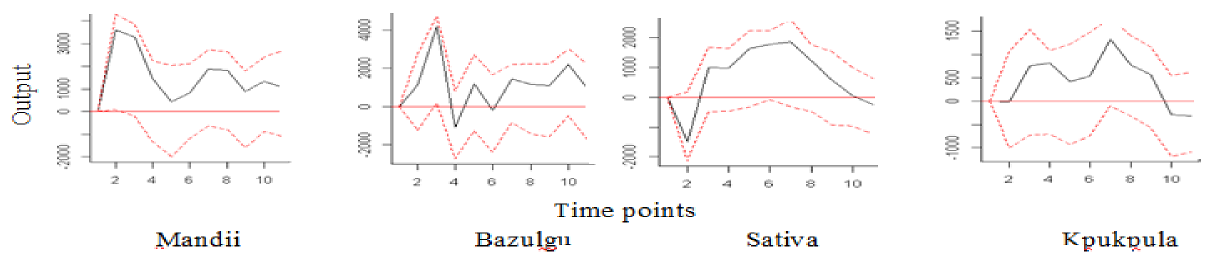


(d) Shocks from Kpukpula on Kpukpula and other rice varieties

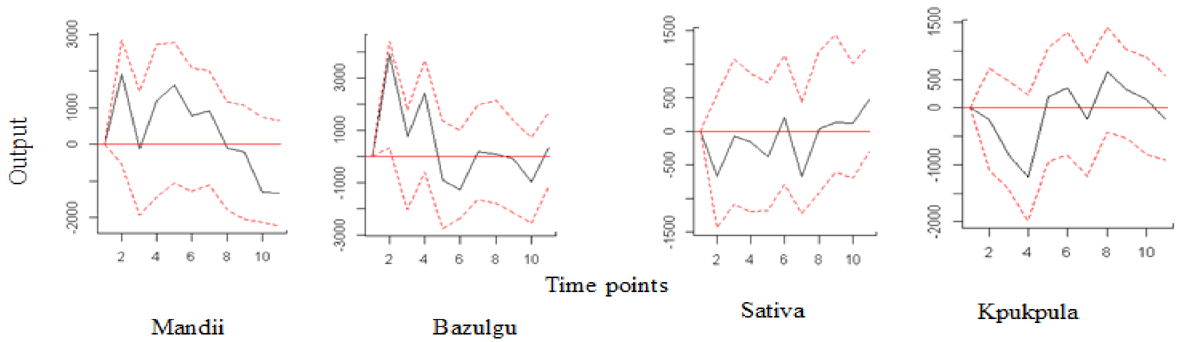
Figure 19: Graphs of Impulse response functions among the rice varieties



(c) Shock from evapo transpiration on rice varieties



(d) Shocks from sunshine on rice varieties



(e) Shocks from wind on rice varieties

Figure 20: Shocks From climate conditions on rice varieties

:

Interpretation of IRFs Graphs

The graphs of the IRF on the rice varieties as a result of shocks from the same rice varieties indicates a steady decline in the yield of rice from time point 0 till the last time point. Also, the yield of rice as a result of shocks of one standard deviation from other rice varieties indicates an initial decline of the yield and a study increase in the yield in continuous time points. The yield of Sativa as a result of shock from Mandii, Sativa receiving a shock from Bazulgu, Kpukpula also receiving a shock from Bazulgu finally Kpukpula receiving a shock from Bazulgu, shows positive response on their yields and stands out to be the highest yield response among the shocks from other varieties. We can therefore infer that Bazulgu as a source of a shock has a positive influence on the yields of Sativa, Mandii and Kpukpula. The influence of climate conditions on the yield of rice varieties from the graphs drawn in figure 15b depicts that, rainfall influence the yield of Bazulgu slightly positive while the other varieties remain almost negative with time. The temperature is a source of shock to all rice varieties shows a decline in the response of the rice yield. Sativa and Mandii, however, show quite positive response on their yield as a result of shock from evapotranspiration. The remaining rice varieties are not sensitive to evapotranspiration. Sunshine appears to have a positive response influence on all four rice varieties from the beginning and a slight decline at the end of the time points. Mandii and Bazulgu show a positive response as a result of shock from wind, while Sativa shows mostly negative response for initial years but fluctuates mostly positive for the remaining time points, and Kpukpula indicating both negative and positive response. In all, sunshine and wind appear to have remarkable shocks on all four varieties. In particular, Bazulgu and Sativa exhibit a positive response to shocks in climate conditions.

Forecast Error Variance Decomposition (FEVD)

FEVD is a standard statistical technique used to define to what extent of the inconsistency that is contained in dependent variables that are lagged by its own. Tables 17, 18, 19 and 20 present the FEVD for five future points.

Table 17: FEVD for Mandii

Year	Mandii	Bazulgu	Sativa	Kpukpula
2017	1.000000	0.000000	0.000000	0.000000
2018	0.979781	0.000023	0.016671	0.003524
2019	0.957405	0.004411	0.016243	0.021940
2020	0.913635	0.011048	0.032125	0.043191
2021	0.850419	0.020620	0.066829	0.062131

Source: Reseacher's Computation(2020)

Table 18: FEVD for Bazulgu

Year	Mandii	Bazulgu	Sativa	Kpukpula
2017	0.292662	0.707338	0.000000	0.000000
2018	0.339720	0.650449	0.009726	0.000105
2019	0.348048	0.639716	0.011941	0.000296
2020	0.3038451	0.563662	0.022881	0.109612
2021	0.2857446	0.530902	0.067407	0.115946

Source: Reseacher's Computation(2020)

Table 19: FEVD for O. Sativa

Year	Mandii	Bazulgu	Sativa	Kpukpula
2017	0.003317	0.004202	0.9924807	0.000000
2018	0.025621	0.012655	0.950422	0.950422
2019	0.036239	0.026612	0.925998	0.011151
2020	0.033590	0.112434	0.838618	0.015359
2021	0.032397	0.131403	0.806510	0.029690

Source: Reseacher's Computation(2020)

Table 20: FEVD for Kpukpula

Year	Mandii	Bazulgu	Sativa	Kpukpula
2017	0.024824	0.004823	0.028495	0.941857
2018	0.033921	0.010092	0.176581	0.779405
2019	0.032122	0.013560	0.22786	0.726455
2020	0.055169	0.017500	0.241666	0.685664
2021	0.060876	0.037077	0.233962	0.668085

Source: Reseacher's Computation(2020)

Interpretation of FEVDs

Tables 17 to 20 are the results of the variance decomposition of each rice varieties for periods from 2017 to 2021 computed. The results of these values indicate that there is a gradual increase in the forecast errors of the variety of interest as time goes on. Mandii, Bazulgu, Sativa and Kpukpula have 15%, 47%, 19% and 34% as the maximum forecast error respectively for the last future error forecast in each case as a result of the presence of other varieties in the model for each variety of interest. Thus, Mandii shows the smallest forecast error.

Forecast of the IVAR(3) On The Response Variables

For the study , the IVAR (3) model was used forecast the yield of the rice varieties up to three years ahead from 2016 using a 95% confidence interval. These are presented in Tables 21 to 24.

Table 21: Forecast for Mandii

Year	Forecast	Lower	Upper	C.I
2017	24895.25	1306.586	48483.90	23588.66
2018	20979.86	-5494.387	47454.11	26474.25
2019	41764.80	12782.712	70746.88	28982.08

Source: Reseacher's Computation(2020)

Table 22 : Forecast for Bazulgu

Year	Forecast	Lower	Upper	C.I
2017	15703.33	-7029.523	38436.19	22732.85
2018	16450.15	-9855.667	42755.97	26305.82
2019	31518.09	1813.138	61223.04	29704.95

Source: Reseacher's Computation(2020)

Table 23: Forecast for Sativa

Year	Forecast	Lower	Upper	C.I
2017	12946.05	806.4044	25085.69	12139.65
2018	17578.80	4104.7689	31052.84	13474.03
2019	10363.44	-5278.4899	26005.37	15641.93

Source: Reseacher's Computation (2020)

Table 24: Forecast for Kpukpula

Year	Forecast	Lower	Upper	C.I
2017	14385.17	1559.338	27211.00	12825.83
2018	25965.69	12417.269	39514.12	13548.43
2019	18520.57	3790.491	33250.66	14730.08

Source: Reseacher's Computation (2020)

Chapter Summary

The main objective of the study is to determine the influence climate conditions exert on the yield of varieties of rice in Northern Ghana. Concerning the literature of this study, even though it concerns with current changes of climate conditions over time and resulting to climate change and its effect on livelihood on humans and crop production, as well as concerned with the Ricardian cross-sectional Hendonic models and computational general equilibrium model which are all biophysical simulation models, it still does not reflect in the methodology or statistical technique we are adopting for our study. The study considered and made use of multivariate time series which was applied in developing the VAR model for only rice varieties, as well as the classical IVAR which included the climate conditions and was used for further analysis in the study to include ganger causality of rice varieties, impulse response functions, variance decomposition etc. The procedures of this study are completely very different from the literature or we can say that the current literature does not have enough information to reflect the current study approach which is applied multivariate time series in determining the effect of climate conditions have on yield of rice varieties.

Our study revealed the following major findings: The methodology we employed revealed that the series data of Mandii and Sativa were not stationary until after first and second difference which was applied to only O.Sativa rice varieties. Climate data were stationary and this was confirmed from the ADF test conducted at 5% level of significance. Two VAR models were developed from the data in the study. One model consists of only the varieties and the other model included the climate conditions and so was an extension of the previous model. Several software such as Excel, Minitab, GRETL and R-Studio to analyze the data at various stages. The data was first explored to see the nature and spread of the data. These parameters of the measure included: mean, median, standard error, total observation of the data all in the descriptive statistics presented in Table 1. A plot of the data, i.e. the varieties one graph, and the climate conditions on another graph. The series plot of the varieties showed some level of none stationarity and therefore had to be differenced to attain stationarity. ADF test was conducted for further confirmation of the stationarity level of the data. The climate data revealed that they were all stationary. Cross correlogram plot of the rice varieties showed that past values of rice production would not be enough in predicting the production of other rice varieties. The yield of the rice varieties showed that they were independent of each other. The VAR model developed from the varieties of rice and the IVAR model which includes climate conditions showed a significant improvement over the model with only rice varieties. The VAR model and IVAR were developed from using a suitable lag order three irrespective of the model type. Other test and model diagnosis were carried out to check the efficacy of the model and how it can resist any shock from external sources. Results from the impulse response indicate that sunshine, evapo-transpirationand wind as a source of the shock of one standard deviation influence positively on the response of the rice varieties over time. Bazulgu as a source of a shock has a positive influence on the response on Sativa, Mandii and Kpukpula.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATION

Overview

This chapter gives an overview of the entire work and presents logical conclusion based on the discussion of the results in Chapter Four. Based on that, we would make recommendations or give room for further research to be carried out.

Summary

Climate conditions changing over time, and resulting in destructions of lives, properties and loss of farm products are on the increase. These are the effects of climate change over time on human life especially the total harvest farmers get from the farm at the end of the farming season. The topic under study seeks to address: The influence of climate conditions on the production of rice varieties and to develop appropriate multivariate models with the climate conditions added and use it for forecasting which would serve as bases for future intervention. The literature has revealed the extent to which climate changes pose a great challenge to food and water security, public health, natural resources, and biodiversity. It is established that the effect of climate change is a reality in most parts of the world. It is consistent in the literature that there is an increase in temperature and decreases in rainfall by the amount of $1^{\circ}C$ per decade and about $2.5^{\circ}C$ per decade, respectively. Records further indicate that temperatures are likely to continue rising in the future. The literature also contains studies, though few, on the determination of the effect of the yield of different types of rice and other agricultural products which incorporates other climate conditions. It is not reported clearly how the two sets of variables are examined in a multivariate fashion using, for example, the Vector Auto-regressive models.

Data collected includes climate conditions and production of rice varieties specifically from 1957 to 2016. Statistical technique applied for the analysis is the vector autoregression because the nature of the data is multivariate. Excel, Minitab, GRETL and R-Studio were the software used for the analysis of the data at various stages of the analysis. The model would be developed in two stages: the first is to develop the model from only the rice varieties, the second is to develop the model which would include the climate conditions. The aim is to determine by how much the rice production would be influenced by climate conditions. The series plot of the varieties showed some level of none stationarity and therefore had to be differenced to attain stationarity. This is consistent in the Error Correction Model (ECM) (Johansen,1992) in the literatureof the study. ADF test was conducted for further confirmation of the stationarity level of the data and is again in accordance with (Dickey & Fuller,1981). The climate data revealed that they were all stationary. These results are how ever are different from what is in the literature since it did not consider VAR models in crop yield performance to incorporate climate conditions.The IVAR model showed a significant improvement over the model of only climate rice.

The results of the models showed that when the reseacher includes climate conditions it gives better R- squares of over 40% of the R squares of each variety without the climate conditions. The R squares of the models for the two categories by varieties are stated as Mandii had R-square value of 63.02% with the climate conditions as compared to 43.57% without the climate conditions. 66.76% as compared to 31.22% for Bazulgu variety without climate conditions. This particular rice variety shows that the equation has at least 100% improvement of R square as compared to its R square value without the climate conditions. The R-square of O.Sativa is 63.71% as compared to 43.28% without climate conditions. Finally, Kpukpula can explain 53.39% of its total variation as compared to 31.29% without the climate conditions. Other test and model diagnosis were carried out to check the efficacy of the model and how it can resist any shock from external sources. These procedures were granger causalities, impulse response function, and variance decomposition. The VAR model was successful in all the test that was carried out on it. O.Sativa formed well among all climate conditions and can result in better yields in long term cultivation. Bazulgu on the other hand

Conclusions

The study has saught to develop appropriate model for the yields of for rice varieties (Mandii, Bazulgu, O.Sativa and Kpukpula) in the Northern Region of Ghana. The Vector Auto Regressive model is what is usually found suitable for this multivariate time series dataset which cover a period 60 years from 1957 to 2016. The yield of the four varieties is naturally influenced by climate conditions,in particular. In the study therefore five climate conditions (Rain, Temperature, Evapo-transpiration, Wind and Sunshine) where examined to determine their effect on rice yield. The classical VAR model is therefore extended to incoperate the best subset model involving climate conditions. The best subset VAR model involving the climate conditions include all that is stated earlier excluding evapotranspiration. The final model for the rice varieties is determine. An order-3 lag model is found for both sets of variables. It is found that inclusion of the climate conditions provides a better model for rice yield than the lagged rice varieties alone. It is also found that temperature and sunshine have a more consistent positive influence on rice yield, particularly O.Sativa. Again the model perform the best for Bazulgu.

These results are how ever are different from what is in the literature since they did not consider VAR models in crop yield performance

Recommendations

The study has saught to develop appropriate model for the yields of for rice varieties(Mandii, Bazulgu, O.Sativa and Kpukpula) in the Northern Region of Ghana. The Vector Auto Regressive model is what is usually found suitable for this multivariate time series dataset which cover a period 60 years from 1957 to 2016. From the study O.Sativa is influenced positively by Temperature and Sunshine better than the other varieties and therefore recommends for it to be cultivated by farmers in long term production.

In developing the VAR to include the five climate conditions , it indicates an improved estimate of the rice yields for each variety better than the VAR model than the lagged rice varieties alone. How ever, further conditions could be explored to improve future estimates since the change in standard errors after inclusion of the five climate conditions are not most significant.

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APPENDICES

APPENDIX A: RESPONSE OF RICE PLANT TO TEMPERATURE

Growth Stages	Critical temperature (^oC)		
	Low	High	Optimum
Germination	10	45	20-35
Seedling establishment	12-13	35	25-30
Rooting	16	35	25-28
Leaf elongation	7-12	45	31
Tillering	9-16	33	25-31
Primordia initiation	15	-	22-23
Panicle differentiation	15-20	38	-

APPENDIX B: ACTUAL AND ESTIMATED YIELDS OF RICE

Appendix B-1: Actual and estimated yields for Mandii

Year	Actual Yield	Estimated Yield	Error
2007	10500	9689	811
2008	8900	8657	243
2009	25000	-5302	30302
2010	14600	12437	2163
2011	11200	8962	2238
2012	7560	7100	460
2013	16000	15402	598
2014	14500	13264	1236
2015	8972	8261	711
2016	12463	10431	2032

Appendix B-2: Actual and Estimated Yields for Bazulgu

Year	Actual yield	Estimated yield	Error
2007	8955	7423	1532
2008	6230	4796	1434
2009	19600	15531	4069
2010	9623	8326	1297
2011	12541	11946	595
2012	8954	6418	2536
2013	14203	12671	1532
2014	84612	73240	11372
2015	6230	7401	-1171
2016	11634	10247	1387

Appendix B-3: Actual And Estimated Yields For Sativa

Year	Actual Yield	Estimated Yield	Error
2007	8640	8506	134
2008	29460	24401	5059
2009	18900	15690	3210
2010	27000	21941	5059
2011	16500	12840	3660
2012	17640	10908	6732
2013	9402	7264	2138
2014	13407	15143	-1736
2015	17941	15722	2219
2016	29400	21493	7907

APPENDIX B-4: Actual And Estimated Yields For Kpukpula

YEAR	Actual Yield	Estimated Yield	Error
2007	7649	5783	1866
2008	8640	6941	1699
2009	29460	16367	13093
2010	18900	11533	7367
2011	27621	24531	3090
2012	16500	17693	-1193
2013	18645	21431	-2786
2014	12478	11648	830
2015	13407	11249	2158
2016	18000	18684	-684