

UNIVERSITY FOR DEVELOPMENT STUDIES

**MODELLING THE DYNAMIC RELATIONSHIP BETWEEN RAINFALL AND
TEMPERATURE IN KASSENA- NANKANA MUNICIPALITY**

ISSAKA MUBARIK

**DISSERTATION SUBMITTED TO THE DEPARTMENT OF STATISTICS,
FACULTY OF MATHEMATICAL SCIENCES, UNIVERSITY FOR
DEVELOPMENT STUDIES IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE AWARD OF MASTER OF SCIENCE DEGREE IN
APPLIED STATISTICS**

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BY

ISSAKA MUBARIK (B.Sc. Mathematical Science (Statistics Option))

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**THESIS SUBMITTED TO THE DEPARTMENT OF STATISTICS,
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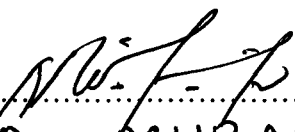
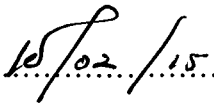
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DECLARATION


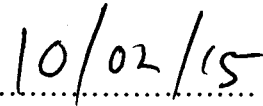
Student

I hereby declare that this thesis is the result of my original work and that no part of it has been presented for another degree in this University or elsewhere. Related works by others which served as a source of knowledge has been duly referenced and acknowledged.

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Supervisor

I hereby declare that the preparation and presentation of this thesis was supervised in accordance with the guidelines on supervision of thesis laid down by the University for Development Studies.

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ABSTRACT

Rainfall and temperature are important climatic inputs for agricultural production especially in the context of climate change. The study employed a Vector Autoregression (VAR) model to examine the dynamic relationship between rainfall and temperature time series data in Kassena-Nankana Municipality, collected from the Navrongo Meteorological Service which spanned from January 2000 to December 2012. The findings revealed that; the coefficient of variation is low in temperature data and high in rainfall data. The linear and exponential trends model was the best to fit rainfall and temperature respectively. VAR model favoured VAR at lag 5 which indicated bi-directional causation from rainfall to temperature and from temperature to rainfall. A univariate ARCH-LM test and Ljung-Box test revealed that the model is free from conditional heteroscedasticity and serial correlation respectively. The Impulse Response Function and the Forecast Error Decomposition were further used to interpret the VAR model. The magnitude of the forecast uncertainty of rainfall that is accounted for by temperature innovations was 13.05% and that of temperature accounted for by rainfall innovations was 9.05%. The study concluded that there is a bi-directional relationship between rainfall and temperature, indicating that rainfall is useful in explaining an appreciable amount of the forecast uncertainty in temperature, and vice versa. Thus modelling rainfall and temperature together in the study area will further improve the forecast of rainfall and temperature respectively. The research strongly recommends that the results should be considered so as to help in planning purposes and appropriate applications in agricultural activities.



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DEDICATION

This thesis is dedicated to my late grandfather Mr. Issahaku De-liman.





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LIST OF ACRONYMS

| | |
|---------|---|
| AIC | Akaike Information Criterion |
| ADF | Augmented Dickey-Fuller |
| ARCH-LM | Autoregressive Conditional Heteroscedasticity Lagrange Multiplier |
| df | Degrees of freedom |
| DF | Dickey-Fuller |
| EPA | Environmental Protection Agency |
| FEVD | Forecast Error Variance Decomposition |
| HQIC | Hannan and Quinn Information Criterion |
| IRF | Impulse Response Function |
| MAD | Mean Absolute Deviation |
| MAPE | Mean Absolute Percent Error |
| Max | Maximum |
| MD | Mean Deviation |
| Min | Minimum |
| MSD | Mean Square Deviation |
| SBIC | Schwarz Bayesian Information Criterion |
| VED | Variance Error Decomposition |



CHAPTER ONE

INTRODUCTION

1.0 Background to the study

The increasing change in precipitation pattern and its impact on surface water resources is an important climatic problem facing most countries in Africa (Akinyemi, 2008). Associated with global warming, there is strong indication that rainfall and temperature changes are already taking place in most of her sub- regional scales. Janki (2011) accentuated that variation in rainfall and temperature has both social and political impact, as in Africa, agriculture largely depends on rain.

Amiro and Nasiir (2011) asserted that there is scarcity of rainfall in most African countries, especially the arid and semi-arid countries. The scarcity of rainfall is further stressed by the growing demand due to increase in economic activities and population growth in most of her developing countries. Addition to these stresses is the uncertain climate change and its consequences on rainfall and temperature. Cantelaube and Terres (2005) stated typically that temperature affects the length of growing season and rainfall affects plant production (leaf area and the photosynthetic efficiency). It was established by Lobel and Field (2007) that rainfall and temperature are important climatic factors affecting agricultural production. Rainfall and temperature therefore contributes enormously to the economy of most African nations and Ghana is of no exception.



In Ghana climate change is manifested through rising temperatures, declining rainfall totals and increased variability, rising sea levels and high incidence of weather extremes and disasters such as flash floods (Minia et al. 2004). Historical data abounds that from the year 1961 to 2000 clearly shows a progressive rise in temperature and decrease in annual rainfall in Ghana.

Agriculture accounts for about one-third of Gross Domestic Product (GDP); 28.3 per cent and employs more than half of the workforce, mainly small landholders. The sector grew by 2.8% against a target of 5.3% in 2011 (2012 Budget report). Irregular rainfall pattern is a feature of climate change with particularly damaging consequences, such as droughts and flood and these are predicted to get worsen over time.

According to the Environmental Protection Agency (EPA) Policy Advice Series, which have been developed to enhance understanding and appreciation of the effects of climate change and disaster risk issues, by policy makers and senior technocrats and to support them to take urgent and needed decisions revealed that agriculture is sensitive to climatic factors namely temperature and rainfall and yields are plummeting and will continue to do so. They further stress that agricultural production's dependence on rainfall is a significant hindrance to the developments of the sector in Ghana. The use of irrigation to counter the effects of poor rainfall is particularly low across the country.

Kasena-Nankana Municipality, our study area in the Upper East Region of Ghana is characterized by the dry and wet season's climatic conditions, which are influenced mainly by two air masses – the North-East Trade winds and the South-West (Tropical



Maritime). The harmattan air mass (North-East Trade Winds) is usually dry and dusty as it originates from the Sahara Desert. During such periods, rainfall is virtually absent due to low relative humidity, which rarely exceeds 20% and low vapour pressure less than 10mb. Day temperatures are high recording 42° Celsius (especially February and March) and night temperatures are as low as 18° Celsius. (Kassena-Nankana Municipal Assembly annual report, 2013).

The Municipality experiences the tropical maritime air mass between May and October. This brings rainfall averaging 950mm per annum. This makes most of the youth in the Municipality idle during the dry seasons (November to April).

It is sufficed saying that agriculture is the mainstay of the Municipality economy; employing over 80 percent of the economically active population. The erratic rainfall and temperature patterns observed in the Municipality for some years now are hindering the prospects of farming activities in the municipality. This challenge is of great concern to the occupants especially the farming population even in the presence of the irrigation facilities at Tono irrigation project areas, which serve as sources of water for dry season farming.

Since rainfall and temperature are critical determinants of crop yield, accurate study of the relationship between rainfall and temperature is important not only for meteorology but also for agricultural economics. The study therefore seeks to model the dynamic relationship between rainfall and temperature time series data in the Kasena-Nankana Municipality.



1.1 Statement of the problem

Rainfall and temperature are important climatic inputs for agricultural production, especially in the context of climate change. Climatic data recorded for some years now in the Kassena-Nankana Municipality revealed that, there is decreasing and increasing rainfall and temperature levels respectively and this is of great concern to the inhabitants especially the conscious farming individuals which form over eighty percent of the economic active population. In this light, accurate study of the relationship between rainfall and temperature will help farmers to make better decisions for reducing their exposure to weather risk or take advantage of the relationship. The research therefore seeks to model the dynamic relationship between rainfall and temperature time series data in the Kassena-Nankana Municipality.

1.2 Objectives of the study

- To model the dynamic relationship between rainfall and temperature in the Kassena-Nankana East Municipality.
- Investigate whether rainfall granger cause temperature or whether temperature granger cause rainfall.
- To determine the magnitude of forecast uncertainty in rainfall that is accounted for by temperature and vice versa.
- To determine the trend models that best fit rainfall and temperature.



1.3 Significance of study

It is envisaged that the study will add to the existing research relating to studies of the impacts of climate change on rainfall and temperature. The study will help farmers in the Municipality to plan for their farming investments. Additionally, it will contribute to the formulation of policies on agricultural activities in the Municipality. Finally, it will serve as bases for further research on rainfall and temperature and ways to improve it for socio-economic activities.

1.4 Research questions

In fact, this study aim to answer the following questions:

- What Vector Autoregression (VAR) model best models the dynamic relationship between rainfall and temperature?
- Does rainfall granger cause temperature or does temperature granger cause rainfall?
- What magnitude of forecast uncertainty in rainfall is accounted for by temperature and vice versa?
- What trend models best fit temperature and rainfall?

1.5 Structure of the Thesis

The thesis is organised into five chapters. Chapter one contains the introduction of the research work. Chapter two comprises of literature review. Chapter three outlines the methodology employed in this research while chapter four presents the analysis and discussion of results. Chapter five is devoted to conclusion and recommendations.





CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

Due to observed significant changes in the climate and its impacts on rainfall and temperature, climatic change is a subject to many studies in recent times. In this Chapter relevant literature on the impacts of climate change is presented.

2.1 Global Climatic change

It has been observed that human-induced climate change (global warming), is changing precipitation and the hydrological cycle, and especially the extremes (Trenberth, 2011). Precipitation is the general term for rainfall, snowfall, and other forms of frozen or liquid water falling from clouds (Dai, 2006). There is a very strong relationship between total column water vapour (TCWV; also known as precipitable water) and sea-surface temperatures (SSTs) over the oceans (Trenberth, 2011).

Precipitation is intermittent, and the character of the precipitation when it occurs depends greatly on temperature and the weather situation (Willet *et al.*, 2008). He further explained that, heated by the sun's radiation, the ocean and land surface evaporate water, which then moves around with winds in the atmosphere, condenses to form clouds, and falls back to the Earth's surface as rain or snow, with the flow to oceans via rivers completing the global hydrological (water) cycle. The same process is essential for



creating precipitation. As air rises into regions of lower pressure, it expands and cools, and that cooling causes water vapor to condense and precipitation to form. The Clausius-Clapeyron (C-C) equation describes the water-holding capacity of the atmosphere as a function of temperature, and typical values are about 7% change for 1°C change in temperature. Consequently, changes in temperature through the C-C relationship provide a very fundamental constraint on the amount and type of precipitation through the water vapor content of the air. (Trenberth, 2011).

Precipitation varies from year to year and over decades, and changes in amount, intensity, frequency, and type (e.g. snow vs. rain) affect the environment and society. Steady moderate rains soak into the soil and benefit plants, while the same amounts of rainfall in a short period of time may cause local flooding and run off, leaving soils much drier at the end of the day.

Among variables relevant to climate change, rainfall and temperature are two important factors which have a large effect on crop yield (Abbate *et. al.*, 2004). Typically, temperature affects the length of the growing season and rainfall affects plant production leaf area and the photosynthetic efficiency (Cantelaube and Terres, 2005).

Climate change is typically discussed in global terms, yet its effects vary quite dramatically among different regions of the earth. What we do know for certain is that over the last 100 years the earth has experienced an approximate .6°C (1.1°F) increase in global mean annual temperature (IPCC, 2001). This warming trend is expected to continue, increasing at dramatic rates. In order to understand better the impact that



climate change has on cities we must look at the scientific evidence of global and regional climate change, its primary causes, and its recorded and projected effects.

The leading scientific research authority on global climate change, the Intergovernmental Panel on Climate Change (IPCC), most recently produced its Third Assessment Report in 2001. In this report, it was projected that there will be a 1.4 to 5.8°C (2.5 to 10.4°F) increase in globally averaged surface temperature between 1990 and 2100. In order to put this number in perspective, the IPCC states that this amount of warming exceeds that of the 20th century by two to ten times, and this rate of warming is faster than any rate within the last 10,000 years. In the Great Lakes region (to which Madison belongs), an accelerating warming trend was also projected by the Great Lakes Regional Assessment Group (GLRAP) in a 2000 report. Between 2025 and 2034, minimum summer temperatures are expected to increase by 1 to 2°C (1.8 to 3.6°F), and maximum temperatures will increase by 0 to 1°C (0 to 1.8°F).

The two models used by this group vary in their winter temperature predictions, but both predict increased warming trends, as much as a 6°C (10.8°F) increase in minimum temperatures and 2°C (3.6°F) increase in maximum. To illustrate the effect of climate change on a city in this region, the group also made projections of the effects of global climate change in Chicago by the end of the 21st century. For example, they expect that the frequency of ten or more days in the summer with high temperatures exceeding 90°F (32°C) will change from a 1-in-25 year event now to a 1-in-10 year event.

Also, the frequency of six or more days in the winter with low temperatures below 0°F (-18°C) is projected to fall from a 1-in-10 year event now to a 1-in-50 year event. The



coldest winters may be similar to normal winters of today, with average snowfall decreasing by as much as half, and typical winter weather may be similar to what is currently experienced during a moderate to strong weather event that originates in the tropical Pacific, but which ultimately affects weather in distant parts of the globe because of global atmospheric circulation. Severe weather events blamed on El Niño include tornadoes, thunderstorms, and fires (NOAA, 2004).

Climate change also occurs as a regional phenomenon known as the “urban heat island effect.” Not to be confused with global warming, urban heat islands involve temperature differences measured over space (urban to rural) not time and the factors that drive them (surface heating, rather than greenhouse-gas-trapped heat) are different. The Heat Island Group at Lawrence Berkeley Laboratories has demonstrated a 6 to 8°F higher temperature in urban areas in the summer than rural areas (Berkeley, 2005). There is evidence that temperatures in urban cities are also increasing every summer. The Heat Island Group cites scientific research that maximum July temperatures in cities such as Baltimore, Phoenix, Tucson, Washington, Shanghai, and Tokyo have increased at a rate of .5 to 1°F every ten years during the last 30 to 80 years.

2.2 Effects of Climate Change

There is no doubt that the climate in Ghana has changed significantly with impacts being felt everywhere in the country. Studies conducted by the Council for Scientific and Industrial Research and Water Research Institute (CSIR – WRI) in 2000, under the United Nations Framework Convention on Climate Change (UNFCCC) and co-ordinated by the Environmental Protection Agency (EPA), showed that, there is 1°C increase in



temperature over a 30-year period from the historical records, increased evaporation, decreased and highly variable rainfall pattern, and frequent and pronounced drought spells. Another study led by EPA in 2008 on “Ghana Climate Change Impacts, Vulnerability and Adaptation Assessment” reported that, over the past 40 years (1960-2000), average annual temperatures have been rising steadily in 5 of the 6 agro-ecological zones of Ghana. This trend is projected to continue into the future.

The impacts of the rising temperatures are already happening. These include: the drying of some rivers in the dry season which were hitherto perennial rivers, more intensive rainfall events such as the rainfall and flood events of 23rd April 2008 and 24th June 2009 in parts of Accra that wreaked havoc on life and properties, frequent events of drought (e.g., the drought that led to power rationing in 2006), due to low levels of water in the Akosombo dam, floods, such as the one that occurred in 2007 which water scarcity in many places in the country. Frequent flood shave the potential to wreak havoc on expensive water infrastructures for domestic water supply, irrigation and hydropower generation. The CSIR-WRI 2000 report on climate change and water resources estimated: a general reduction in annual river flows in Ghana by 15-20 % for the year 2020 and 30-40 % for the year 2050, a reduction in groundwater recharge of 5-22 % for 2020 and 30-40% for 2050, an increased irrigation water demand of 40-150% for 2020 and 150-1200 % for 2050, a reduction in hydropower generation of 60% for 2020 and, by the year 2020, all river basins will be vulnerable and the whole country will face acute water shortage.

Climate change holds possible threats to all countries of the world; some of the threats are already being experienced. They include sea level rise, increased frequencies of



extreme weather events such as floods and droughts, affected about 332,600 people and caused the death of fifty-six persons in the Upper East, Upper West and Northern regions and parts of Western regions, and unpredictable weather, especially late start of the rainfall season and or shorter rainy season. All these are evidence of the impact of climate change in Ghana.

In northern Ghana, for instance, high temperatures that were previously recorded in March (peak of the dry season) are now being recorded also in January. The start of the rainy season has become more difficult to predict. In the past, the rainy season started in April and ended around late September or early October. However in recent times, the rainy season starts in June or July with extreme heavy rainfall in September or October, often resulting in floods that destroy crops, life and properties or ending abruptly and resulting in drought conditions.

With projected average temperatures showing a rising trend, the impacts of climate change are likely to be more severe in the future. Studies done by the International Food Policy Research Institute (IFPRI) show that, even though food prices in Ghana will rise in the near future, climate will make it worse. The price of Rice that is projected to increase by 60% without climate change could go up by as much as 121% due to climate change, instead of just more than 60% without climate change.

Climate change comes with great challenges for water management in Ghana and certainly, adaptation and innovative management will be a necessary response. For, instance, water managers may be required to change design criteria of water facilities, planning and allocation decisions, to incorporate the impacts of climate change. The



general perception in the populace that water is an infinite resource would also have to change through mass education on water utilization practices.

2.3 Rainfall Variability in Ghana

Declining rainfalls have been reported throughout West Africa over the past 50 years and may be viewed in the long term (Weldeab *et al.*, 2007) as part of general southward shift in the seasonal migration of the Inter-tropical Convergence Zone (ITCZ). A great deal of research into the nature and causes of rainfall variability in the sub-region has concentrated on the Sahel (Mahe *et al.*, 2001). Nicholson *et al.*, (2000) argue that practical difficulties in obtaining data outside the Sahel may be a contributing reason, while on a more practical note Servat *et al.*, (1997) conclude that, the tragic consequence of drought on the countries in the Sahel is what explains, and justifies, the regional focus. At higher frequencies, Gu and Adler (2003) observe that a high (low) south Atlantic sea surface temperature (SST) is associated with high (low) rainfall in the Guinea coast (south of 8°N) and low (high) rainfall in the Sahel. Limited studies within the humid zone itself point to a similar reduction in annual rainfall totals, for example in Côte d'Ivoire (Servat *et al.*, 1997) and in Ghana (Gyau-Boakye and Tumbulto 2000).

Much of the literature on rainfall in Ghana has concentrated on selected regions or stations (for example, Adiku *et al.*, 1997, Tanu, personal communication and Gyau-Boaakye and Tumbulto, 2000). Tanu analyzed rainfall variability in Ho and Tamale, and observed the risk of a dry spell during the rainy season to be higher in the south, (Ho), than the north (Tamale). Similar patterns are present in the intra-seasonal rainfall variability of Accra and Tamale (Adiku *et al.*, 1997). The national study of Opoku-Ankomah and Cordery (1994) suggests that variability in the northern zone is distinct

from the remainder of the country, due to the movement of the ITCZ and influence of Atlantic SSTs, as noted by Boateng (1967).

Natural and human induced changes have been investigated as the cause of the anomalous low rainfall in the sub-region (Giannini *et al.*, 2003). Diagnostic studies (Ward 1998; Giannini *et al.*, 2003) provide information concerning the forcing of West Africa rainfall by global sea surface temperature (SST). Continental surface conditions also play a role in determining the persistence of the drought condition (Zheng and Eltahir, 1998). The loss of vegetation, associated increase in soil albedo and declining temperatures, was proposed as a cause of Sahelian drought by Charney (1975). However, this mechanism of self-perpetuating drought (Leroux, 2001) was quickly challenged and these arguments have resurfaced recently (Govaerts and Lattanzio, 2007). SSTs alone do not explain variability throughout West Africa, although sub-Saharan rainfall is negatively correlated with SSTs in the South Atlantic (Opoku-Ankomah and Cordery 1994), and positively correlated with the Gulf of Guinea (Adler *et al.*, 2000). This echoes the dipolar structure of higher SSTs in the South Atlantic and at the Equator, and lower SSTs in the North Atlantic which has been used to explain reductions in areas affected by the monsoon (Leroux, 2001), and is consistent with observations of SSTs in the North Atlantic and the strength and location of the Azores anticyclone (Hastenrath, 1991), and similar variations in the South Atlantic anticyclone (Leroux, 2001). Other factors investigated include variations in the African Easterly Jet (AEJ) and the Tropical Easterly Jet (TEJ), (Leroux 2001; Price *et al.*, 2007), and ENSO (Ofori-Sarpong and Annor, 2001). At best ENSO is only strongly associated with rainfall in the Sahel with a non-stationary or no clear association with the Guinea Coast region (Ward *et al.*, 1997).





2.4 Rainfall Variability in the Kassena-Nankana Municipality

Rainfall variability is the single most important vulnerability-imposing climatic factor. In the Kasene-Nankana Municipality of northern Ghana, these fluctuations provoke stunting, drying up and destruction of plantations. Especially dramatic were the drought events in the early 1970s in Burkina Faso, whose impacts were worsened by the weak institutional situation after independence; the droughts in northern Ghana 1981 and 1984 and the consequent famines and outmigration (Yaro, 2004), or the dry spell in May 2007 which badly affected the early millet yields and the heavy rainfall events and floods in August and September that destroyed late crops such as sorghum, rice and groundnut (Kanchebe, 2010). As climatic factors show high instability, several studies have identified sets of measures that need to be implemented to minimize those risks: improvement of irrigation efficiency, encourage the use of groundwater and promotion of community-based water management (Braimoh 2004; Sandwidi, 2007). In addition, there need to be changes in farming practices, such as shifting of cultivation timing and proper soil preparation, simultaneous cultivation of multiple plots, preference for drought-resistant species, multi-cropping, and traditional manure management practices (Tripp 1982; Kanchebe, 2010). Besides crop production, other farming and off-farming activities, like small animals rearing, food processing, commerce and temporary migration are less vulnerable to changes in precipitation (Yilma 2006; Awo 2010; Kanchebe 2010; Schravem, 2010). Government institutional measures such as establishing an efficient irrigation infrastructure and facilitating credit access may reduce the vulnerability of the farmers (Schindler, 2009).



2.5 Temperature Variability in Ghana

Climate change is projected to have significant impacts on Ghana. Although there will be fluctuations in both annual temperatures and precipitation, the trend for temperature over the period 2010–50 indicates warming in all regions. The highest temperature increases will be in the Northern, Upper East, and Upper West regions, while the lowest will be in the Brong Ahafo region. For example, under one of the climate scenarios (Ghana Dry), temperatures in the three regions of the North will rise by 2.1–2.4°C by 2050. In comparison, the predicted rise in the Ashanti, Western, Eastern, Central, and Volta regions will be 1.7–2.0°C, and the rise in the Brong Ahafo region will be 1.3–1.6°C. (Ghana Meteorological Service Department report, 2011)

2.6 Temperature Variability in Upper East Region

By its tropical location and geomorphology, incoming solar radiation is relatively constant as are the temperatures. In the southern Sudanian savanna, a night-day variation of 20°C is usual (Bagayokon, 2006, Schindler 2009) but northwards in central Burkina Faso and near the Sahel, average temperatures of 25°C in January and 32°C in April and relative humidity of 6% during the dry season and 95% in the rainy season are common. Moreover, temperatures can oscillate strongly, from 15°C during the night to more than 40°C during the day (Sandwidi, 2007). Recent observations have found a rise in the average temperature of 1°C between 1960 and 1990 (Ouédraogo, 2004; Sandwidi, 2007).



2.7 Relationship between Rainfall and Temperature

Spatially, it is generally believed that there exists significant correlation between rainfall and temperature over tropical oceans and land. For example, Aldrian and Dwi (2003) examined the relationship between rainfall and sea surface temperature and found that Indonesian rainfall variability revealed some sensitivity to sea-surface temperature variability in adjacent parts of the Indian and Pacific Oceans. Black (2005) also studied the relationship between Indian Ocean sea surface temperature and East Africa rainfall and concluded that strong East African rainfall was associated with warming in the Pacific and Western Indian Oceans and cooling in the Eastern Indian Ocean. Temporally, it is generally believed that the correlation between rainfall and temperature changes between months. For example, Rajeevan *et al.*, (1998) examined the temporal relationship between land surface temperature and rainfall. They found that temperature and rainfall were positively correlated during January and May but negatively correlated during July. Using annual data Huang *et al.*, (1993), also found a negative correlation between rainfall and temperature in Yellow River basin of China.

2.8 Effects of Rainfall and Temperature on crop production

Weather is the key source of uncertainty affecting crop yield especially in the context of climate change. For example, Vergara *et al.*, (2008) studied the potential impact of catastrophic weather on the crop insurance industry and found that 93% of crop loss was directly related to unfavorable weather. Accurate modelling of the relationship of weather distributions would allow farmers to make better decisions for reducing their exposure to weather risk or take advantage of favorable climatic relationships. Among variables



relevant to weather, rainfall and temperature are two important factors which have a large effect on crop yield. Typically, temperature affects the length of the growing season and rainfall affects plant production (leaf area and the photosynthetic efficiency).

There is a lot of literature studying the effects of temperature and rainfall on crop yield. Erskine and El-Ashkar (1993) quantified the effect of rainfall on lentil seed yield and found that rainfall accounted for 79.8% of the variance of seed yield. Lobell and Field (2007) studied 12 major Californian crops and found rainfall was able to explain more than 60% of the observed variability in yields for most crops. Cooper *et al.*, (2008) found that not only the seasonal rainfall totals and their season-to-season variability were important, but also the “within season” variability had a major effect on crop productivity, which implies that monthly data is needed in crop production analysis.

Muchow *et al.*, (1990) found that lower temperature increased the length of time that the maize could intercept radiation and hence grow. Lobell and Field, (2007) found a roughly 17% relative decrease in both corn and soybean yield in the USA for each degree of increase in growing season temperature. From the above, it is well established that rainfall and temperature are two important climatic factors affecting agricultural production.

Since temperature and rainfall are critical determinants of crop yield, accurate modelling of the dynamic relationship between temperature and rainfall is important not only for meteorology but also for agricultural economics.



2.9 Review of Time Series Methods

2.9.1 Unit Root Tests

Time series modelling require the use of stationary data. On the contrary, most time series data are found to be non-stationary. In line with the work of Fuller (1976) and Dickey and Fuller (1979) advocates Dickey-Fuller (DF) test and Augmented Dickey-Fuller (ADF) test) in which a null hypothesis is a non-stationary process with a unit root and an alternative hypothesis is a trend stationary process, several methods for testing unit root have been developed. Nelson and Plosser (1982) used the tests developed by Dickey and Fuller to test the economic indicators of the American economy. They found that almost all economic time series such as the Gross National Product have unit root.

Next, Phillips and Perron (1988) weakened a strong assumption on the error term and extended the Dickey-Fuller test to a more general test (Phillips-Perron (PP) test). However, the PP-test did not alter the result of Nelson and Plosser (1982), even using the same data as Nelson and Plosser (1982).

Another important contribution on unit root test was made by Kwiatkowski *et al.*, (1992). They developed a unit root test that reversed the null hypothesis and alternative hypothesis (KPSS test) and verified that only half of the economic time series had unit root using the same data set as Nelson and Plosser's (1982).

In addition, Christiano (1992) criticised Perron's exogenous treatment of a structural change and devised a method with which structural changes with a drift term and a trend can be detected endogenously and proposed a test whose null hypothesis is a unit root



process without a structural change and whose opposing hypothesis is a stationary process with a structural change.

Again, another test whose null hypothesis is a unit root process without any change in a drift term and whose alternative hypothesis is trend stationary process with a structural break was proposed by Zivot and Andrews (1992). This proposed test can detect a time point of a structural change endogenously and its asymptotic distribution is constant regardless of the time points of structural changes.

Dickey *et al.*, (1984) following the methodology suggested by Dickey and Fuller (1979) for the zero-frequency unit-root case, proposed the Dickey, Hasza and Fuller (DHF) test to test for seasonal unit root. The DHF test only allows for unit roots at all of the seasonal frequencies and has an alternative hypothesis which is considered rather restrictive, namely that, all the roots have the same modulus. Trying to overcome these drawbacks Hylleberg *et al.*, (1990) propose a more general testing (HEGY's test) strategy that allows for unit roots at some (or even all) of the seasonal frequencies as well as the zero frequency. HEGY's methodology allows testing for unit roots at some seasonal frequencies without maintaining that unit roots are present at all seasonal frequencies.

Finally, Banerjee *et al.*, (1992) proposed three kinds of unit root tests. Firstly, a recursive test that is extended on the basis of a structural stability test of Brown *et al.*, (1975) which uses recursive residuals. Secondly, a rolling test that shifts a partial testing period successively among the whole sample period and thirdly a sequential test that conducts *t*-tests or Quandt likelihood ratio tests while shifting a time point of a structural change among the whole sample.



2.9.2 Traditional Time Series Methods

Treating time series in a stochastic sense began in the mid-1920s (Gottman, 1981). Yule (1927) first developed an Autoregressive (AR) model when working on wolfer's sunspot data. Slutsky (1927) first developed a Moving Average (MA) model when studying a white-noise series. Box and Jenkins (1970) developed the Autoregressive Moving average (ARMA) model and gave a full account of the Integrated Autoregressive Moving average (ARIMA) model.

Furthermore, Mann and Wald (1943) proved a theorem to estimate the AR (p) parameters by the least squares method. Quenouille (1947) presented a simple test for AR (p) models and later extended to MA models. Also, Anderson (1971) developed a procedure to estimate the order of the AR model as well as the AR parameter.

In addition, a non-linear least squares technique procedure that led to a technique of approximated likelihood solution for ARMA (p, q) models was developed by Box and Jenkins (1976). Again, an exact likelihood method for estimating parameters of MA (q) models and for ARMA (p, q) models was developed by Newbold (1974). The Box-Pierce statistics was developed by Box and Pierce (1970) and modified by Ljung and Box (1978).

Next, an information criterion to assist in the selection of an ARIMA model was proposed by Akaike (1974). A model with the smallest Akaike Information Criterion (AIC) is the best model to have minimum forecast mean square errors. On the information criterion, Schwarz (1975) indicated that AIC was not consistent when probability approaches one, and proposed a Bayesian Information Criterion (BIC).



Also, Harvey and Phillips (1979) developed an exact likelihood procedure to estimate parameters of an ARIMA model in State-Space form. The State-Space models are also called Structural Time Series (STS) models. Many researchers have pointed out the advantages of the State-Space form over the ARIMA models (Durbin and Koopman, 2001). A time series might be characterised with trend, seasonal cycle and calendar variations, together with the effects of explanatory variables and interventions. These components can be processed separately and for different purposes for a State-Space model. On contrary, the Box-Jenkins ARIMA model is a black-box model, which solely depends on the data without knowledge of the system structure that produces the data. The second advantage is the recursive nature of the State-Space model that obviously allows change of the system overtime, while ARIMA models are homogenous through time, based on the stationary assumption.

Moreover, Granger and Joyeux (1980) and Hosking (1981) adopted an Autoregressive Fractionally Integrated Moving average (ARFIMA) model to study a long memory time series. The autocorrelation function in an ARFIMA (p, d, q) model decays at a hyperbolic rate for non-zero d which is slower than the usual geometric rate of a stationary ARMA (p, q) model.

Another important contribution in the area of time series analysis was made by Engle (1982) when he introduced the Autoregressive Conditional Heteroscedasticity (ARCH) model, to model changing volatility. The non-linear term is the variance of the disturbance. An extension of the ARCH model to the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model was made by Bollerslev (1986).



Again, Weiss (1984) proposed an ARMA-ARCH model, in which an ARMA model is used to model mean behaviour and an ARCH model to model the residuals of the ARMA model. The quasi-maximum-likelihood method is used to estimate model parameters.

Furthermore, another remarkable contribution was made by Hillmer and Tiao (1979) in the area of multivariate time series. They developed an exact likelihood technique for Vector Autoregressive Moving average (VARMA) model. Harvey and Peters (1984) further proposed a state-space method to estimate parameters of VARMA (p, q) models.

In addition, a cointegrated multivariate time series and Error Correction Models (ECM) were proposed by Engle and Granger (1987). The cointegrated concept captures the phenomenon of univariate non-stationary time series moving together. The ECM procedure involves two steps. The first step involves modelling the long term relationship between endogenous and exogenous variables. The variables involved have to comply with two constraints; non-stationary and being stationary after first differencing. In the second step, the dynamic short term process is modelled and only stationary variables enter the regression equation.

Also, a Vector Autoregressive Fractionally Integrated Moving average (VARFIMA) was developed by Robinson and Yajima (2002) to handle multivariate time series cointegration problems.

2.9.3 Vector Autoregression Model

Vector Autoregression (VAR) is a widely use econometrics technique for multivariate time series modelling. The VAR model specifically resembles the form of simultaneous



model (SEM), but VAR approach imposes fewer and weaker restrictions in specifying a model than SEM (Sims, 1980; Chowdhury, 1986). VAR has some very attractive features and has provided a valuable tool for analysing dynamics among time series processes. A VAR model posits a set of relationship between lagged values of all variables and the current values of all variable in the system (Mcmillin, 1991; Lu, 2001).

VAR models have been used in many empirical studies. Park (1990) used VAR models in forecasting the U.S cattle market; Bessler (1984) used VAR models to study Brazilian agricultural prices, industrial prices and money supply; Kaylen, (1988) used VAR and other forms of model to forecast the U.S Hog market; Haden and VanTassell (1988) estimated VAR model using Panel data; Estenson, (1992) used VAR model to explore the dynamics of the Keynesian theory; McCarty and Schmidt (1997) used the VAR model to study State-Government expenditure; Enders and Sandler (1993) used VAR and Intervention analysis to study various attack modes used by transnational terrorists; Freeman *et al.*, (1989) compared VAR model and familiar Structural equation (SEQ) to study politics; Backus (1986) use VAR to elicit the empirical facts concerning the movement of the Canadian-U.S exchange rate; Lu (2001) apply a VAR model for the dynamics of the U.S population between 1910 and 1990; Saluwa and Olubusoye (2006) compared VAR and other estimation techniques on macroeconomic models in Nigeria; Andersson (2007) in his thesis compared the forecast performance of RW, AR and VAR models to forecast Swedish real GDP growth; Adenomon *et al.*, (2013) applied VAR approach on the relationship between rainfall and temperature in Niger State, Nigeria. In fact, the empirical applications of VAR model are numerous.

2.10 Conclusion

In summary, it is well established that rainfall and temperature are two important climatic factors affecting agricultural production. (Lobell and Field, 2007; Kaufmann and Snell, 1997; Riha *et al.*, 1996).

Reviewing of the literature has exposed us to the diverse techniques that researchers have employed in studying dynamic relationship between variables. However among the diverse techniques the Vector Autoregression model was employed in this study to model the dynamic relationship between rainfall and temperature time series data in Kassena-Nankana Municipality because this was the technique used frequently in literature.



CHAPTER THREE

METHODOLOGY

3.0 Introduction

This chapter deals with the data and statistical techniques that were employed in order to achieve the objectives of the study. The chapter is divided into eleven main headings namely; area of study, study variables, data and source, trend analysis, vector autoregression model, unit root test, casualty test, impulse response function, variance error decomposition, lag selection criteria, and model diagnostic.

3.1 Area of study

The Kassena-Nankana East Municipality lies within the Guinea Savannah woodlands. It is one of the nine (9) districts in the Upper East Region. The Municipality shares boundaries to the North with Burkina Faso, to the East with Bolgatanga Municipality, West with the Builsa District and South with West Mamprusi District (in the Northern Region). The drainage system of the Municipality is constituted mainly around the tributaries of the Sissili River-Asibelika, Afumbeli, Bukpegi and Beeyi. A tributary of the Asibelika River (Tono River) has been dammed to provide irrigation facilities, which is of great economic importance to the entire District. There are some few dugouts and ponds, which are used for livestock, crop farming in the dry seasons and domestic purposes. This feature makes the district a suitable destination for irrigation development. However, the climate conditions of the Municipality are characterized by the dry and wet seasons, which are influenced mainly by two (2) air masses – the North-East Trade winds



and the South-Westerlies (Tropical Maritime). The Harmattan air mass (North-East Trade Winds) is usually dry and dusty as it originates from the Sahara Desert. During such periods, rainfall is virtually absent due to low relative humidity, which rarely exceeds 20 per cent and low vapour pressure less than 10mb. Day temperatures are high recording 42° Celsius (especially February and March) and night temperatures are as low as 18° Celsius. The Municipality experiences the tropical maritime air mass between May and October. This brings rainfall averaging 950mm per annum. This makes most of the youth in the district idle during the dry seasons (November to April). (Kassena-Nankana Municipal Assembly annual report, 2013).

3.2 Study variables

The variables or factors that are considered in the study were rainfall and temperature.

3.3 Source of data and data collection procedure and analysis

The data for this research was mainly secondary data. To these end monthly values of temperature and rainfall were obtained from the Kassena-Nankana Municipal Meteorological service department which spanned from January 2000 to December 2012. The statistical package that was used for the analysis was Stata, Gretl and Minitab.



3.4 Trend analysis

Climatic variables time series data exhibit trend. It is therefore imperative to investigate what the nature of the trend is. A trend is a slow, long-run, evolution in the financial or economic variable (Dheerasinghe, 2006). Thus, the trend reflects the long-run growth or decline in the time series. The trend in a time series data may appear as a linear function of time, non-linear function of time or the trend may be characterised by a constant growth rate. The trend analysis applied in this study was an attempt to fit linear, quadratic, exponential type models to the time series of rainfall and temperature as follows;

$$\hat{Y}_t = \alpha + \beta_t \quad (3.1)$$

$$\hat{Y}_t = \alpha + \beta_1 t + t^2 \quad (3.2)$$

$$\hat{Y}_t = a * \beta^{**t} \quad (3.3)$$

The best-fitted model of time trend for each variable was chosen using the following statistical criteria of Mean Deviation (MD), Mean Square Deviation (MSD), Mean Absolute Deviation (MAD) and Mean Absolute Percent Error (MAPE) as stated by Makridakis and Wheelwright (1986).

$$MD = \sum_{i=1}^n e_i / n \quad (3.4)$$

$$MSD = \sum_{i=1}^n e_i^2 / n \quad (3.5)$$

$$MAD = \sum_{i=1}^n |e_i| / n \quad (3.6)$$



$$MAPE = \sum_{i=1}^n |(X_i - F_i/X_i) * 100|/n \quad (3.7)$$

where X_i is the measured value is at time i , F_i is the predicted value at the same time, $e_i = X_i - F_i$ and n is the number of measurements. The closer the average MD is to zero and the smaller the values of MSD, MAD and MAPE, the better the model fits the time-series (Statgraphics, 1987).

3.5 Vector Autoregression (VAR) Model

Vector Autoregression (VAR) is a generalized reduced form which helps to detect the statistical relationship among the variables in the system. It allows all the variables in the system to interact with self and with each other, without having to impose a theoretical structure on the estimates. It provide additional method that help in analysing the impact of a given variable on itself and on all other variables using Impulse Response Functions (IRFs) and Variance Error Decompositions (VED) (Ansari and Ahmed, 2007).

In this study we consider the VAR (p) model as;

$$M_t = K + A_1 M_{t-1} + A_2 M_{t-2} + \dots + A_n M_{t-n} + \varepsilon_t \quad t = 0, \pm 1, \pm 2.. \quad (3.8)$$

Where $M_t = [m_{it} \dots m_{kt}]'$ is $(n \times 1)$ random vector, the A_i are fixed $(n \times n)$ coefficient matrices, K is a $n \times 1$ vector of constants (intercept) allowing for the possibility of non-zero mean $E(M_t)$. Finally, $u_t = [u_{it} \dots u_{kt}]'$ is a k -dimensional white noise or innovation process that is $E(\varepsilon_t) = 0$, $E(\varepsilon_t \varepsilon_t^1) = \Sigma_u$ and $E(\varepsilon_t \varepsilon_s^1) = 0$ $s \neq t$. The covariance matrix Σ_u is assumed to be non-singular (Lutkepohl, 2005).

We say that M_t is stable VAR (p) process if $\det(I_k - A_1 Z - \dots A_p Z^p) \neq 0$ for $|z| \leq 1$. Hence this condition provides an easy tool for checking the stability of a VAR process.



Since the explanatory variables are the same in each equation, the Multivariate Least Squares is equivalent to the Ordinary Least Squares (OLS) estimator applied to each equation separately, as was shown by Zeller (1962).

3.6 Unit Root Test

In VAR, it is useful to tests for time series characteristics such as unit root, Granger causality and cointegration (Ansari and Ahmed, 2007). Broadly speaking, a stochastic process is said to be stationary if its mean and variance are constant overtime and the value of the covariance between the two time periods depends only on the distance or gap or lag between the two time periods and not the actual time at which the covariance is computed (Gujarati, 2003). A test of stationarity (or non stationarity) that has become widely popular over the past several years is the unit root test known as Augmented Dickey-Fuller (ADF) test (Engle and Granger, 1987; Ajayi and Mougoue, 1996).

Thus in this study the Augmented Dickey-fuller (ADF) test was used to test for unit root.

3.7 Augmented Dickey-Fuller (ADF) Test

The ADF test proposed by Dickey and Fuller (1979) was an improvement of the Dickey-Fuller (DF) test. The test is based on the assumption that the series follows a random walk. Consider an autoregressive process of order one, AR (1), below

$$Y_t = \phi Y_{t-1} + \varepsilon_t \quad (3.9)$$

where ε_t denotes a serially uncorrelated white noise sequence with a mean of zero and constant variance. If $\phi = 1$, equation (3.9) becomes a random walk model without drift, which is known as a non-stationary process. The basic concept of the ADF test is to



simply regress Y_t on its lagged value Y_{t-1} and find out if the estimated ϕ is statistically equal to one or not. Equation (3.10) can be manipulated by subtracting Y_{t-1} from both sides to obtain

$$\Delta Y_t = \delta Y_{t-1} + \varepsilon_t \quad (3.10)$$

where $\delta = \phi - 1$, and $\Delta Y_t = Y_t - Y_{t-1}$. In practice instead of estimation equation (3.9), we rather estimate equation (3.10) and test for the null hypothesis of $\delta = 0$ against the alternative $\delta \neq 0$. If $\delta = 0$, then $\phi = 1$, meaning that the series have a unit root. Under the null hypothesis $\delta = 0$, the t -value of the estimated coefficient of Y_{t-1} does not have an asymptotic normal distribution (Erdogdu, 2007).

The decision to reject the null hypothesis or not is based on the DF critical values of the τ -statistic. The DF test is based on the assumption that the error terms are uncorrelated. However, the errors of the DF test usually show evidence of serial correlation. In order to overcome this problem, the ADF test includes the lags of the first difference series in the regression equation to make the error term white noise and therefore the regression equation is presented in the following form

$$\Delta Y_t = \delta Y_{t-1} + \sum_{i=1}^p \gamma_i \Delta Y_{t-i} + \varepsilon_t \quad (3.11)$$

To be more specific, the intercept may be included as well as time trend t , after which the model becomes

$$\Delta Y_t = \alpha + \beta t + \delta Y_{t-1} + \sum_{i=1}^p \gamma_i \Delta Y_{t-i} + \varepsilon_t \quad (3.12)$$

where α is a constant, β the coefficient on time trend series, $\sum_{i=1}^p \gamma_i \Delta Y_{t-i}$ is the sum of the lagged values of the dependent variable ΔY_t and p is the lag order of the autoregressive process. The parameter of interest in the ADF test is δ . For $\delta = 0$, the series contains unit root and hence non-stationary. The choice of the starting augmentation order depends on; data periodicity, significance of γ_i estimates and white noise residuals. After preliminary estimation, non-significant parameter augmentation can be dropped in order to enjoy more efficient estimates. The test statistic for the ADF test is given by

$$F_{\tau} = \frac{\hat{\delta}}{SE(\hat{\delta})} \quad (3.13)$$

where $SE(\hat{\delta})$ is the standard error of the least square estimate of $\hat{\delta}$. The null hypothesis is rejected if the test statistic is greater than the critical value.

3.8 Lag length Selection in Vector Autoregressive Models

The optimal lag length (p) is usually determined using one of the following popular criterion and q is chosen to be the order that minimizes the following criterion (Gujarati, 2003; Beenstock and Felsenstein, 2007). The criteria are;

$$AIC_{(p)} = \ln|\Sigma(q)| + \frac{2}{T}pk^2 \quad (3.14)$$

$$SBIC_{(p)} = \ln|\Sigma(q)| + \frac{\ln T}{T}pk^2 \quad (3.15)$$

$$HQIC_{(p)} = \ln|\Sigma(q)| + \frac{2\ln\ln T}{T}pk^2 \quad (3.16)$$

where $\Sigma(q)$ = estimated covariance matrix and T = number of observations,



Akaike Information Criterion (AIC); Schwarz Bayesian Information Criterion (SBIC); Hannan and Quinn information Criterion (HQIC). Finally the lag length (q) that is associated with the minimum AIC, SBIC and HQIC values from a set of AIC, SBIC and HQIC values is selected as the appropriate lag length (p) for the VAR model.

3.9 Model Diagnostics

In order to use any developed model to draw any meaningful conclusion or make generalisation, it is important to diagnose the model to see whether there is concordance of the model with the real world observations. Thus, we employed the Ljung-Box, ARCH-LM and in diagnosing the developed models.

3.9.1 Ljung-Box Test

One of the major problems that a researcher is likely to encounter in fitting time series models is serial correlation. That is, temporal dependency between successive values of the model residuals. In this study, the Ljung-Box test proposed by Ljung and Box (1978) was used for testing the assumption that the residuals contain no serial correlation up to any order k . The test procedure is as follows;

H_0 : There is no serial correlation up to order k .

H_1 : There is serial correlation up to order k .

The test statistic is given by;

$$Q_m = T(T + 2) \sum_{k=1}^m (T - k)^{-1} r_k^2 \quad (3.17)$$



where

r_k^2 represent the residual autocorrelation at lag k

T is the number of residuals

m is the number of time lags included in the test

When the p -value associated with Q_m is large, the model is considered adequate else the whole estimation process has to start again in order to get the most adequate model.

3.9.2 ARCH-LM Test

The issue of conditional heteroscedasticity is one of the key problems that a researcher is likely to encounter when fitting models. This happens when the variance of the residuals is not constant. To ensure that the fitted model is adequate, the assumption of constant variance must be achieved. The ARCH-LM test proposed by Engle (1982) was used to test for the presence of conditional heteroscedasticity in the model residuals. The test procedure is as follows;

H_0 : There is no heteroscedasticity in the model residuals

H_1 : There is heteroscedasticity in the model residuals

The test statistic is

$$LM = nR^2 \quad (3.18)$$

where n is the number of observations and R^2 is the coefficient of determination of the auxiliary residual regression.

$$e_t^2 = \beta_0 + \beta_1 e_{t-1}^2 + \beta_2 e_{t-2}^2 + \dots + \beta_q e_{t-q}^2 + v_t \quad (3.19)$$

where e_t is the residual. The null hypothesis is rejected when the p -value is less than the level of significance and is concluded that there is heteroscedasticity.

3.10 Causality Test

Granger causality test is a technique for determining whether one time series is useful in forecasting another (Granger, 1969). The series x_t is said to Granger cause y_t if the past of x_t has additional power in forecasting y_t after controlling for the past of y_t (Gelper and Croux, 2007). Gujarati (2003), distinguished four cases of causality. They are unidirectional causality from Y; unidirectional causality from Y to X; bilateral causality of Y and X; and independence of Y and X. The steps involved in implementing Granger causality test can be found in Gujarati (2003).

3.11 Impulse Response Function (IRF)

The Impulse Response Function (IRF) is used to determine how each endogenous variable responds over time to a shock in its own value and in every other variable. Again any VAR can be modelled as a triangular moving average process (Beenstock and Felsenstein, 2007).

$$Y_t = \mu + \theta_0 n_t + \theta_1 n_{t-1} + \theta_2 n_{t-2} \quad (3.20)$$



From this equation we can observe changes in M_t given a change in the residual.

Plotting the IRF maps out the cyclic created in all variables given a shock in one variable.

$$\frac{\partial M_{i,t+s}}{\partial n_{i,t}} = \frac{\partial M_{i,t}}{\partial n_{i,t-s}} = \theta_{i,j}, j = 1, 2, \dots, n, s > 0 \quad (3.21)$$

It is common to draw bootstrapped confidence interval around IRF.

3.12 Forecast Error Variance Decomposition (FEVD)

If the innovation which actually drive the system can be identify, a further tool used to interpret VAR model is forecast error variance decompositions. It is denoted as;

$$W_{jk,h} = \frac{\sum_{i=0}^{h-1} (e_j \theta_i e_k)^2}{\sum_{i=0}^{h-1} e_j \theta_i \sum_t \theta_i e_j} \quad (3.22)$$

Which denote the k-th column of I_k by the e_k , the proportion of the h-step forecast error variance of the variable k. Detailed can be found in Lutkepohl (2005).

3.13 Conclusion

The chapter dealt with the statistical techniques employed in this study. It presented the techniques in a clear, precise and concise manner



CHAPTER FOUR

DATA ANALYSIS AND DISCUSSIONS OF RESULTS

4.0 Introduction

This chapter analyses, discusses and interprets the results obtained from the study. The chapter is organised into preliminary analysis, further analysis and discussion of results.

4.1 Preliminary Analysis

This section explains the descriptive statistics of the time series data on rainfall and temperature in the Kassena-Nankana Municipality.

The descriptive statistics on rainfall and temperature are presented in Table 4. 1. For the period considered the average rainfall was 3.107mm with maximum rainfall of 26.700mm and the minimum rainfall was 0.000mm, while the average temperature was 29.511°C with maximum temperature of 37.100°C and minimum temperature of 25.450°C. The coefficient of variation (CV) is high in rainfall data and low in temperature data.

Table 4.1: Descriptive Statistics

| Variable | Observation | Minimum | Maximum | Mean | CV |
|-------------|-------------|---------|---------|--------|-------|
| Rainfall | 156 | 0.000 | 26.700 | 3.107 | 1.371 |
| Temperature | 156 | 25.450 | 37.100 | 29.511 | 0.082 |

In Figure 4.1 and Figure 4.2 shows the time series plot of the rainfall and temperature data respectively, the graph display some level of Stationarity in the data as both series fluctuate about a fixed point.

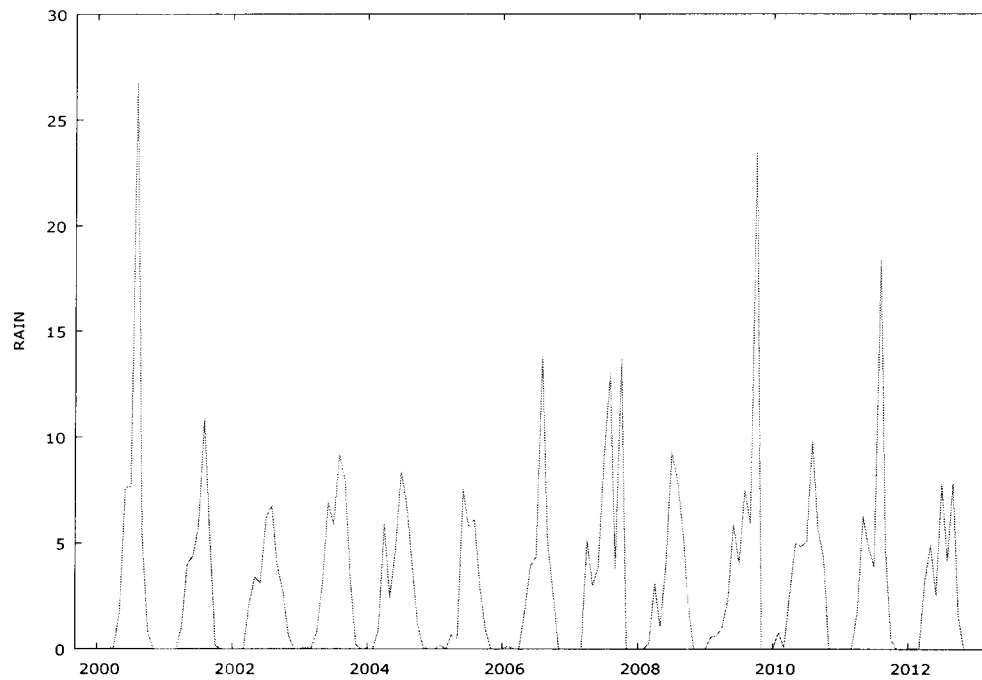


Figure 4.1: Time series plot of Rainfall data.

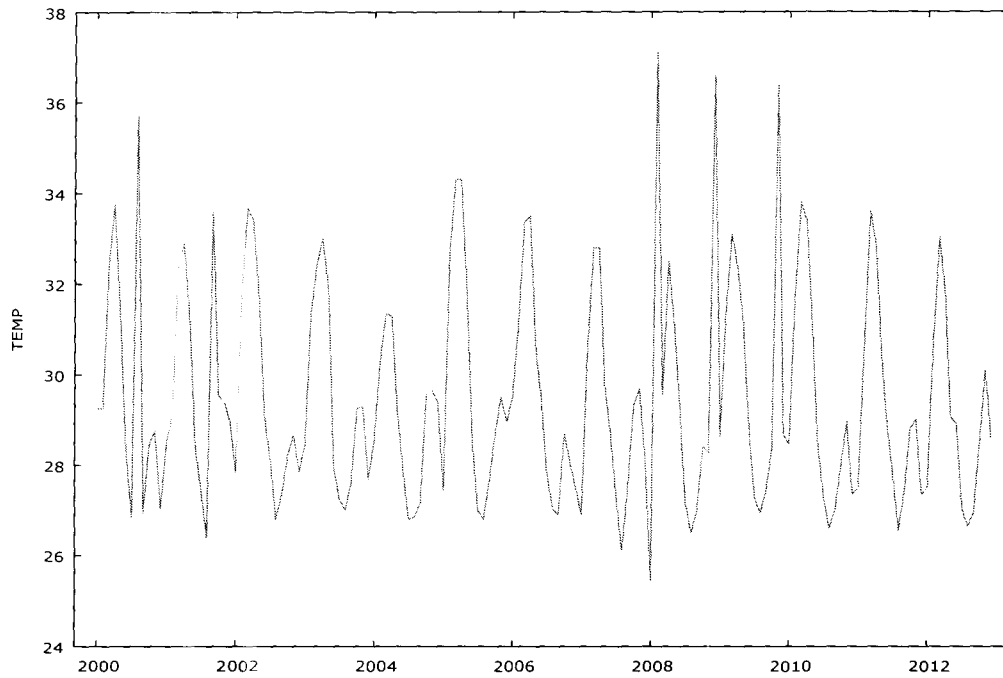


Figure 4.2: Time series plot of Temperature data

4.1.1 Trend Analysis of Rainfall

An investigation of the nature of the trend in the rainfall time series data was carried out using linear and quadratic trend models as shown in Table 4.2. The linear trend model was observed as the best since it had the least MSD, MAD and MAPE values. This result affirms that rainfall trend is generally flat with slight increment over a certain time period. The exponential trend model was not investigated and this may be due to zero values recorded in the rainfall data.



Table 4.2: Trend analysis of rainfall

| Model | MAD | MAPE | MSD |
|-----------|---------|----------|---------|
| LINEAR | 3.079 * | 672.005* | 18.018* |
| QUADRATIC | 3.080 | 675.742 | 18.025 |

*Means best based on the selection criteria.

The parameters of the linear trend model were estimated. As shown in Table 4.3, all the parameters were significant at the 5% level of significance. The estimated linear model revealed that the rainfall is linear and trends generally flat. The adjusted R-squared was about 76.3% reflecting the fact that the trend is responsible for a large part of the variation in rainfall. Thus, the estimated linear trend model is given by;

$$\hat{Y}_t = 2.883 + 0.00287 * t$$

Table 4.3: Estimated parameters of the linear trend model

| Variable | Coefficient | Standard error | T-statistic | P-value |
|----------------|-------------|---|-------------|---------|
| Constant | 2.8827 | 0.6875 | 4.1929 | 0.0001 |
| Time | 0.0029 | 0.0076 | 0.3776 | 0.0201 |
| AIC = 897.8201 | | R-Squared = 0.7625 | | |
| BIC = 903.9198 | | Adj. R-Squared = 0.7524 Durbin-Watson = 1.2237 | | |

4.1.2 Trend Analysis of Temperature

A carefully study of the trend analysis of temperature revealed that the exponential model was the best, since it recorded the least values of MSD, MAD and MAPE as shown in Table 4.4 This implies the growth in the temperature data follows an exponential pattern.

Table 4.4: Trend analysis of Temperature

| Model | MAD | MAPE | MSD |
|-------------|----------|----------|----------|
| Linear | 1.97214 | 6.56627 | 5.84259 |
| Quadratic | 1.97182 | 6.56521 | 5.84249 |
| Exponential | 1.94673* | 6.45898* | 5.84102* |

*Means best based on the selection criteria.

Also the parameters of the exponential trend model were estimated. As shown in Table 4.5, all the parameters were significant at the 5% level of significance. The estimated exponential model revealed that the temperature trend shows some level of growth. The R-squared was about 85.6% reflecting the fact that the trend is responsible for a large part of the variation in temperature. Thus, the estimated exponential trend model is given by;

$$\hat{Y}_t = 29.7303 * 0.999864^t$$

Table 4.5: Estimated parameters of the exponential trend model

| Variable | Coefficient | Standard error | T-statistic | P-value |
|------------------|-------------|---|-------------|---------|
| Constant | 3.3922 | 0.0129 | 263.45 | 0.0001 |
| Time | -0.0001 | 0.0001 | -0.9525 | 0.0408 |
| AIC = -343.2380 | | R-Squared = 0.8558 | | |
| SBIC = -337.1383 | | Adj. R-Squared = 0.8438 Durbin-Watson = 1.1671 | | |

4.2 Further Analysis

4.2.1 Stationarity Test

To examine whether the two time series data are non-stationary, the ADF unit root was employed. The ADF tests for rainfall and temperature series are presented in Table 4.6. The test was carried with and without trend. The results revealed that both series were stationary at 5% significant level. This implies that the data is good for fitting VAR model.

Table 4 6: ADF Test for Rainfall and Temperature Series without and with Trend

| Variable | Constant | | Constant+ Trend | |
|-------------|----------------|---------|-----------------|---------|
| | Test Statistic | P-value | Test Statistic | P-value |
| Rainfall | -1.655 | 0.000 | -3.443 | 0.000 |
| Temperature | -1.655 | 0.000 | -3.443 | 0.000 |

4.2.2 The VAR Model and Lag selection

In Lutkepohl and Saikkonen, (1997) showed that the fitted VAR model order is assumed to increase with the sample size that is, $p = \sim(T)^{\frac{1}{3}}$ where T is the size of the time series. And they concluded that VAR (p) are fitted to data such that h goes to infinity with sample size. Using this idea, in this work T=156, then $p \approx (156^{\frac{1}{3}}) \approx 5$. Then using VAR (5), we considered VAR models from lag 1 to lag 5, and VAR model at lag 5 was chosen by AIC, SBIC and HQIC criteria as shown in Table 4.7.

Table 4.7: Lag Selection Criteria

| Information Criteria | Lag 1 | Lag 2 | Lag 3 | Lag 4 | Lag 5 |
|-----------------------------|--------------|--------------|--------------|--------------|--------------|
| AIC | 9.6513 | 9.5583 | 9.3721 | 9.2868 | 9.1663* |
| HQIC | 9.7751 | 9.7645 | 9.6608 | 9.6581 | 9.6200* |
| SBIC | 9.7016 | 9.6421 | 9.4894 | 9.4377 | 9.3507* |

*Means best based on the information criteria.

Table 4.8 presents the parameter estimates of the VAR (5) model. Lag 4 and lag 5 values for rainfall are useful in predicting itself while its lag 1, lag 2 and lag 3 are not. The lag 1 and lag 4 values of temperature are useful in predicting rainfall while the lag 2, lag 3 and lag 5 values of temperature are not. Also, the lag 2 and lag 3 values of rainfall are useful in predicting temperature where as its lag 1, lag 3 and lag 4 values are not. In addition, the lag 1, lag 3 and lag 4 values of that of temperature are useful in predicting itself but its lag 2 and lag 5 values are not.



Table 4.8: Parameter estimates of VAR (5) model

| | | Coefficient | Standard error | t-ratio | P-value |
|--------------------|-------------|--------------------|---------------------------|----------------|----------------|
| rainfall | Rainfall | | | | |
| | L1 | 0.0808248 | 0.0808508 | 0.9997 | 0.3192 |
| | L2 | 0.0848062 | 0.0773204 | 1.0970 | 0.2746 |
| | L3 | 0.0463973 | 0.0758362 | 0.6118 | 0.5416 |
| | L4 | 0.1441410 | 0.0745805 | 1.9330 | 0.0553* |
| | L5 | 0.2722760 | 0.0732608 | 3.7170 | 0.0003* |
| | Temperature | | | | |
| | L1 | 0.4600510 | 0.1112600 | 4.1350 | 6.07e-05* |
| | L2 | 0.0580858 | 0.1334200 | 0.4353 | 0.6640 |
| | L3 | 0.1580500 | 0.1329230 | 1.1890 | 0.1580 |
| | L4 | 0.3042470 | 0.3042470 | 2.3040 | 0.0227* |
| | L5 | 0.1947150 | 0.1217220 | 1.6000 | 0.1119 |
| Temperature | Rainfall | | | | |
| | L1 | -0.0391630 | 0.0497466 | -0.7872 | 0.43247 |
| | L2 | -0.0933580 | 0.0474240 | -1.9686 | 0.05098* |
| | L3 | -0.1305550 | 0.0474618 | -2.7507 | 0.00673* |
| | L4 | -0.0475979 | 0.0488263 | -0.9748 | 0.33132 |
| | L5 | -0.0614132 | 0.0476757 | -1.2881 | 0.19982 |
| | Temperature | | | | |
| | L1 | -0.07240710 | 0.0860495 | -0.8415 | 0.40153 |
| | L2 | -0.22740500 | 0.0834694 | -2.7244 | 0.00726* |
| | L3 | -0.17600800 | 0.0856864 | -2.0541 | 0.04188* |
| | L4 | -0.06331380 | 0.0883956 | -0.7163 | 0.47503 |
| | L5 | -0.0391630 | 0.0497466 | -0.7872 | 0.43247 |

*Means significant at 5%



4.2.3 Stability Condition of VAR model

Table 4.9 shows the results on the stability condition of VAR (5) model. The results revealed that all the eigenvalues lie inside the unit circle, because the modulus of the eigenvalues are less than 1. Suggesting that the VAR (5) satisfies the stability condition. This further suggests that both series (rainfall and temperature) were stationary as specified by the ADF test in Table 4.6.

Table 4.9: VAR stability Conditions

| Eigenvalue | Modulus |
|---------------------------|----------|
| $0.8101273 + 0.4669606i$ | 0.935071 |
| $0.8101273 - 0.4669606i$ | 0.935071 |
| $0.4570009 + 0.6740583i$ | 0.814374 |
| $0.4570009 - 0.6740583i$ | 0.814374 |
| $-0.2689549 + 0.6118575i$ | 0.668361 |
| $-0.2689549 - 0.6118575i$ | 0.668361 |
| $-0.6400341 + 0.0140518i$ | 0.640188 |
| $-0.6400341 - 0.0140518i$ | 0.640188 |
| $-0.2168902 + 0.5383157i$ | 0.580366 |
| $-0.2168902 - 0.5383157i$ | 0.580366 |

The Ljung-Box was employed to test for the presence of serial correlation in the model residuals. The Ljung-Box test result shown in Table 4.10, failed to reject the null hypothesis of no serial correlation in the residuals of the VAR (5) model, this indicate that the model is free from serial correlation.

Table 4.10: Univariate Ljung-Box test

| Equations | Lag | Test statistics | <i>P</i> -value |
|-------------|-----|-----------------|-----------------|
| Rainfall | 21 | 4.672 | 0.968 |
| | 24 | 15.336 | 0.911 |
| | 36 | 22.359 | 0.963 |
| Temperature | 12 | 19.325 | 0.281 |
| | 24 | 37.699 | 0.081 |
| | 36 | 57.681 | 0.062 |

The ARCH-LM test was employed to test for constant variance assumption. The ARCH-LM test result shown in Table 4.11, failed to reject the null hypothesis of no ARCH effect in the residual. Hence, the selected model satisfies all the assumptions and it can be concluded that VAR (5) model provides an adequate representation of the rainfall and temperature time series data.



Table 4.11: Univariate ARCH-LM test

| Equations | Lag | Test statistics | P-value |
|-------------|-----|-----------------|---------|
| Rainfall | 21 | 0.957 | 0.081 |
| | 24 | 9.149 | 0.037 |
| | 36 | 16.413 | 0.012 |
| Temperature | 12 | 18.922 | 0.090 |
| | 24 | 32.816 | 0.108 |
| | 36 | 38.609 | 0.353 |

The Granger causality test in Table 4.12 revealed a bi-directional relationship between Rainfall and Temperature that is; the relationship is running from rainfall to temperature (rainfall-temperature) with p-value less than 0.001 also the relationship runs from temperature to rainfall (temperature-rainfall) with p-value less than 0.001. These results indicated that rainfall is useful in forecasting temperature, and temperature is useful in forecasting rainfall in Kassene -Nankana East Municipality.

Table 4.12: Granger Causality Test

| Equation | Excluded | Chi 2 | df | prob>Chi2 |
|-------------|-------------|--------|----|-----------|
| Rainfall | Temperature | 69.945 | 5 | 0.000 |
| Rainfall | All | 69.945 | 5 | 0.000 |
| Temperature | Rainfall | 75.637 | 5 | 0.000 |
| Temperature | All | 75.637 | 5 | 0.000 |



As started earlier, the individual VAR coefficients are difficult to interpret, but the Impulse Response Function (IRF) and the Forecast Error Decomposition (FEVDC) help us to interpret the dynamic relationship between time series data.

The IRF in Figure 4.3 depicts the way rainfall and temperature in the model interacts following a shock in the VAR model. When the impulse variable is rainfall, in the first period rainfall react positively to a shock in its own values followed by a negative response in the second period. The third period show a positive response followed a negative response in the fourth and fifth periods. Rainfall reacted negatively to a shock in temperature in the second period, followed by a positive response to the rest of the periods. Temperature reacted positively to a shock in rainfall in the second period followed by a negative response in the third and fourth period and then a positive response in fifth period. Temperature reacted positively to a shock in itself in the first period followed by a negative response to the rest of the periods.

The IRF do not show the magnitude of these relationships. For these reasons, it is necessary to examine the Variance Decompositions.

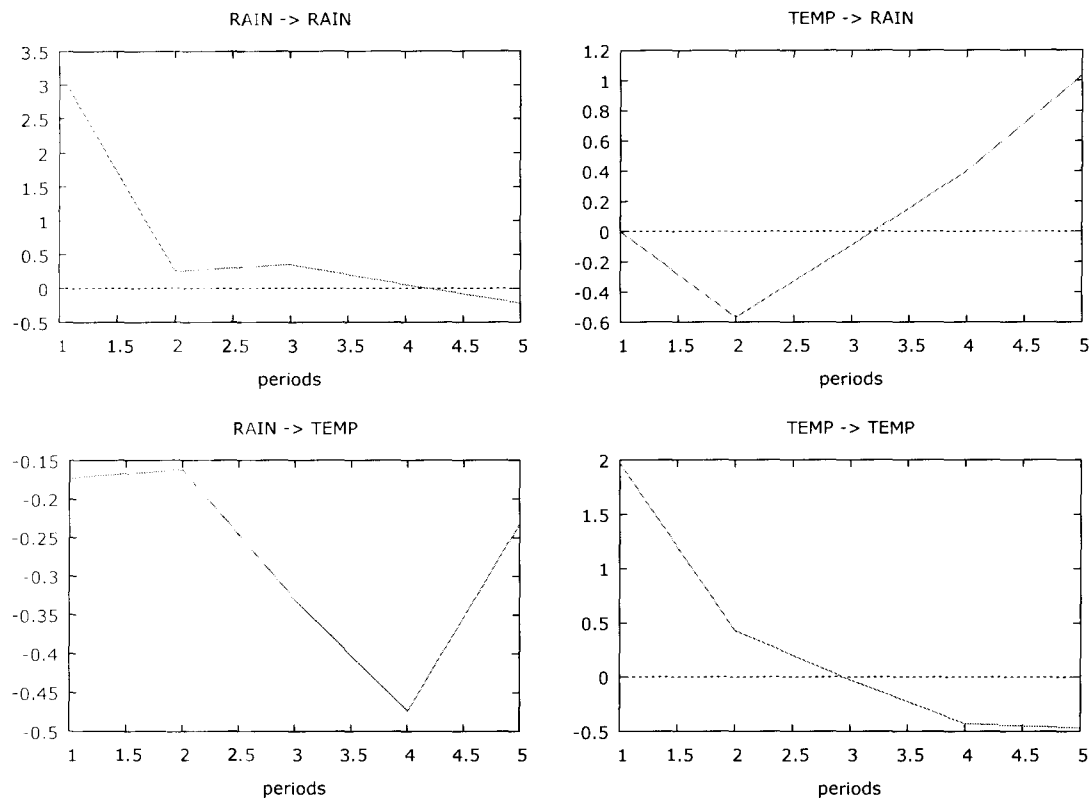


FIGURE 4.3: Impulse Response Analysis of VAR (5) model.

2.2.4 Forecast Error Variance Decompositions

The Forecast Error Variance decomposition (FEVD) results are presented in Table 4.13 and Table 4.14. The result at period five revealed that over 86% of the forecast uncertainty in Rainfall appears to have been explained by innovations in Rainfall, while over 13% was explained by innovations in temperature. Also, over 90% of the forecast uncertainty in temperature appears to have been explained by innovations in temperature, while over 9% was explained by innovations in rainfall. This result was similar to the result obtain by Granger causality test of bi-directional relationship. This result affirms

the bidirectional relationship between rainfall and temperature. This means that rainfall account appreciable to the forecast uncertainty in temperature and vice versa.

Table 4.13: Decomposition of variance for Rainfall

| Period | Std. Error | RAINFALL | TEMPERATURE |
|--------|------------|----------|-------------|
| 1 | 3.18565 | 100.0000 | 0.0000 |
| 2 | 3.24595 | 96.9425 | 3.0575 |
| 3 | 3.26635 | 96.9020 | 3.0980 |
| 4 | 3.29127 | 95.4701 | 4.5299 |
| 5 | 3.45647 | 86.9542 | 13.0458 |

Table 4.14: Decomposition of variance for Temperature

| Period | Std. Error | RAINFALL | TEMPERATURE |
|--------|------------|----------|-------------|
| 1 | 1.97641 | 0.7611 | 99.2389 |
| 2 | 2.02884 | 1.3622 | 98.6378 |
| 3 | 2.05572 | 3.9081 | 96.0919 |
| 4 | 2.15278 | 8.4233 | 91.5767 |
| 5 | 2.21534 | 9.0547 | 90.9453 |



4.3 Discussion of Results

Table 4.1 shows that for the period considered the average rainfall is 3.107mm with average temperature being 29.511°C, the coefficient of variation is low in temperature data while in rainfall data is high. The high variation in rainfall data is attributed to the uncertain patterns of rainfall experienced in the study area.

Clearly, the results revealed that there was a trend in both rainfall and temperature distribution. The appropriate trend model that best fits the rainfall data was linear; whose trends explain about 76.25% of the variation in the rainfall distribution. The exponential model was best to fit temperature and account for about 85.58% of its variation. The coefficient was positive indicating that unit changes in the time trend will see a rise in temperature.

Table 4.6 shows the ADF test performed on rainfall and temperature time series data. The test performed with constant only and with constant and trend revealed that the data was stationary. The stationarity in rainfall and temperature is affirmed by the time series plot of the data. As shown in Figure 4.1 and Figure 4.2, the data for the rainfall and temperature fluctuates about a fixed point indicating that the rainfall and temperature data is stationary. This property of the data is a good justification for fitting the Vector Autoregressive model.

The appropriate lag order for the model was selected using the information criterion: From Table 4.7, the AIC, HQIC, and SBIC selected lag 5 as the optimum lag order for the model as it had the least value for all the information criteria. Thus, VAR (5) model was estimated for rainfall and temperature in Table 4.8. Lag 4 and lag 5 values for



rainfall are useful in predicting itself while its lag 1, lag 2 and lag 3 are not. The lag 1 and lag 4 values of temperature are useful in predicting rainfall while the lag 2, lag 3 and lag 5 values of temperature are not. Also, the lag 2 and lag 3 values of rainfall are useful in predicting temperature where as its lags 1, lag 3 and lag 4 values are not. In addition, the lag 1, lag 3 and lag 4 values of that of temperature are useful in predicting itself but its lag 2 and lag 5 values are not.

The stability of the VAR (5) model was investigated. The results revealed the model was stable as all the eigenvalues have modulus less than one as shown in Table 4.9. This affirms that all the series used are stationary as revealed by the ADF test in Table 4.1. Also, the univariate Ljung-Box test and ARCH-LM test were used to diagnose the model and as shown in Table 4.10 and Table 4.11, the model residuals are free from serial correlation and conditional heteroscedasticity respectively; this indicates that the fitted model is adequate. The model was then used to investigate Granger causality between rainfall and temperature. Table 4.12 revealed that rainfall Granger-cause temperature and temperature Granger-cause rainfall, thus there is a bi-directional relationship between rainfall and temperature (Rajeevan *et al.*, 1998; Black, 2005; Adenomon *et al.*). These results imply that, rainfall is useful in forecasting temperature and temperature is useful in forecasting rainfall.

The Impulse Response analysis in Figure 4.3 depicts the way rainfall and temperature interacts following a shock in the VAR model. When the impulse variable is rainfall, in the first period rainfall react positively to a shock in its own values followed by a negative response in the second period. The third period show a positive response



followed by a negative response in the fourth and fifth periods. Rainfall reacted negatively to a shock in temperature in the second period, followed by a positive response to the rest of the periods. Temperature reacted positively to a shock in rainfall in the second period followed by a negative response in the third and fourth period and then a positive response in fifth period. Temperature reacted positively to a shock in itself in the first period followed by a negative response to the rest of the periods. The Impulse Response analysis does not clearly show the magnitude of the relationship among the variables.

The Variance Decomposition for the variables was therefore examined. Table 4.13 and Table 4.14 display the Variance Decomposition for Rainfall and Temperature. Aside Rainfall itself, the influence of temperature contributes most in forecasting the uncertainty of rainfall. For instance at period five, in Table 4.13 about 86.03% of the forecast uncertainty in Rainfall appears to have been explained by innovations in Rainfall, while 13% was explained by innovations in Temperature. At period five in Table 4.14 about 90.94% of the forecast uncertainty in temperature appears to have been explained by innovations in Temperature, while 9.05% was explained by innovations in rainfall.

4.4 Conclusion

This chapter dealt with the analysis and discussion of results. It presented the major findings of the study in a clear, detailed, precise and concise manner.



CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.0 Introduction

This chapter provides conclusion and recommendations that could address the problems under study. The conclusion and recommendations were strictly based on the findings of the study area.

5.1 Conclusion

The study set out to model the dynamic relationship of rainfall and temperature in Kassena-Nankana Municipality and to fit the trend models of rainfall and temperature using monthly data from January 2000 to December 2012. The results revealed that; the coefficient of variation is low in temperature and high in rainfall. The linear ($\widehat{Y}_t = 2.883 + 0.00287 * t$) and the exponential ($\widehat{Y}_t = 29.7303 * 0.999864^t$) trends model was the best to fit rainfall and temperature respectively, this result affirms that the pattern of rainfall is flat with slight increament over a certain time period and that of temperature grows over time. The ADF test was used to test the non stationarity of the series, the test revealed that rainfall and temperature time series are both stationary which was also confirmed by the VAR stability condition of both series being stationary. This revealed the suitability of the VAR model for studying the dynamic relationship between rainfall and temperature. The VAR models favored VAR at lag 5 using AIC, SBIC and HQIC criteria. The VAR (5) model was diagnosed using the univariate ARCH-LM test and the Ljung-Box test, the results of both test failed to reject the null hypothesis of no ARCH



effect and serial correlation respectively in the residuals of the VAR (5) model indicating that the VAR (5) model provides an adequate representation of rainfall and temperature series in the study area. The results from the Impulse Response Functions and Forecast Error Variance Decompositions revealed that over 86% of the forecast uncertainty in rainfall appears to have been explained by innovations in rainfall, while over 13% was explained by innovations in temperature. Also, over 90% of the forecast uncertainty in temperature appears to have been explained by innovations in temperature, while over 9% was explained by innovations in rainfall. This result was similar to the result obtained by Granger causality test of bi-directional relationship. The research concludes that there is a bi-directional relationship between rainfall and temperature that is; the relationship is running from rainfall to temperature (rainfall-temperature) and also runs from temperature to rainfall (temperature-rainfall). This indicates that rainfall is useful in explaining an appreciable amount of the forecast uncertainty in temperature, and temperature is useful in explaining an appreciable amount of the forecast uncertainty in rainfall. Thus modelling rainfall and temperature together in Kassena-Nankana Municipality will further improve the forecast of rainfall and temperature respectively.

5.2 Recommendation

In line with the findings of the study, the following recommendations are made for consideration;

- The study considered vector autoregression model. Further studies should be carried out by including covariates in this model to fit a vector autoregression model with independent variables.



- Further studies should be carried out by comparing vector autoregression model with multivariate volatility models to see which of them is suitable for modelling the climate data.
- The meteorological service department in the region should make data readily available to help researchers contribute to the areas of climate studies.
- Finally the studies recommend that further studies on other climatic variables with rainfall should be carried out to investigate their relationship.

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APPENDIX A

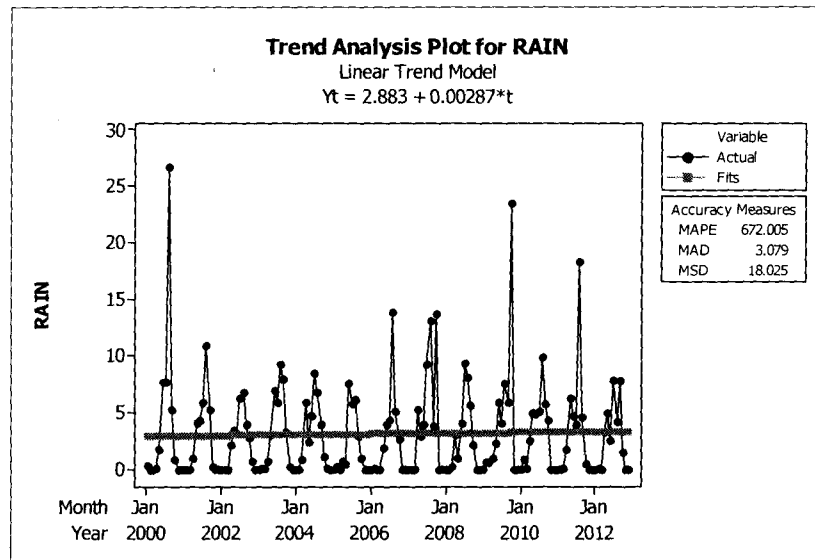


Figure 5.1 Trend plots of Rainfall

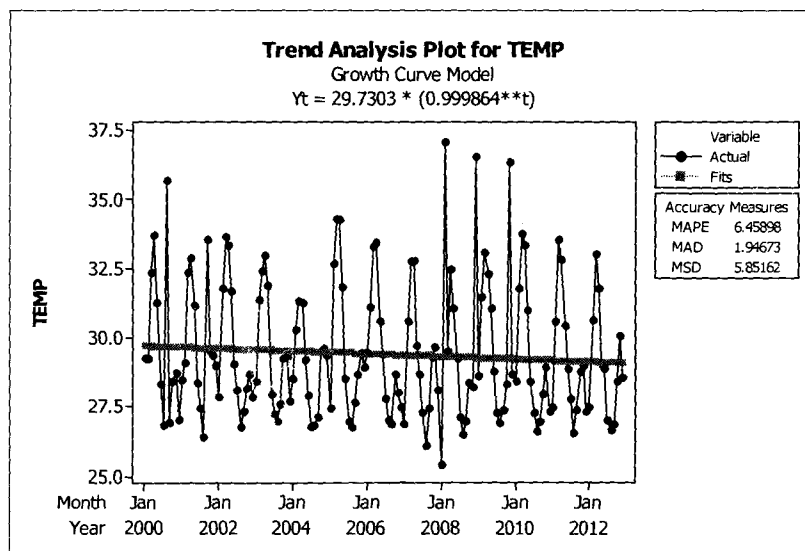


Figure 5.2 Trend analysis plot of Temperature