CLIMATE VARIABILITY AND ITS IMPACT ON WATER RESOURCES OF LOWER KADUNA RIVER CATCHMENT NIGERIA

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DEPARTMENT OF WATER RESOURCES AND ENVIRONMENTAL ENGINEERING,

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ZARIA, NIGERIA

JANUARY 2013

DECLARATION

I hereby declare that this Dissertation is authentic and a result of my original work carried out at the Department of Water Resources and Environmental Engineering, Faculty of Engineering, Ahmadu Bello University, Zaria, The research was supervised by a Supervisory Committee headed by Dr. J. A. Otun with Dr .A. Ismail and Prof. C. A. Okuofu, as members.

All the work within this text is original except where cited from an additional source. Quotations and other indirect information have been clearly marked and acknowledged by means of references. This work has not, in part or whole, been previously submitted by the Author for any other Diploma, Degree or Qualification at this or any other Institution and is currently unpublished.

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Daniel Aimaje Attah **Signature & Date**

PhD/ENG/16072/2007-2008

CERTIFICATION

This Dissertation titled **CLIMATE VARIABILITY AND ITS IMPACT ON WATER RESOURCES OF LOWER KADUNA RIVER CATCHMENT NIGERIA** meets the regulations governing the award of the degree of Doctor of Philosophy (Ph.D) of Ahmadu Bello University and is approved for its contribution to knowledge and literary presentation.

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ABSTRACT

Climate Variability in Study Area, located between latitude 10° 15' and 10° 45' North and longitude 6° 15' and 7° 45' East with an area of 1647 square kilometers in Kaduna State and within the Northern Guinea Savannah Climatic/Ecological zone and its Impacts on Water Resources of the Area were investigated in this report using 47years (1960-2006) record of hydro-meteorological data. The Climate variability was evaluated using a simple approach which considered variability as the difference between the means and standard deviations of climatic elements of two equal -length time periods. Other methods used include coefficient of variation, time series methods and anomaly approach. The impacts of climate variability on water resources of the study area were investigated using comparative and correlation analyses. From the results, the hottest year within the zone was 1993 with day time temperature increase of 15.3℃ and a zonal average of 0.08℃, indicating warming while within the catchment, the highest increase in maximum temperature was 2.6℃. The maximum increase in the minimum temperature was 8.2℃ in 1998 within the zone but 9.2℃ in the catchment area in 1979.The increase in the annual minimum temperature over the zone averaged 0.26℃, indicating warmer nights. The historical observations of temperatures, rainfall and evaporation in the study area indicated annual maximum temperature trend of 0.12℃, annual minimum temperature trend of 0.88℃ ,annual mean temperature trend of 0.48℃, annual rainfall trend of 100mm and annual evaporation trend of 99mm which are all statistically significant except for the annual maximum temperature. Based on the coefficient of variation, the variations in the climatic elements ranged from low to moderate. The trend analyses of the discharges for the period, 1960 – 2006, showed that the annual total discharge, the annual maximum discharge and mean discharge have increased significantly during the past 47 years, whereas, the annual minimum discharge during the same period indicated a decline, which is not statistically significant.. From the anomaly analyses of the discharges and rainfall data in the study area, the increased annual rainfall relative to the 1961-1990 mean values between 1998 and 2003 coincided with the high annual discharges of Kaduna River within the same period respectively, which generated excessive surface runoff in River Kaduna system in recent years. This is in addition to the effects of urbanization due to population increase. These periods of excessive rainfalls and discharges, also, coincided with the periods of increases in the annual minimum temperatures, indicating positive impacts. The implication of this is that the tendency for flood events is increased. The declining minimum discharge increases water supply demand for domestic, industrial and agricultural uses especially, during dry season. The presence of positive significant trends in the historic temperature, rainfall and discharges indicate that the hydrologic changes, especially the recent incidences of flood events, in the study area and Kaduna River system may be attributed to Climate Variability. A Programme of monitoring of the Kaduna River system and forecasting should be established so that mitigation action can be planned ahead.

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ABBREVIATIONS

WMO - World Meteorological Organization

WCP - World Climate Programme

UNFCCC - United Nation Framework Convention for Climate Change

IPCC - Intergovernmental Panel on Climate Change

UNEP - United Nation Environmental Programme

GDP - Gross Domestic Product

DFID - Department for International Development of United Nation

GHG - Greenhouse gas

USAID - United States Agency for International Development

UNDP - United Nation Development Programme

NGS - Northern Guinea Savannah

NPC - National Population Commission

ITCZ - Inter-Tropical Convergence Zone

CO_2 - Carbon Dioxide

O_2 - Oxygen

CH_4 - Methane

N_2O - Nitrous Oxide

Ppb - part per billion

CFC - Chlorofluorocarbon

IMO - International Meteorological Organization

cT - Tropical Continental

mT - Tropical Martine

AOGCM - Atmospheric-Ocean General Circulation Model

EBM - Energy Balance Model

EMIC - Earth Model of Intermediate Complexity

GCM - General Circulation Model

ARIMA - Autoregressive Integrated Moving Average Model

ARMA - Autoregressive Moving Average Model

ACF - Autocorrelation Function

PACF - Partial Autocorrelation Function

AIC - Akaike Information Criteria

BIC - Bayesian Information Criteria

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND OF THE STUDY

Climate, in a narrow sense, is usually defined as the "average weather" or more rigorously, as the statistical description, in terms of the mean and variability, of meteorological variables (temperature, rainfall or precipitation, wind) over a period of time ranging from months to thousands or millions of years. The traditional period is thirty (30) years as defined by World Meteorological Organization (WMO, 1988). The climate of an observational site is usually described by the average values of relevant observations such as temperature, precipitation or wind. Climate in a wider sense is the state of the global climate system including a statistical description of all the relevant meteorological variables. The term weather describes the day-to-day and hour-to-hour changes in the atmospheric conditions at any given location.

Although the terms climate and weather are often used interchangeably, there is an important distinction. While weather describes the atmospheric conditions at a given time and place, climate is the synthesis of the day-to-day variations into a set of average conditions based on statistical summary such as 30-year record of weather observations.

The terms climate variability and climate change are sometimes used interchangeably just as weather and climate though they represent different phenomena. They are often distinguished based on the time scale. Generally, there are three categories of climate change and these are: long –term, short-term and fluctuations depending on the time scale. Climate Changes occurring over time scales greater than or within those associated with the orbital forcing frequencies of between 41,000 and 9,508,000 years are defined as long-term. Climate Changes occurring over time scales shorter than those associated with the orbital forcing frequencies are defined as short-term while climate fluctuations on time scales less than 100years are usually considered as climate variability (Mtondo et al, 2004). Climate variability, therefore, is the fluctuations and variations experienced on shorter time scales (less than 100years) such as years or decades whereas climate change refers to variations on longer time scales (greater than 100 years).

Climate variability refers to the variations in the mean and other statistics (such as standard deviations, coefficient of variations, and the occurrence of extreme events) of the climate variables on all temporal and spatial scales beyond that of individual weather events. Climate variability may be as a result of natural internal processes within the climate system (internal variability) or variations in natural or anthropogenic external forcing (external variability). Climate change, however, is a statistical significant variation in either the mean variables of the climate or in its variability over an extended period of time (typically, decades, 30-year period or longer).

The terms climate variability and climate change refer to two different concepts of the climate process, in particular, to climate represented by a stationary process and a non-stationary process, respectively. It further implies that climate is viewed as a process which is non-stationary on a long time scale, but can be approximated by a stationary process on a shorter time scale of a few decades (WMO, 1988). In summary, climate variability can be regarded as the variability inherent in the stationary stochastic process approximating the climate on a scale of a few decades, while climate change can be regarded as the differences between the stationary processes representing climate in successive periods of a few decades.

Climate variability, its impacts and vulnerabilities are growing concerns worldwide. The climate of Nigeria, and in particular the study area, is changing and it is becoming more unpredictable every year. Global warming induced changes in temperature and rainfall are already evident in many parts of the world, as well as Nigeria (Odjugo, 2010) including the study area. Hazards such as floods and droughts which are aggravated by climate variability are being experienced more frequently than ever before in Nigeria and in particular the study area. Rapid population growth and movement into areas exposed to floods, landslides, coastal storm surges, tornadoes or drought have produced increasing loss of life and economic losses in many countries during the recent decades. The increases in the frequency of these extreme weather events have been attributed to climate variability due to human activities which led to increases in the green house gas emissions.

The consequence of climate variability on the world climate system is global warming which has been recognized since 1970s of the 20th century (Gruza and Rankova, 2004). The public and policy-makers understand climate variability as being synonymous with global warming. The number of researches concerning climate variability due to both natural and anthropogenic forcing has increased sharply since then. The science has become more irrevocable than ever. The evidence of climate change or variability is all around us and unless we act, we will see catastrophic consequences including sea level rise, drought and famine and the loss of plant and animal species. It is now becoming evident that the monitoring of the current climate variables is required.

The first statement on a threat to global climate was made by the World Meteorological Organization (WMO) in 1976. In 1979, after the First World Climate Conference, the WMO established the World Climate Programme (WCP) which laid the foundations for international activity on climate (Gruza and Rankova, 2004). WCP activities are aimed at applying existing climate information for the benefit of mankind, improving the understanding of climate processes and the monitoring of the significant climate change and variations.

In 1992, the United Nations Framework Convention on Climate Change (UNFCCC) was established. The Intergovernmental Panel on Climate Change (IPCC) was established by the World Meteorological Organization and United Nations Environmental Program (UNEP) for the scientific support of UNFCCC activities. Its

goals include the comprehensive and objective estimation of observed and expected climate changes/variability and anthropogenic impacts. The IPCC has published three scientific reports on climate: IPCC-1990, IPCC-1995 and IPCC-2001 (IPCC, 2001). These reports provide the basic data on the observed climate and its variations, climate models, and the degree of agreement between model results and observations.

The existence of climate variability has long been recognized, including even the possibility of quite significant variations over comparatively short periods of time, but due to lack of any real means of predicting such variations, they were not seen as being of any great relevance to regional or national planning. Our present ability to predict these variations is still very limited and any predictions that are made are hotly debated. The current interest and urgency in climate variability issue is as a result of the fact that man himself may be the cause of such variations in climate.

Climate and the world's water resource system have a special relationship insofar as water resources depend on the hydrological cycle which is itself part of the climate system. Hence there are hydrological and water resource aspect in all four components of the WCP which are commonly grouped under the general title World Climate Programme-Water (WCP-Water) (WMO, 1988). The basic aim of WCP-Water is "to meet more effectively the socio-economic needs which depend on water resource system, through the improved application of climate data and information" (WMO, 1988).

Natural climate variability has direct and fundamental bearing on water resources and its management. Many water resources development and management decisions are aimed at coping with climate variability (flood and drought). Also, the evolution of hydrology in many ways is a reflection of mankind's struggle to deal with seasonal and inter-annual variations of rainfall and streamflows. Coping with floods and droughts is a major part of the responsibility of water agencies across the world and their ability to deal with climate variability and its unpredictability is clearly a factor in determining the efficiency and effectiveness of water use.

1.2 AIM AND OBJECTIVES OF THE STUDY

This research study will attempt to evaluate quantitative evidence of Climate variability within Kaduna State of Nigeria in general and Lower Kaduna River Catchment in particular, especially, variations in Temperatures, Annual rainfall and Evaporation, as well as estimate the impact of the climate variability on the water resources (stream flow) of Lower Kaduna River Catchment. This is to improve our knowledge of hydrological variability in the context of climate variability considering the fact that stream flow data represent filtered climate data. The aim of this study will be achieved by the following objectives which are to:

1. Assess the variations in the occurrence of the climate variables within the Lower Kaduna River Catchment.

2.Estimate the impact of this climate variability on the Water Resources Variables (stream flows) of Lower Kaduna River Catchment.

1.3 STATEMENT OF PROBLEM

The fact that climate is varying globally and across regions and within drainage basins is no longer disputable (Kottegoda, 1980; Hengeveld, 2000; IPCC, 2001; Gaye and Auta, 2003; DFID, 2004).The causes of these variability have been attributed to natural and anthropogenic (human activities on the earth) factors (IPCC, 2001, 2007; Le Trent et al, 2007; UNDP, 2007).In the last four decades, the anthropogenic factors have become more dominant. The increase in the generation and emission of greenhouse gases (GHG) through industrial activities and the burning of fossil fuels, deforestation and urbanization are some of the human activities that have continued to increase the temperature regimes in the lower atmosphere (IPCC, 2001, 2004, 2007; USAID, 2005) These have led to the occurrence of extreme weather events such as floods, droughts, cyclones and tornadoes and increase in their frequencies of occurrence (IPCC,2001; Gaye, and Auta,.2003: Marx et al,2005).The distribution of rainfall globally and across continents and within drainage basins has continued to change due to climate variability (Chaponniere, and Smakhtin, 2006; UNDP,2007). Since most developing countries like Nigeria depend heavily on agriculture, the effects of global warming on productive croplands is likely to threaten both the welfare of the population and the economic development of the countries. Tropical regions or countries of the developing world are particularly vulnerable to potential variations in climatic variables because the poor soils that cover large areas of these regions already have made much of the land unusable for agriculture (Paul, et al, 1998; Robert, and Ariel, 1999; DFID, 2004; UNDP, 2007).

In recent decades, Kaduna River within the study area had experienced a number of flood events along the floodplain which led to loss of lives, property, farmlands and livestock. Also, a number of Earth Dams across some of the tributaries of Kaduna River, within Kaduna state, had been overtopped and collapsed pre-maturely in recent decades. Recent study had attributed the increase in the frequency of the flood events in the study area to urbanization and encroachment on the floodplain by residents (Alayande and Agunwamba, 2010). However, from literature, several incidences of flood in many countries and basins, in recent decades, had been attributed to climate variability due to increases in the green house gas emissions, hence this study.

It is obvious that the capacity of Nigerian government and Nigerians to manage these hazards associated with climate variability is far from being perfect due to lack of awareness and understanding of the mechanism and the level of climate variability among the population and policy makers. Effective mitigation of these hazards associated with climate variability will thus require continued development of our understanding of the magnitude of climate variability and its effects on such resources as water and the responses of the human communities to the climate related hazards. In

the study area, there is general lack of awareness and knowledge of the effects of climate variability. This study will attempt to create awareness of the effects of climate variability through the quantification the climate variables to determine the level of their variability and how the variability impacts on the water resources of the study area using statistical approach. Furthermore, Kaduna River within the study area serves as the main source of raw water supply for domestic as well as industrial needs of Kaduna metropolis. Managers of water within the study area will require the knowledge of climate variability and its impact on Kaduna River for the proper management of the municipal water supply.

1.4 JUSTIFICATION OF THE RESEARCH STUDY

Subsistence rain-fed agriculture is the mainstay of most African economies contributing Gross Domestic Product (GDP) that ranges from 10 to 70%, Also, African agriculture has the lowest record of productivity increase in the world and it is the only major region with decline in food production per capita during the period,1990 – 2000(UNDP, 2007). The dependence of Africa and indeed Nigeria on rain-fed agriculture means that production is vulnerable to climate variability which can severely affect food and human security and exports

The impacts of the extreme events (floods and droughts) have the potential to destabilize development activities in the country in general and within Kaduna State of Nigeria and the Lower Kaduna River Catchment in particular if their frequencies increase. It is expected that if the society can cope with the current climate variability shocks, then it has high probability of adapting to the impacts of future climate variability. In this regard, factoring of climate variability forecast and early warning products in our entire socio-economic sector is critical for sustainable development. Climate variability forecast would help the government plan for the construction of buffer dams and reservoirs to take care of excess runoff and reduce damage to life and property. There is therefore, need to integrate climate variability concerns into our planning and development processes. This would require wide ranging changes in government policies in order to adapt fast to the emerging trends in climate variability. The knowledge of climate variability will empower famer to make informed decision about crop management for maximum yield.

In many countries like Canada, United States of America and other developed countries, it is a standard practice, at least for the design of large water resources projects, to make allowances for the effects of variability in hydro-meteorological elements (Karl et al, 1996, McFarlane et al, 2007). These allowances are commonly based on short time series and assumptions that are difficult, if not impossible, to check in practice. Also, in the operation of such projects, it is common for very little allowance to be made for future variability. Those responsible for water resources

planning and management can therefore benefit from a comprehensive description of climate variability and the resulting variability in hydro-meteorological elements in the study area. It is hoped that this study will assist in this regard and so engender a new awareness of the importance of climate variability and its impact on water resources for efficient development of water resources. Accurately predicting and mitigating the impact of future climate variability is critical for development. The study is also necessary to support adaptation decisions.

1.5 SCOPE OF STUDY

This Study has been limited to the following:

1. The collection of climatic (temperature, rainfall and evaporation) data from the twelve (12) existing meteorological stations within Kaduna State for a period of 47 years C1960-2006) and the analyses of these climatic variables in order to determine the variability within the study area and Kaduna state of Nigeria.
2. The collection of hydrological (stream flows) data and climatic (temperature and rainfall) data from Kaduna South guaging and meteorological stations respectively for the period of 47years and the analyses of these data to determine the responses of the stream flows to the variability of the annual mean temperature and the annual rainfall within the Lower Kaduna River Catchment.

1.6 THE STUDY AREA

The Study Area is located within the Northern Guinea Savannah (NGS) (Fig.1.1). The Northern Guinea Savannah covers about 285,000square kilometers in the coastal countries of West Africa with an estimated population of 44million people (Weber et al, 1995). It is one of the most intensive farming areas of Nigeria (Salami et al, 2011). The special features such as daily solar radiation of 270 to 350cal/cm^2/day during the planting season and 440cal/cm^2/day during the dry months, well distributed and reliable rainfall of between 900mm and 1200mm with a mean of 1060mm and lower night temperatures promote dry matter accumulation and partitioning leading to higher harvest index and yield. The length of the planting period is about 150 to 180 days occurring between May and October (Salami et al, 2011). The annual and monthly daily rainfalls are usually characterized by high temporal spatial variations. High rainfall intensities are frequent and result in high risk of soil erosion. The predominant soils are alfisols of shallow depth and low structural stability (Weber et al, 1995). The

Northern Guinea Savannah, therefore, has the potential to be one of the most productive regions of the world (Salami et al, 2011).

The benchmark site, which is Kaduna State, is located in Northern Nigeria between longitudes 6° and 9° east of the Greenwich Meridian and latitudes 9° 02' and 11° 32' north of the Equator. The benchmark site is chosen to represent the larger eco-regional and climatic zone and it covers an area of about 46,053 square kilometers with a population of over 6million people who are mostly (80%) farmers (NPC. 2006). The site has all the features observed for the whole ecological/climatic zone to allow extrapolation to the total zone (Salami et al, 2011).

Based on the location of the Inter-Tropical Convergence Zone (ITCZ) the benchmark site is located within the climatic zone II of Nigeria which covers a distance of about 200- 300Km south of ITCZ. The zone experiences a mixture of the dry easterly to northeasterly winds (at high altitude) and the moist southwesterly winds (closer to the surface). The zone is characterized by relatively high night temperatures and high humidity values. Early morning fog in the form of stratus (low) clouds is often experienced.

The Lower Kaduna River Catchment (Figure 1.2) is located between latitude 10° 15' and 10° 45' North and between longitude 6° 15' and 7° 45' East with an area of 1647 square kilometers. It is within the highland climatic zone of Nigeria with an Altitude of 591metres and a mean annual rainfall of 1230mm.The rainy season is between May and October when about 80% of the annual rainfall occurs. The mean evaporation loss annually is 2448mm. The mean maximum and minimum temperatures are respectively 39℃ and 12℃. It is drained by River Kaduna and its major tributaries; Rivers Rigachikun, Ruza and Romi. Kaduna River takes its source from the Kangimi Hills in the Jos Plateau and flows for about 210km to Kaduna Town. It crosses the town, dividing it into North and South areas. The River flows beyond Kaduna for about 100km into the Shiroro dam and continues until it finally discharges into the River Niger about 200km from Shiroro dam (Bamgboye, 2004).

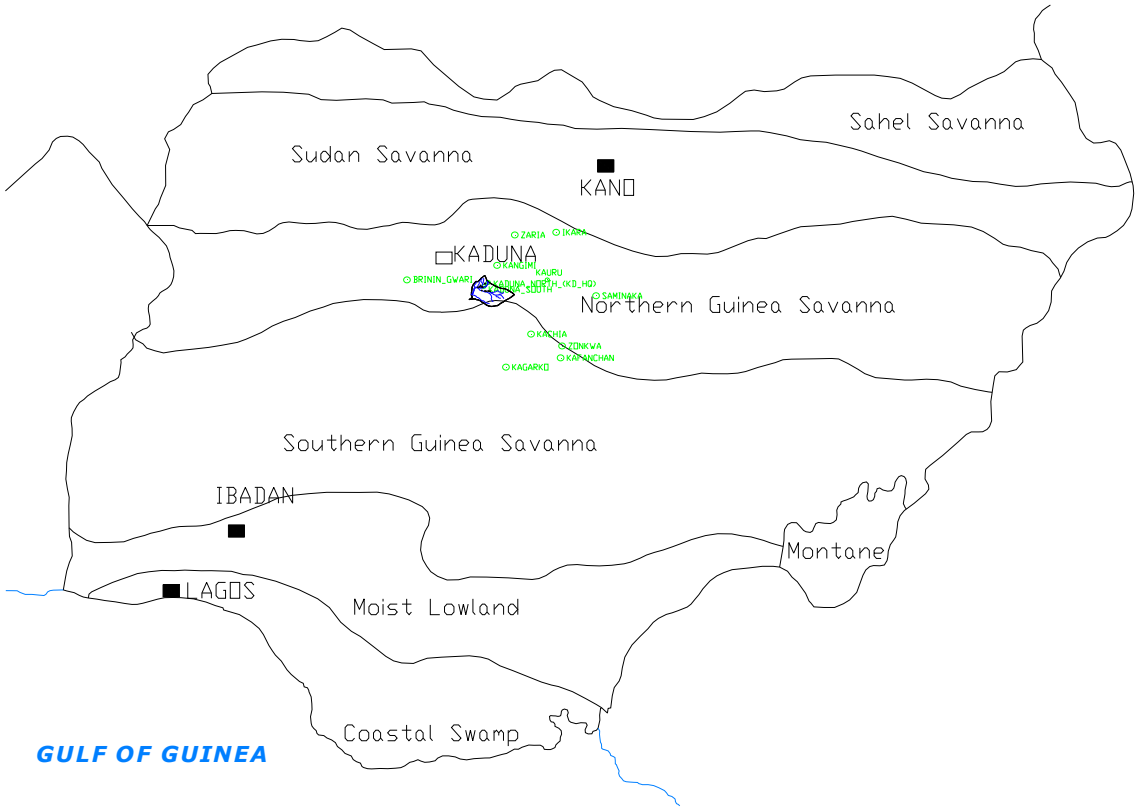


Figure 1.1 Climatic/Ecological Zones of Nigeria

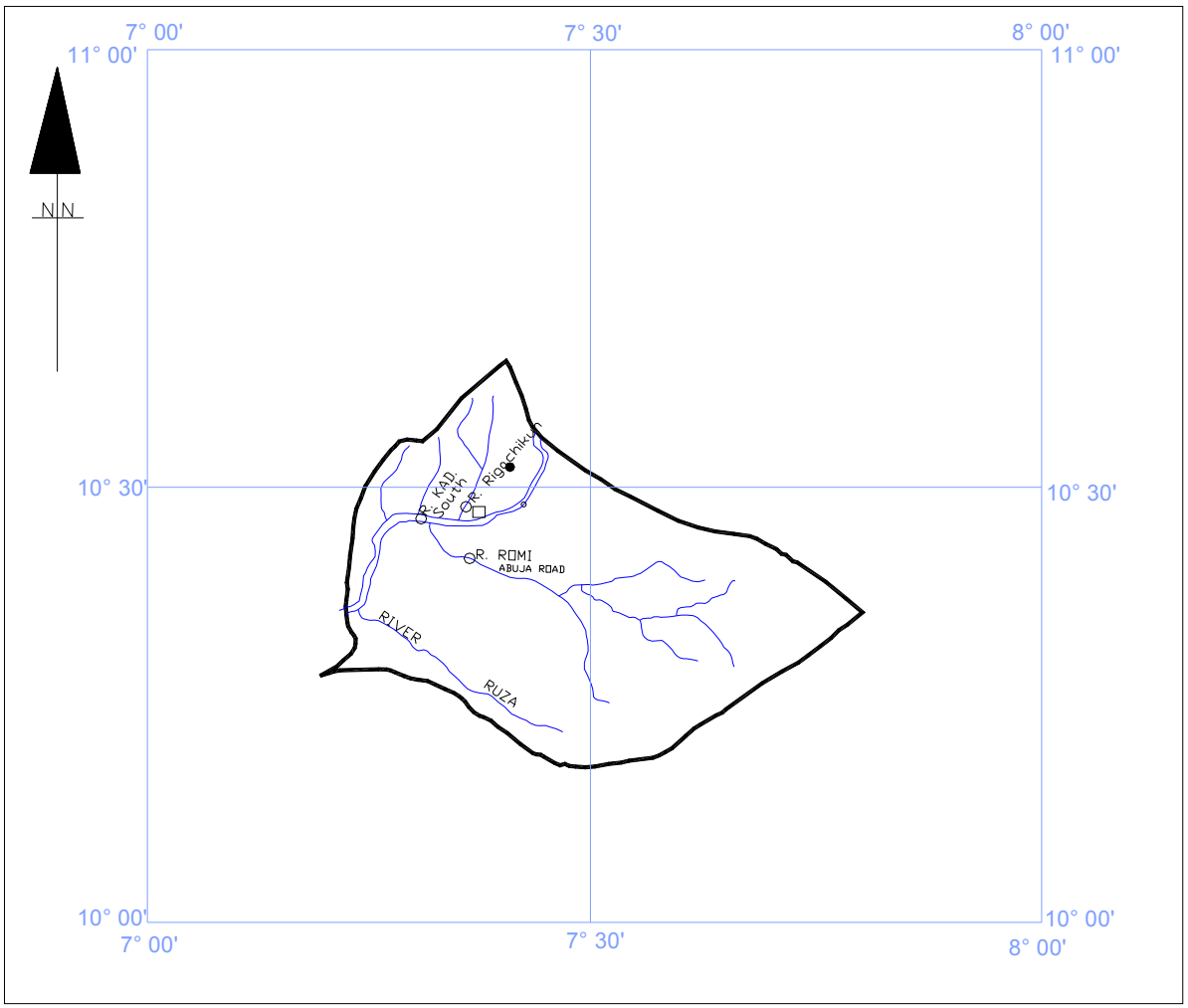


Figure 1.2 Hydro-meteorological Stations of the Study Area

Legend

○ Kaduna South River Guaging Station

□ Meteorological Station

CHAPTER TWO

LITERATURE REVIEW

2.1 THE GLOBAL CLIMATE SYSTEM

The global climate system is a complex, interactive system consisting of the atmosphere, land surface, snow and ice, oceans and other water bodies and living things. The atmospheric component of the climate system majorly characterizes the climate. The climate system evolves in time under the influence of its own internal dynamics and due to changes in the external factors that affect climate called "forcings" (IPCC, 2007). External forcings include natural phenomena such as volcanic eruptions and solar radiations as well as human-induced changes in the atmospheric composition. Solar radiation from the sun powers the climate system. The radiation balance of the earth can be changed in three fundamental ways: By changing the incoming solar radiation (for example, changes in the earth orbit or in the sun itself); by changing the fraction of solar radiation that is reflected, called "albedo" or reflectivity coefficient (for example, by changes in cloud cover, atmospheric particles or vegetation) ;and by altering the long wave radiation from the earth back towards the space (by changing greenhouse gases concentrations). Climate, in turn, responds directly to such changes, as well as indirectly, through a variety of feedback mechanisms (IPCC, 2007).

Climate forcing is the change in the vertical difference in net radiative energy flux (W/m^2) in the atmosphere and the change in net radiative energy flux (W/m^2) at the surface due to change in the external factors of the climate system such as a change in carbon dioxide CO_2 concentrations, aerosols or solar energy flux (MingCai, 2009). Feedback is defined as the subsequent changes in both non-temperature induced radiative and non-radiative energy fluxes of the climate system that either strengthen or weaken or even oppose the original forcing. The non-temperature induced radiative energy flux include changes in the vertical difference in net radiative energy flux in the atmosphere and change in net radiative energy flux at the surface due to changes in the water vapour, cloud, or surface albedo (thermodynamic feedback). The non-radiative energy flux includes:

1. The changes in the vertical and horizontal difference of the transport of total energy (sum of moist static and kinetic energy) in the atmosphere and changes in the surface turbulent energy exchanges within the atmosphere; and
2. The changes in horizontal difference of oceanic transport of total energy in the column (MingCai, 2009).

Climate response, therefore, is the changes in temperatures of the atmosphere and the surface in response to climate forcing and climate feedback (MingCai, 2009).

Since climate is generally defined as average weather, climate change and weather are intertwined. Observations can show that there have been changes in weather but it is the statistics of the changes over time that identifies climate change. The chaotic nature of weather makes it unpredictable beyond a few days, but projecting changes in climate (that is, long-term average weather) due to changes in atmospheric composition or other factors is very different and a much more manageable issue. As an analogy, while it is impossible to predict the age at which any particular man will die, it is possible to say with high degree of confidence that the average age of death for men in industrialized countries is about 75. When weather is averaged over space and time, the fact that the globe is warming emerges clearly from data (IPCC, 2007). The warming process is a function of the radiation balance of the Sun.

The Sun powers the earth's climate system, radiating energy at very short wavelengths, predominantly in the visible or near visible part of the spectrum. Roughly one-third of the solar energy that reaches the top of the earth's atmosphere is reflected directly back to space, while the remaining two-thirds is absorbed by the surface and to a lesser extent, by the atmosphere (IPCC, 2007). In order to balance the absorbed incoming solar energy, the earth must, on average, radiate the same amount of energy back to space. Since the earth is much colder than the sun, it radiates at much longer wavelengths. Much of this thermal radiation emitted by the land and ocean is absorbed by the atmosphere, including cloud and re-radiated back to the earth. This is called greenhouse effect (IPCC, 2007). The glass walls in a greenhouse reduce airflow and increase the temperature of the air inside but through a different physical process, the earth's greenhouse warms the surface of the planet earth. Without the natural greenhouse, the average temperature at earth's surface would be below the freezing point of water (IPCC, 2007). Thus, earth's greenhouse effect makes life possible. However, human activities, primarily the burning of fossil fuels and clearing of vegetation or forests, have greatly intensified the natural greenhouse effect, causing global warming (Kottegoda, 1980; Hengeveld, 2000; IPCC, 2001; Chaponniere and Smakhtin, 2006; USAID, 2007). These concerns for changing climate were reflected in the UNFCCC draft which was opened for signatures at the Earth Summit in Rio de Janeiro, Brazil in June 1992. The Draft requires the developing countries to conduct vulnerability and adaptation assessment of climate change. These assessments explore, and if possible, quantify the vulnerability of the various systems and sectors to climate variability and climate change at the country scale.

2.2 HISTORICAL PERSPECTIVE OF GLOBAL CLIMATE VARIABILITY

The high-accuracy measurements of atmospheric CO_2 concentration, initiated by Keeling in 1958, constitute the master time series documentation of the changing composition of the atmosphere (Le Treut, et al, 2007). These data have iconic status in climate change science as evidence of the effect of human activities on the chemical

composition of the global atmosphere .Keeling's measurements on Mauna Loa in Hawaii provided a true measure of the global carbon cycle, an effectively continuous record of the burning of fossil fuel. They also maintain an accuracy and precision that allowed scientists to separate fossil fuel emissions from those due to the natural annual cycle of the biosphere, demonstrating a long-term change in the seasonal exchange of CO_2 between the atmosphere, biosphere and ocean. Later observations of parallel trends in the atmospheric abundances of the $13CO_2$ isotope (Le Treut, et al 2007) and molecular oxygen (O_2) (Le Treut et al, 2007) uniquely identified this rise in CO_2 with fossil fuel burning

In order to place the increase in CO_2 abundance since the late 1950s in perspective, and to compare the magnitude of the anthropogenic increase with natural cycles in the past, a longer-term record of CO_2 and other natural greenhouse gases is needed. These data came from analysis of the composition of air enclosed in bubbles in ice cores from Greenland and Antarctica (Le Treut et al, 2007). The initial measurements demonstrated that CO_2 abundances were significantly lower during the last ice age than over the last 10,000years of the Holocene (Le Treut et al, 2007). From 10,000years before present up to the year 1750, CO_2 abundances stayed within the range 280 ± 20 mg/l (Le Treut et al, 2007). During the industrial era, CO_2 abundance rose roughly exponentially to 367 mg/l in 1999 (IPCC, 2001a) and to 379 mg/l in 2005

Direct atmospheric measurements since 1970 (Le Treut et al, 2007) have also detected the increasing atmospheric abundances of two other major greenhouse gases, methane (CH_4) and nitrous oxide (N_2O). Methane abundances were initially increasing at a rate of about 1% per year (Le Treut et al, 2007) but then slowed to an average increase of 0.4% per year over the 1990s with the possible stabilization of CH_4 abundance (ibid). The increase in N_2O abundance is smaller, about 0.25% per year and more difficult to detect (Le Treut et al, 2007). In order to go back in time, measurements were made from air trapped in snow pack dating back over 200 years, and these data showed an accelerating rise in both CH_4 and N_2O into the 20th century (Le Treut et al, 2007). When ice core measurements extended the CH_4 abundance back 1,000 year, they showed a stable, relatively constant abundance of 700 ppb until the 19th century when a steady increase brought CH_4 abundances to 1,745 ppb in 1998 (IPCC, 2001a) and 1,774 ppb in 2005 (Le Treut et al, 2007). This peak abundance is much higher than the range of 400 to 700 ppb seen over the last half-million years of glacial-interglacial cycles, and the increase can be readily explained by anthropogenic emissions. For N_2O the results are similar: the relative increase over the industrial era is smaller (15%), yet the 1998 abundance of 314 ppb (IPCC, 2001a), rising to 319 ppb in 2005 is also well above the 180- to-260 ppb range of glacial- interglacial cycles (Le Treut et al, 2007).

Several synthetic halocarbons (chlorofluorocarbons (CFCs), hydrofluorocarbons, and perfluorocarbons, halons and sulphur hexafluoride) are greenhouse gases with large global warming potentials. The chemical industries have been producing these gases and have been leaking into the atmosphere since about 1930. Atmospheric abundances of all the synthetic halocarbons were increasing until the 1990s, when the abundance of

halocarbons phased out under the Montreal Protocol began to fall (Le Treut et al, 2007). In the case of synthetic halocarbons (except perfluoromethane), ice core research has shown that these compounds did not exist in ancient air (Le Treut et al, 2007) and thus confirms their industrial human origin.

At the time of the Third Assessment Report of IPCC, scientists could say that the abundances of all the well-mixed greenhouse gases during the 1990s were greater than at any time during the last half-million years, and this record now extends back nearly one million years. Given this daunting picture of increasing greenhouse gas abundances in the atmosphere, it is noteworthy that, for simpler challenges but still on a hemispheric or even global scale, humans have shown the ability to undo what they have done. Sulphate pollution in Greenland was reversed in the 1980s with the control of acid rain in North America and Europe (IPCC, 2001), and CFC abundances are declining globally because of their being phased out undertaken to protect the ozone layer.

2.2.1 Global Surface Temperature

Shortly after the invention of the thermometer in the early 1600s, efforts began to quantify and record the weather. The first meteorological network was formed in northern Italy in 1653 (Le Treut et al, 2007) and reports of temperature observations were published in the earliest scientific journals. By the latter part of the 19th century, systematic observations of the weather were being made in almost all inhabited areas of the world. Formal international coordination of meteorological observations from ships commenced in 1853 (Le Treut et al, 2007). The International Meteorological Organization (IMO) was formed in 1873 to promote a Uniform System of Meteorological Observations, and exchange standardized meteorological observations. It was later succeeded by the World Meteorological Organization (WMO). Yet even with uniform observations, there are still four major obstacles to turning instrumental observations into accurate global time series: (1) access to the data in usable form; (2) quality control to remove or edit erroneous data points; (3) homogeneity assessments and adjustments where necessary to ensure the fidelity of the data; and (4) area-averaging in the presence of substantial gaps (Le Treut et al, 2007).

Köppen (Le Treut et al, 2007) was the first scientist to overcome most of these obstacles in his quest to study the effect of changes in sunspots. Using data from more than 100 stations, Köppen averaged annual observations into several major latitude belts and then area-averaged these into a near-global time series. While the data and analysis techniques have changed over time, all the time series show a high degree of consistency since 1900. The high degree of agreement between the time series resulting from these many different analyses increased the confidence that the changes they indicate are real.

Using the knowledge of past climates to qualify the nature of ongoing changes has become a concern of growing importance during the last decades, as reflected in the

successive IPCC (2001) reports. When linked together at a technical level, detection and attribution have separate objectives. Detection of climate change is the process of demonstrating that climate has changed in some defined statistical sense, without providing a reason for that change. Attribution of causes of climate change is the process of establishing the most likely causes for the detected change with some defined level of confidence. Using traditional approaches, unequivocal attribution would require controlled experimentation with our climate system. However, with no spare Earth with which to experiment, attribution of anthropogenic climate change must be pursued by: (a) detecting that the climate has changed ;(b) demonstrating that the detected change is consistent with computer model simulations of the climate change 'signal' that is calculated to occur in response to anthropogenic forcing; and (c) demonstrating that the detected change is not consistent with alternative, physically plausible explanations of recent climate change that exclude important anthropogenic forcing. Both detection and attribution rely on observational data and model output. In spite of the efforts, estimates of century-scale natural climate fluctuations remain difficult to obtain directly from observations due to the relatively short length of most observational records and a lack of understanding of the full range and effects of the various and ongoing external influences. Model simulations with no changes in external forcing (for example, no increases in atmospheric CO_2 concentration) provide valuable information on the natural internal variability of the climate system on time scales of years to centuries. Attribution, on the other hand, requires output from model runs that incorporate historical estimates of changes in key anthropogenic and natural forcing, such as well-mixed greenhouse gases, volcanic aerosols and solar irradiance. These simulations can be performed with changes in a single forcing only (which helps to isolate the climate effect of that forcing), or with simultaneous changes in a whole suite of forcing.

As the science of climate change progressed, detection and attribution research ventured into more sophisticated statistical analyses that examined complex patterns of climate change. Climate change patterns were no longer limited to a single variable such as temperature or to the Earth's surface. More recent detection and attribution work made use of precipitation and global pressure patterns, and analysis of vertical profiles of temperature change in the ocean and atmosphere. Studies with multiple variables make it easier to address attribution issues. While two different climate forcing may yield similar changes in global mean temperature, it is highly unlikely that they will produce exactly the same climate changes that are identical as a function of latitude, longitude, height, season and history over the 20th century. Such model-predicted evidence of anthropogenic climate change is clearly statistically identifiable in observed data. The common conclusion of a wide range of studies conducted over the past 15 years is that observed climate changes cannot be explained by natural factors alone (IPCC,2001,2004 and 2007). A substantial anthropogenic influence is required in order to best explain the observed changes. The evidence from this body of work strengthens the scientific case for a discernible human influence on global climate.

2.2.2 Aspects of Climate Change or Variability

In 1988, the World Meteorological Organization (WMO) and the United Nations Environmental Programme (UNEP) established the Intergovernmental Panel on Climate Change (IPCC) to assess all aspects of climate change including how human activities can cause such changes and can be impacted by them. IPCC, in its Third Assessment Report (TAR) which was approved by IPCC member governments in January, 2001, describes, in summary, the current state of understanding of climate system as follows:

1. The global average surface temperature has increased over the 20^{th} century by about 0.6ºC.
2. The temperatures have risen during the past four decades in the lowest 8 kilometers of the atmosphere.
3. Snow cover and ice extent have decreased.
4. Global average sea level has risen and ocean heat content has increased.
5. In mid and high latitudes of the Northern Hemisphere, there has been a 2 – 4% increase in the frequency of heavy precipitation events over the latter half of the 20^{th} century.
6. Since 1950, there has been a reduction in the frequency of extreme low temperatures with a small increase in the frequency of extreme high temperatures.
7. Emissions of greenhouse gases (GHG's) and aerosols due to human activities continue to alter the atmosphere in ways that are expected to affect the climate.

2.2.3 Projected Future Climate Change

The future climate changes projected by IPCC (2001) include the followings:

1. Global increase in the surface air temperature of 1.3 – 4.5ºC with an average of +3ºC for global high emission scenario and of 0.9 – 3.4ºC with an average of +2ºC for lower carbon dioxide (CO_2) emission scenario. It estimates an increase of 1.4 – 5.8ºC over the period 1990 – 2100 for the full range of emission scenarios.

2.Global increase in average water vapour, evaporation and precipitation as a consequence of the temperature increase which speeds up the hydrologic cycle. Both precipitation increase and decrease will be experienced in different regions simultaneously.

3.Increase in the frequency of hot days and heat waves over all land areas and especially in areas where soil moisture decrease occurs. Heat index is expected to increase due to the changes in surface air temperature and near-surface absolute humidity of the air.

4.Global increase of the intensity and frequency of extreme precipitation events.

5.The extreme events (floods and droughts) are perhaps the major issues associated with climate change. Adaptation to them requires changes in both infrastructure and strategies and activities of water management. Therefore, the impacts of climate change on water resources have to be identified and quantified in order to cope with them in the future.

2.2.4 Expected Effects of Climate Change/ Climate Variability in Nigeria

In her first National Communication under the United Nations Framework Convention on Climate Change (UNFCCC) in November, 2003, the main features of Climate Change scenarios in Nigeria were summarized as follows:

1.The most significant indicator of climate changes are temperature and temperature related parameters such as rainfall, humidity, evaporation and sea level rise. Changes in the minimum and maximum temperatures of the order of 7°C or more could be expected in certain parts of the country in the 21st century given the current emission scenarios. These may impact negatively or positively on human health in the aspect of incidence of malaria and water related diseases), water resources, biodiversity, agriculture and food security and forestry.

2. Night time temperatures will generally increase at a higher rate than day time temperatures'

3. There has been an observed trend towards aridity in the northern part of the country. There are also possibilities that additional water demand resulting from higher temperatures may not be met by the increases in rainfall.

4. Rainfall and humidity will decrease while temperature will increase from the sea.

5. It is estimated that with the present Accelerated Sea Level Rise(ASLR) of 0.2m, about 10 to 20% of the people in the coastal zones are being affected by physical changes such as flooding, erosion, and increased salinization of both surface and groundwater. With the projected climate change and sea level rise of 0.2 to 1.0m, the capital values at risk would be about $8.05billion and $17.5billion respectively if no measures are taken.

6. The uncertainties associated with climate change will most likely be in terms of magnitude rather than direction (Federal Rep. of Nigeria, 2003).

2.3 THE REGIONAL CLIMATE PATTERN IN WEST AFRICA

2.3.1 General Circulation Over West Africa

Three anticyclones control general circulation in West Africa. These are the Azores and the Libyan anticyclones in the Northern Hemisphere and the St. Helena anticyclone in the Southern Hemisphere. While the Azores anticyclone is permanent; the Libyan anticyclone may become relatively weak during the summer in the Northern Hemisphere. The St. Helena anticyclone normally oscillates northwards during Northern Hemisphere winter. Between the three sub-tropical high pressure cells are: the Sahara Desert, sub-Sahara West Africa and the Gulf of Guinea. This is the sphere of influence of two air masses, which migrate in concert with the high-pressure cells. There is a tropical continental (cT) Air, warm, dry, and dusty, which extends from the Sahara, reaching its maximum southern extent in January between latitude 5^{o} and 7^{o} N. Alternating seasonally with this is the mass of Tropical Maritime (mT) Air, warm and humid, which has its source region over the south Atlantic. It moves overland from the ocean, reaching its maximum northern extent in August at about 17^{o} N from the coast and about 21^{o} N inland (Adejuwon, 2006). The cT Air is characterized by dry, north-easterly winds while the mT Air is characterized by moisture laden south-westerly winds.

The seasonal climate of West Africa is largely determined by the migration and pulsation of the two air masses. The boundary between the two air masses slopes southwards so that for a distance of 50km to 100km, a wedge of warm humid air underlies the mass of overriding cool and dry air (Adejuwon, 2006). The presence of the moist southwest air stream makes itself felt in the scattered cumulus clouds, which develop as the sun climbs in the sky. The bases are generally around 800 to 1000m above the surface, but rarely do they grow to any great heights. The air above 1200-1600 m is still dry; hence the cumulus clouds rapidly dissipate as they rise to higher levels. South of the wedge, and extending for about 600 to 800 km, the moist air is not vertically restricted by an overburden of dry air. This zone is characterized by scattered and linear 14convection leading to the ascent of most air, the development of cumulus and cumulonimbus clouds, thunderstorms and heavy tropical rainfall; characteristics which earn it the name of Inter-tropical Convergence Zone (ITCZ). South of this zone and extending far into the South Atlantic the mT air continues to prevail.
Most of the precipitation in West Africa is a product of the ITCZ and its associated weather mechanisms (Adejuwon, 2006). At the boundary of West Africa with the Sahara Desert, Latitude 15^{o} N, nearly all the rainfall occurs as a result of perturbations within the zone of convergence. Ninety percent of the precipitation results from ITCZ weather at Latitude 9^{o} N, However in certain parts of the sub-continent, notably in the coastal area; rainfall is not significantly correlated with the ITCZ. For example, in the coastal areas of Ghana, only 30 percent of the precipitation is related to this weather mechanisms (Adejuwon, 2006) .Since the boundary between the two air masses moves in sympathy with the oscillation of the controlling anticyclones, the belt of ITCZ weather also moves north and south. Such movement is responsible for the characteristic intra-annual patterns of rainfall distribution (Adejuwon, 2006). Specifically, they are responsible for the differentiation of the dry and the rainy seasons. The varying degrees of persistence of the ITCZ over east-west aligned zones are also the main cause of the regional disposition of the main climatic types in the sub-continent. Perennially humid climate characterizes areas south of latitude 7.5^{o} N. The atmosphere in this zone is always humid as it lies permanently south of the ITCZ.

However, there may be up to three months without rain. A sub-humid climate characterizes the region between latitudes 7.5^{o} and 9.5^{o} N. As the area is alternately covered by dry northern and moist southern air, there are two distinct seasons, wet and dry, corresponding to the period of occurrence of each of the two dominant air masses. The climate is described as sub-humid because the dry season is much less in length than the wet season. Between the area characterized by the sub-humid climate and the Sahara Desert, the climate is recognized as semi arid with dominant, arid tropical conditions (Adejuwon, 2006). The diagnostic feature of the humid climate is the Tropical Rain Forest. Within it, one could recognize a moist evergreen forest where mean annual rainfall is more than 2,000 mm and a dry evergreen rain forest where the mean annual rainfall is between 1,250 mm and 2,000 mm. The diagnostic feature of the sub-humid climate is the Guinea savannah vegetation characterized by mesophytic tall

grasses and deciduous trees. There is sufficient contrast between the northern and the southern parts of the Guinea savannah to justify the recognition of a Northern Guinea Savannah zone and a Southern Guinea Savannah zone. The vegetation of the semi-arid zone is characteristically xeromorphic in its tree layer. However, two zonal types are recognized including the Sudan in the wetter, southern areas and the Sahel in the areas by the side of the Desert. The main difference in the vegetation is in the grass layer, which tends to be mesophytic in the Sudan and xeromorphic in the Sahel. Thus, from the coastal southern areas, to the boundary with the Sahara Desert, five zonal climate and ecological types can be recognized, including: Rain Forest, Southern Guinea Savannah, Northern Guinea Savannah, Sudan Savannah and Sahel Savannah. Sometimes within the rain forest belt, drier and wetter sub-types are recognized. Also there is substantial support for the recognition of Derived Savannah vegetation zone, which was formerly under rain forest, but whose plant cover has since been converted to savannah as a result of intensive agricultural practice (Adejuwon, 2006).

2.3.2 Climate Variability in Nigeria

IPCC (2001) and Hengeveld et al (2005) provided indicators that can be used to assess evidence of climate variability in a region. These include increasing temperature, increasing evaporation, decreasing rainfall amount in the continental interiors, increasing rainfall in the coastal areas, increasing disruption in climate patterns and increasing frequency and intensity of extreme weather related events such as thunderstorms, lightning, floods, landslides, droughts, unpredictable rainfall pattern, sea level rise, increase desertification and land degradation, drying up of rivers and lakes and constant loss of forest cover and biodiversity.

A study on the regional evidence of climate variability in Nigeria by Odjugo (2010) revealed that the air temperature increased gradually between 1901 and 1970 and at a higher rate since 1970. The mean air temperature in Nigeria between 1901 and 2005 was 26.6°C, while temperature increase for the 105 years was 1.1°C. This is obviously higher than the global mean temperature increase of 0.74°C recorded since 1860 when actual scientific measurement of temperature started (IPCC, 2007). If this trend is allowed to continue, Nigeria may experience between the middle (2.5°C) and high (4.5°C) risk temperature increase by the year 2100(Odjugo, 2010).

The rainfall trend in Nigeria between 1901 and 2005 showed a general decline. Within the 105 years, rainfall amount dropped by 81mm. The decreasing rainfall became worst from the early 1970's and the pattern had continued till date (Odjugo, 2010). Although there is a general decrease in rainfall in Nigeria, the coastal areas were observed to be experiencing increasing rainfall which may have been partly responsible for the increasing floods in coastal cities such Lagos, Warri, Calabar and Port Harcourt (Odjugo, 2009 and, 2010).

The increasing temperature and decreasing rainfall in semi-arid region of Sokoto, Katsina, Nguru and Maiduguri may have resulted in the increasing evaporation, drought and desertification in Northern Nigeria as reported by Odjugo and Ikhuoria

(Odjugo, 2010). Constant loss of forest cover and biodiversity in Nigeria has been linked to climate variability (Odjugo, 2010).

Another indicator is the increasing frequency and intensity of extreme weather related events such as erratic rainfall pattern, floods and sea level rise among others which have been confirmed, by recent researches, to exist in Nigeria (Odjugo, 2010). The decreasing rainfall, increasing temperature and evaporation have resulted in either the reduction of water levels or total drying up of some rivers and lakes in Northern Nigeria while Lake Chad is reported to be shrinking at an alarming rate since 1970's (Odjugo, 2010). In the coastal region of Nigeria, sea level rise of 0.20m and incursion of salt water into the coastal plain for about 2016 to 3400km^2 had been reported (Odjugo, 2010). Odjugo (2010) observed that the number of rainy days dropped by 53% in the North-eastern Nigeria and 14% in the Niger-Delta coastal areas. The study also showed that while the areas experiencing double rainfall maximal was shifting southward, the short dry season (August break) was being experienced more in July as against its normal occurrence in the month of August prior to 1970's. These are major disruptions in climate patterns of Nigeria indicating evidence of climate variability.

2.4 CLIMATE CHANGE DETECTION AND ATTRIBUTION

The response to anthropogenic changes in climate forcing occurs against the backdrop of natural internal and externally forced climate variability that can occur on similar temporal and spatial scales. Internal climate variability occurs on all time-scales from weeks to centuries and millennia. Slow climate components such as oceans, have particularly important roles on decadal and century time-scales because they integrate high-frequency weather variability (Hasselmann, 1976) and interact with the faster components. Thus, the climate is capable of producing long time-scale internal variations of considerable magnitude without any external influences (IPCC, 2007).

The presence of this natural climate variability means that the detection and attribution of anthropogenic climate change is a statistical "signal-in-noise" problem (IPCC, 2007). Detection is the process of demonstrating that an observed change in climate system is significantly different (in statistical sense) from what can be explained by natural variability (Mitchell, et al, 2007). However, the detection of change in climate does not necessarily means that its causes are understood. The attribution of climate change to anthropogenic causes would require controlled experimentation with climate system in which the supposed agents of change are systematically varied in order to determine climate sensitivity to these agents. This approach is obviously not possible. Thus, from practical perspective, attribution of observed climate change to a given combination of human activity and natural influences requires statistical analysis and careful assessment of multiple lines of evidence to demonstrate, within specified margin of error that the observed changes are:

1. Unlikely to be due to internal variability;
2. Consistent with the estimated responses to the given combination of anthropogenic and natural forcing; and
3. Not consistent with alternative physically plausible explanations of recent climate change that exclude important elements of the given combination of forcings.

Detecting climate change and then attributing it to specific physical mechanism is, therefore, basically a statistical problem that can be resolved using regression analysis (Barnett, et al, 1999). The current detection methods are: conventional, Bayesian and optimal fingerprinting. Both the conventional and Bayesian methods require that the model-predicted signal (in spatial pattern and amplitude, and its change with time) have acceptable counterpart in the observations before detection and attribution can be claimed (Barnett, et al, 1999). Most detection methods in use today are "optimal" in the sense that they define, through a rotational transform, the search-for signal patterns to be as distinguishable as possible from the patterns of natural climate variability. This is referred to as prefiltering operation of the data prior to application of regression techniques (Barnett, et al, 1999).

2.4.1 Conventional Method of Climate Change Detection

A standard assumption of all detection and attribution methods is that the observed climate change vector $\varphi(t)$ can be represented to first order as a linear superposition: $\varphi(t) = a(t)g(t) + n(t)$ of the signal ag and noise $\boldsymbol{n}$, where the signal is decomposed into amplitude a and a suitably normalized signal pattern **g**. This notation applies to a single pattern case and can easily be generalized to multiple patterns. The climate change signal pattern (t), observed climate change vector$\varphi(t)$, and climate variability noise $n(t)$ are defined here in the space of some set of climate variables such as temperature, precipitation, evaporation and so forth, for which individual or grid-averaged measurements exist in some spatial distribution.

In both the Conventional and Bayesian methods, the task is to extract from the data an estimate of the climate change signal and a measure of the signal-to-noise ratio. This is usually achieved by applying a suitable linear filter (t), to the data (North and Kim, 1995; Barnett, et al, 1999). Where applicable, the filter is designed to yield a detection variable d that maximizes the signal-to-noise ratio. Thus, the goal is to design a filter (t) that projects the observed data onto a detection variable d, as $d = \int_{t_0}^{t_1} f^T(t)\varphi(t)dt$; where T denotes transpose in matrix notation, such that the square signal-to-noise ratio; $S = d_g^2/\langle d_n^2 \rangle$, is maximized. Where d_g = detection variable for the case of a pure signal without noise ($\varphi(t) = g(t)$) and d_n = detection variable computed for the complementary case of pure noise in the absence of signal ($\varphi(t)$ = (t)). The cornered parentheses denote expectation values. Maximizing S is also equivalent to maximizing

the square ratio $\langle d^2 \rangle / \langle d_n^2 \rangle$ of signal plus noise to noise. The detection variable d can then be written in the more compact notation as: $d = f^T \varphi$. Where φ denotes the climate state trajectory.

It is important to note that the optimal filter differs from the predicted climate change signal (**g**(x, t)). The signal pattern is sometimes used as a detection filter, although, this is not the optimal choice, as it ignores the properties of the national variability noise characterized by the covariance matrix C =$\langle n\, n^T \rangle$, which is usually suppressed relative to the signal. Mathematically, the signal and the filter patterns represent co- and contra variant duals with respect to a matrix given by the inverse of the covariance matrix C.

The mean square of the residual r between the observed climate change and estimated signal is minimized with respect to the matrix C: $\langle r^T C^{-1} r \rangle$ = minimum; where r = φ - **g** and = best estimate of amplitude a. Minimizing the residual is equivalent to maximizing the probability that the residual can be attributed to the natural climate variability and therefore contains no external forcing signals (Barnett, et al, 1999).

If the amplitude is estimated from the observations by some linear process, that is, by the application of a filter$\hat{f}$, as = $\hat{f}^T \varphi$, the optimal filter that minimizes the mean square error (Barnett, et al,1999), is found to be $\hat{f}$ =**f** so that = d. Thus, the detection variable, also, represents the optimal estimate of the signal amplitude.

In the conventional approach, the detection and attribution problems are separated. First, it is determined whether the detection variable d exceeds some critical value d_c associated with some given probability, c = 5%, that d can still be attributed to the natural variability noise. For Gaussian noise, $d_{\%} = 2\delta_d$, where $\delta_d = \sqrt{\langle d_n^2 \rangle}$. If $d > d_c$, the null hypothesis is rejected at the risk level c and a climate change signal is said to be detected at the significance level 1-c (95%).

2.4.2 Bayesian Method for Climatic Change Detection

Bayesian statistics is concerned with subjective probabilities of the validity of hypotheses. Prior to the performance of some test E, some probability p (H) (prior) is assigned to the validity (H=h= "true") or invalidity (H = $\bar{h}$ = "false") of a hypothesis H. The outcome E = e (positive) or E = $\bar{e}$ (negative) of the hypothesis test E changes the prior probability into the posterior probability p (H/E). The relationship between the prior and posterior probabilities is given by Baye's basic theorem as: $\frac{p(H/E)}{p(H)} = \frac{p(E/H)}{p(E)}$ which follows directly from the relevant definitions of conditional probability. For the case that the hypothesis H is correct, H=h, and the test outcome is positive, E=e, the above equation may be written as: $C = C_o / \{C_o l + (1 - C_o)\hat{l}\} = (1 + \beta \hat{l}/l)^{-1}$ where$\beta = \frac{1-C_o}{C_o}$. Given that the prior probability$c = p(h/e)$, posterior probability c_o=$p(e/h)$, the true hypothesis $l = p(e/h)$ for the likelihood of positive outcome of the test for the case that the hypothesis is true, $\hat{l} = p(e/\bar{h})$ (corresponding to the

conventional null hypothesis statistic of a positive test outcome for the case that the hypothesis is false, then the complementary likelihood $p(e)$ is given as :

$$p(e) = p\left(\frac{e}{h}\right)p(h) + p(e/\bar{h})p(\bar{h}) = lC_o + \hat{l}\,(1 - C_o) \quad \text{.....(2.1)}$$

2.4.3 Optimal Fingerprinting Method for Climatic Change Detection

Optimal fingerprinting is a generalized multivariate regression adapted to the detection of climate change and the attribution of change to externally forced climate change signals (Hegerl et al, 2007). The regression model has the form y = Xa +u, where vector y is a filtered version of the observed record, matrix X contains the estimated response patterns to the external forcing (signals) that are under investigation, a is a vector of scaling factors that adjusts the amplitudes of those patterns and u represents internal climate variability. Vector u is usually assumed to be a Gaussian random vector with covariance matrix C. Vector a is estimated with â = (X*T*C-1X)-1X*T*C-1y, which is equivalent to (X□*T*X□)- Xt, where matrix X□ and vector ỹ represent the signal patterns and observations after normalization by the climate's internal variability. This normalization, standard in linear regression, is used in most detection and attribution approaches to improve the signal-to-noise ratio (Hegerl et al, 2007).The matrix X typically contains signals that are estimated with either an Atmospheric-Ocean General Circulation Model (AOGCM), an Atmospheric General Circulation Model (AGCM) (Hegerl et al, 2007) or a simplified climate model such as an Energy Balance Model (EBM). Since AOGCMs simulate natural internal variability as well as the response to specified anomalous external forcing, AOGCM simulated climate signals are typically estimated by averaging across an ensemble of simulations. If an observed response is to be attributed to anthropogenic influence, X should at a minimum contain separate natural and anthropogenic responses. In order to relax the assumption that the relative magnitudes of the responses to individual forcing are correctly simulated, X may contain separate responses to all the main forcing, including greenhouse gases, sulphate aerosol, solar irradiance changes and volcanic aerosol (Hegerl et al, 2007).
The vector a, accounts for possible errors in the amplitude of the external forcing and the amplitude of the climate model's response by scaling the signal patterns to best match the observations. Fitting the regression model requires an estimate of the covariance matrix C (that is, the internal variability), which is usually obtained from unforced variation simulated by AOGCMs (for example, from long control simulations) because the instrumental record is too short to provide a reliable estimate and may be affected by external forcing. Atmosphere-Ocean General Circulation Models may not simulate natural internal climate variability accurately, particularly at small spatial scales, and thus a residual consistency test (Hegerl et al, 2007) is typically used to assess the model-simulated variability at the scales that are retained in the analysis. In order avoid bias (Hegerl et al., 2007), uncertainty in the estimate of the vector of scaling factors are usually assessed with a second, statistically independent estimate of the covariance matrix C which is ordinarily obtained from an additional, independent sample of simulated unforced variation. Signal estimates are obtained by

averaging across an ensemble of forced climate change simulations, but contain remnants of the climate's natural internal variability because the ensembles are finite. When ensembles are small or signals weak, these remnants may bias ordinary least-squares estimates downward. This is avoided by estimating a with the total least-squares algorithm (Hegerl et al, 2007). The use of optimal techniques can increase the detectability of forced climate changes. These techniques increase signal –to –noise ratio by looking at the components the response away from the direction of the highest internal variability.

2.4.4 Methods of Inference for Climatic Change Detection and Attribution

Detection and attribution questions are assessed through a combination of physical reasoning (to determine, for example, by assessing consistency of possible responses, whether other mechanisms of change not included in the climate model could plausibly explain the observed change) and by evaluating specific c hypotheses about the scaling factors contained in a. Most studies evaluate these hypotheses using standard frequency methods (Hegerl et al, 2007). Several recent studies have also used Bayesian methods (Hegerl et al, 2007; Schnur and Hasselmann, 2005). In the standard approach, detection of a postulated climate change signal occurs when its amplitude in observations is shown to be significantly different from zero, that is., when the null hypothesis *HD:* a = 0 where 0 is a vector of zeros, is rejected, with departure from zero in the physically plausible direction.

Subsequently, the second attribution requirement (consistency with a combination of external forcings and natural internal variability) is assessed with the 'attribution consistency test' (Hegerl et al, 2007) that evaluates the null hypothesis *HA:* a = 1 where 1 denotes a vector of units. This test does not constitute a complete attribution assessment, but contributes important evidence to such assessments (Hegerl et al, 2007). Attribution studies usually also test whether the response to a key forcing, such as greenhouse gas increases, is distinguishable from that to other forcing, usually based on the results of multiple regression using the most important forcing simultaneously in X. If the response to a key forcing (for example, due to greenhouse gas increases) is detected by rejecting the hypothesis that its amplitude a GHG = 0 in such a multiple regression, this provides strong attribution information because it demonstrates that the observed climate change is 'not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcing' (Hegerl et al, 2007).

Bayesian approaches are of interest because they can be used to integrate information from multiple lines of evidence, and can incorporate independent prior information into the analysis (Hegerl et al, 2007). Essentially two approaches have been taken till date. In both cases, inferences are based on a posterior distribution that blends evidence from the observations with the independent prior information, which may include information on the uncertainty of external forcing estimates, climate models and their responses to forcing. In this way, all information that enters into the analysis is declared

explicitly. Schnur and Hasselmann (2005) approached the problem by developing a filtering technique that optimizes the impact of the data on the prior distribution in a manner similar to the way in which optimal fingerprints maximize the ratio of the anthropogenic signal to natural variability noise in the conventional approach. The optimal filter in the Bayesian approach depends on the properties of both the natural climate variability and model errors. Inferences are made by comparing evidence, as measured by Baye's Factors (Hegerl et al, 2007), for competing hypotheses. Other studies using similar approaches include Min et al. (Hegerl et al, 2007) and Min and Hense (Hegerl et al, 2007)). In contrast, Berliner et al. (Hegerl et al, 2007)) and Lee et al. (Hegerl et al, 2007) use Bayesian methods only to make inferences about the estimate of a that is obtained from conventional optimal fingerprinting.

2.5 CLIMATE MODELLING

Climate models are mathematical representations of the climate system based on established physical laws, such as conservation of mass, energy and momentum with observations and expressed as computer codes which are run on computers (Randall et al, 2007). The key feature of models, generally, is that they are simplified representations of the thing that they represent, designed to describe some aspects of the system accurately but omitting many less relevant or important details in the interest of clarity and simplicity. The basic idea of mathematical modelling is to keep this basic approach but do away with the physical representation, describing the modelled system by some equations rather than by physical object.

Climate models derived from fundamental physical laws are usually subjected to physical approximations (parameterizations) appropriate for the large-scale climate system and then further approximated through mathematical discretization. Computational constraints restrict the resolution that is possible in the discretized equations and therefore, some representations of the large-scale impacts of unresolved processes is required, that is, parameterizations, (Randall et al, 2007).

Parameterizations are typically, based on simplified physical models of the unresolved processes. Parameterizations also involve numerical parameters that must be specified as input. Some of these parameters can be measured, at least in principle, while others cannot (Randall et al, 2007). It is therefore common to adjust the parameter values in order to optimize model simulation of a particular variable or improve global heat balance. This process is called "tuning". The tuning should be such that:

1. Observationally based constraints on parameter ranges are not exceeded; and

2. The number of degree of freedom in the tune able parameter is less than the number of degree of freedom in the observational constraints used in the model evaluation.

Despite the constraints in describing accurately, the climate system by mathematical models, there is considerable confidence that climate models provide credible

quantitative estimates of future climate change, particularly at the continental scales and above. The confidence in model estimates is higher for some climate variable (for example, temperature) than for others (for example, precipitation) (Randall et al, 2007). In over several decades of development, climate models have consistently provided a robust and unambiguous picture of the significant climate warming in response to increasing greenhouse gases (Randall et al, 2007).

The inability to explicitly represent all potentially relevant processes in climate models has many sources: finite spatial and temporal resolution of numerical approximations to the underlying differential equations imposed by computational limitations; filtering of high-frequency processes out of the original equations of motion; poor understanding of the basic physical processes operating on smaller scales as a result of inadequate observations; and the desire to avoid the problem that deep understanding of climate models tends to decrease as the number of explicitly resolved processes increase (Imkeller and Monahan, 2002). In any event, for any climate model, there will be a class of processes or scales of variability that may have an effect on the resolved variables but which are themselves not represented explicitly or are simply ignored altogether.

In the construction of the climate model, therefore, decisions must be made as to which scales are to be represented explicitly and which are to be parameterized. How this separation is made depends largely on where the model falls within the hierarchy of climate models. This hierarchy consist of heuristic conceptual models (based on energy balance in the climate system) designed to capture the essence of important processes in the climate system. This is simple enough for their parameter space to be investigated but too simple to be treated as quantitatively accurate; The Earth System Models of Intermediate Complexity (EMIC) which represent some climate subsystems (for example, ocean or atmosphere) in detail while parameterizing the dynamics of other subsystems, and the full General Circulation Models (GCM) which attempt to represent the climate system in as great detail as computational and conceptual limitations allow (Imkeller and Monahan, 2002).

A general circulation model (GCM) of climate system is a prognostic system of equations representing the physical and dynamic processes which control the climate (Meehl, 1984). In the hierarchy of climate models, GCM's are generally the most complex, expensive (in terms of computer time) and realistic in the way they simulate many variables of the climate system. Due to the great amount of details included in the GCM's, they are potentially the most powerful tools presently available for the study of the earth's climate. However, a major difficulty associated with GCM's is the task of interpreting their results. The artificial climates generated by these models are as complicated as the earth's climate. Also, the spatial resolution of most GCM's in use today is around 250 to 700km (Meehl, 1984). Stuart and Judge (Trenberth and Hoar, 1997) using three General Circulation Models to reproduce the present temperature and precipitation of the Mackenzie Valley in Canada found that the GCM's generated large errors with differences as much as 5°C between modelled and observed temperatures

and between one model and another over relatively large areas. Therefore, it is not possible for GCM's to resolve processes for smaller scales at national or local levels (Meehl, 1984; Trenberth and Hoar, 1997).These must be included as parameterizations and are usually referred to as sub grid scale processes.

The central issues in climate modelling are, thus, which processes to represent explicitly and which to parameterize and how to construct accurate parameterizations. The traditional approach to the solution of parameterizations problem is to represent those terms in the dynamic equations associated with unresolved phenomena by deterministic functions of the resolved variables, introducing new parameters whose numerical values are determined from observational data, from theory, or by being tuned until the model behaves "realistically" (Imkeller and Monahan, 2002; Idowu, 2008). A theoretical justification for this approach to the problem of parameterizations follows from an analogy to connection between statistical mechanics and thermodynamics. An ideal gas is characterized by variability both on the molecular micro-scale and on the macro-scale on which it is sensible to define quantities such as pressure and entropy. The aggregate effect of essentially random molecular motion on micro-scale is to produce essentially deterministic dynamics on the macro-scale. In the climate system, it is argued, if the unresolved scales are in statistical equilibrium with the resolved scales, then parameterization of their effects on the resolved variables is appropriate (Imkeller and Monahan, 2002). However, an essential difference between a typical statistical mechanical system and the climate system is that in the former, there is an effectively infinite separation of scales between the micro and macro while no such clear separation of scales exists in climate system.

Consequently, it is not obvious that the aggregate effect of the turbulent unresolved scales on the resolved scales is and can be modelled by a deterministic function of the resolved variables. Instead, the appropriate solution to the parameterization problem may involve an element of randomness (Imkeller and Monahan, 2002). Parameterization by stochastic processes of variability not resolved explicitly was first suggested by Hasselmann (1976) in his seminar paper in 1976 and has recently been argued for on the basic theoretical grounds (Imkeller and Monahan, 2002; Lobanov and Lobanova, 2008).It demonstrated considerable success in the study of the dynamics of El Nino and southern oscillation (Trenberth and Hoar, 1997); glacial climate variability etc (Imkeller and Monahan, 2002).

The field of stochastic climate models is diverse and growing. From July 9 through July 11, 2001, 50 researchers from mathematics and climate communities met in Chorin, Germany to discuss the idea of stochastic representation of unresolved variability in climate models. Also, the foundation of stochastic climate models through stochastic reduction of multi-scale deterministic processes describing climate phenomena was one of the main focal points of the forerunner meeting in Chorin in June 1999(Imkeller and Monahan, 2002).

Till date, stochastic hydrology is based on the theory of random samples and distribution function theory and they are suitable for homogeneous and stationary conditions (Lobanov and Lobanova, 2008). From the position of this approach, a time series of any hydrological characteristics can be represented in the form of stationary-homogeneous model of random sample with autocorrelation between consecutive time values (model of the simple Markov's chain). Each per year hydrological characteristic (annul minimum, annual maximum, annual runoff, and so forth.) is a random event and model of such random events is a distribution function with three main parameters: mean (μ), variation coefficient (C_v), and skewness coefficient (Cs) which are assumed as constant values for long- term period (Lobanov and Lobanova, 2008).On the basis of these parameters, any quantile of a given return period can be obtained as a design value. The largest record of observations is the main assumption for an effective assessment of parameters in stationary conditions, because the more the sample, the smaller the random errors of parameters and quantiles. The assumptions of homogeneity and stationarity are suitable when records of observations are short for detailed analysis (Lobanov and Lobanova, 2008).

An important class of stochastic models for describing climatic time series which has received a great deal of attention is the stationary models (Kallache, et al, 2005; Wilberforce, 2007; Idowu, .2008; Ogolo, 2010).Stationary models assume that the process remains in statistical equilibrium with probabilistic properties that do not change over time, in particular, varying about a fixed constant mean level and with constant variance. The stochastic model for which the exponentially weighted moving average forecast yields minimum mean square error is a member of a class of non-stationary processes called Autoregressive Integrated Moving Average (ARIMA) process (Box, et al, 2008). These wider classes of processes provides a range of models, stationary and non-stationary, that adequately represent many of the time series encountered in practice. ARIMA modelling has been successfully applied in various water and environmental management applications (Nail and Momani, 2009); Karl et al (1996) utilized Autoregressive Moving Average (ARMA) for the study of climate variability in the United States of America (USA.) and found that the climate extreme indices and USA. greenhouse climate response index increased abruptly during the 1970s; Liang and Kershaw (1995) used ARMA model to evaluate climate change in Mackenzie Mountain, Canada; Lund et al (2001) used ARMA model to analyze and model temperature trends in the United States of America; Hughes et al (2006) used ARMA model to study the variations of minimum and maximum temperatures in the Antarctic Peninsula .

Models used for the study of the variations in hydro-meteorological variables from year to year have not been based on the analysis of causal factors but on the decomposition of the time series into its basic components by means of the dynamic series model given as:

$$y(t) = u(t) + v(t) + s(t) + e(t) \quad \ldots\ldots (2.2)$$

Where: $u\,(t)$ = trend due to the action of permanent factors; $v\,(t)$ = cyclic variations due to the action of rhythmical factors; $s\,(t)$ = stochastic components assumed to follow an autoregressive moving average Process; $e\,(t)$ = random component due to the action of random factors. There is an obvious connection between these components of the series and the actual physical processes or situations. Thus, the general trends reflect the general direction of the dynamics of the phenomenon; the cyclic variations or component give the periodical fluctuations about the trend or mean; and the stochastic and the random components or variations are as a result of the impacts of random factors on the natural development of the phenomenon (Haidu et al, 1987).

Trend of Hydro-meteorological variables

The general trend of the hydro-meteorological series can be ascribed to climate change or the influence of man's activities such as agriculture, deforestation and urbanization (Haidu et al, 1987) on the climate system. The extraction of the trend component from the raw data series can be achieved by means of a polynomial fit given as:

$$u\,(t) = a_1 + a_2 t + a_3 t^2 + \cdots \ldots \ldots + ant^{n-1} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2.3)$$

For parsimony, that is, using a model with the fewest possible number of parameters and greatest number of degrees of freedom among all models for adequate representation, the trend can be extracted by means of the basic statistical model for linear trend given as: $u(t) = a + bt + e(t)$; Where a = intercept; b = slope of the regression line and $e(t)$ = random error component. The parameters a and b are estimated using the least square method if the error terms are uncorrelated. The principal complication with this method in the case of climate data is usually that the data are autocorrelated, in other words, the terms cannot be taken as independent (Smith, 2007). In climate change detection and attribution study and evaluation, IPCC (2007) uses the generalized multivariate regression approach called optimal fingerprinting. The regression model has the form: $y = Xa + u$, where vector y is a filtered version of the observed record; matrix X contains the estimated response patterns to the external forcing (signals) that are under investigation; a is a vector scaling factors that adjust the amplitudes of those patterns; and u represents internal climate variability (Hegerl et al, 2007). With regards to long-term variation, the trend component represents a linear variation in some cases and parabolic variation in others.

The detection of trend in measured time series data can also be posed as a hypothesis testing problem in which the null hypothesis (H_o) is that there is no trend in the data and the alternative hypothesis (H_1) is that there is trend in the data (McCabe et al, 1997). The reality will be that either the null or alternative hypothesis is true or a statistical test will indicate that either the null or alternative hypothesis is true. The power of the statistical test is the probability of accepting the alternative hypothesis when it is true based on the p-value. The p-value indicates the level of probability of

accepting or rejecting either the null or the alternative hypothesis. Generally, reject H_o if p-value ≤ 0.05.

After the elimination of the trend component, the dynamic series becomes:

$$R(t) = v(t) + s(t) + e(t). \quad \text{(2.4)}$$

In order to establish the general structure of the resulting series or residual series $R(t)$, the correlogram method is used. The autocorrelation coefficient γ_k, is determined as follows:

$$\gamma_k = [\sum_{t=1}^{N-k}\{(Rt - Rm)(R(t + k) - Rm\}]/\sum_{t=1}^{N}(Rt - Rm)^2 \quad \text{(2.5)}$$

Where N = the length of the time series; k =the difference between two values of the series expressed in time units, Rm = mean value of the series.

The correlogram is obtained by graphical representation of the variations of γ_k with k. If the data series is random, the computed value of γ_k is other than that due, only, to internal (random) variations of the series, the points of the correlogram being very close to the horizontal axis. The confidence limit (CL) corresponding to a given significant level is expressed as: $CL(\gamma_k) = [-1 \pm Z_\propto(N - k - 2)^{1/2}]/(N - k - 1)$, where $Z_\propto$ = standard normal deviate corresponding to the probability $\propto$. For $\propto$ = 5%, the significant level $Z_\propto$ = 1.645.

Periodic Component

The determination of the periodic component is achieved by means of a Fourier series of the form: $v(t) = \frac{1}{2}a_0 + \sum_{n=1}^{\infty}(a_n cos\frac{2\pi}{T}nt + b_n sin\frac{2\pi}{T}nt)$, where n = the order of the harmonic corresponding to the period established by the analysis of the correlogram. $\frac{2\pi}{T}$ = the frequency of the oscillations. a_0, a_n, b_n = Fourier coefficients. The remainder of the dynamic series is given as:

$$R(t) - v(t) = s(t) + e(t) = stochastic\ component. \quad \text{(2.6)}$$

After eliminating the trend and periodic components from the original data series, the resulting series is a stochastic process which can be modelled by means of parametric models of an autoregressive moving average (ARMA) type (Haidu et al, 1987 and Box et al, 2008).

The general structure of a non-stationary ARIMA type (p, d, q) model is given as:

$$w_t = \emptyset_1 w_{t-1} + \ldots\ldots\ldots + \emptyset_p w_{t-p} + a_t - \theta_1 a_{t-1} - \ldots\ldots\ldots - \theta_p a_{t-q} \quad \text{(2.7)}$$

Where d = difference order; $\emptyset$ = parameters of the autoregressive process; θ= parameters of the moving average process; p= order of the autoregressive process; q = order of the moving average process; and a_t = current value of an independent random variable with zero mean and constant variance δ_a^2 (of the "white noise" type).

When d = 0, $w_t = s_t - \mu$, where s_t = the current value of the modelled series at moment t; μ = parameter determining the level of the process, in the case of stationary process μ is the mean of the series.

The steps necessary for establishing the ARIMA type model to describe, optimally, the data series are:

1. Estimation of the order p, q, and d of the model by the analysis of the autocorrelation and partial autocorrelation functions;
2. Determination of the parameters $\emptyset, and\ \theta$ by means of the maximum likelihood and least square methods; and
3. Analysis of the structure of the residuals obtained after the application of the model in order to verify appropriateness of the chosen model. If the residuals obtained do not comply with the above mentioned criteria indicated, the model should be re-analyzed.

The details of ARMA processes and the procedure for estimating the coefficients are given in the subsequent sections:

2.5.1 ARIMA Model Description

In ARIMA terms, a time series is a linear function of past values and random shock (error terms or white noise) given as:

$$Y_t = f\left[Y_{t-k},\ e_{t,k}\right] + e_t \quad \text{.......} \quad (2.8)$$

Where k> 0, and $f\left[Y_{t-k,}e_{t,k}\right]$ = the pattern which may be random, seasonal, trend, cyclic or a combination of patterns. e_t = model residuals (white noise or model error).

The purpose of time series analysis is to extract all possible information from a time series so that the e_t,s are distributed as white noise. White noise is normally and independently distributed, having no pattern, zero mean and an error variance that is less than the variance of Y_t .Consequently, the task is to find the pattern that , when subtracted from Y_t has white noise residuals which are randomly distributed.

An ARIMA model is composed of autoregressive process, moving average process and integrated process. The model is usually denoted as ARIMA (p, d, q). The notations are designated by the level or order of the autoregressive, integrated and moving average processes respectively. It identifies the orders of Autoregression by p, integration or differencing by d and moving average by q.

That is ARIMA (p, d, q): ……. (2.9)

Where p = order of Autoregression (AR), d =order Integration (differencing) (I), q = order of Moving Average (MA)

2.5.1.1 .Autoregressive Process –ARIMA (1, 0, 0)

Autoregression is an extension of simple linear regression. The ARIMA (1,0,0) model, commonly called AR (1) is given as:

$Y_t = \theta_o + \emptyset Y_{t-1} + e_t$…….. (2.10)

Where θ_o and $\emptyset$ are coefficients chosen to minimize the sum of square errors.

For an ARIMA (1, 0, 0) model, the absolute value of the coefficient $\emptyset$ is normally constrained to be less than one. This constraint is called the bound of stationarity. If this bound is exceeded, then the series is not autoregressive. It is drifting or trending and differencing should be used to model the series.

2.5.1.2 .Moving Average Process-ARIMA (0, 0, 1)

This is similar to exponential smoothing. It is given as:

$Y_t = \mu - \theta_1 e_{t-1} + e_t$…… (2.11)

Where θ_1 = estimated coefficient; μ = mean of the series.

Y_t , is only correlated with the previous forecast error e_{t-1}

The absolute value of θ_1 for moving average (MA) model is constrained to be less than one. This constraint is called the bound of Invertibility, a concept related to stationarity. If this bound is exceeded, the series is not stationary. Invertibility means that the series could be converted into autoregressive process, that is, a process with convergent set of parameters. Finite-order moving average models are inappropriate for direct application in hydrology (Kottegoda, 1980). They are included as a prelude to ARIMA and ARMA models.

2.5.1. 3. *Integrated Process-ARIMA (0, 1, 0)*

Deterministic Trend is a systematic period-to-period increase or decrease that persists for many time periods (DeLurgio, 1998). Because trends represent important long-run general movements in a time series, they are necessary to model.

Integrated Processes are level-nonstationary series. Trend and random walks are level-nonstationary because their means (levels) are not constant. A random walk behavior is called stochastic trend, while a consistent period-to-period change is called deterministic trend. Integrated series include random walks and trends. If a series is a

random walk, then the previous actual value is the best estimate or predictor of all future values. This gives the following ARIMA (0, 1, 0) random walk model:

$\hat{Y}_{t=} Y_{t-1}$ …… (2.12)

$Y_t = Y_{t-1} + e_t$ …….. (2.13)

The deterministic trend, ARIMA (0, 1, 0)1 model is given as:

$\hat{Y}_{t=} \theta_o + Y_{t-1}$ …… (2.14)

$Y_t = Y_{t-1} + \theta_o + e_t$ …… (2.15)

Where θ_o = estimated parameter = mean of trend or period-to-period changes.

2.5.1.4. Mixed Autoregressive –Moving Average Model (ARMA)

To achieve greater flexibility in the fitting of actual time series, it is sometimes advantageous to include both autoregressive and moving average terms in the model. This leads to the Mixed Autoregressive –Moving Average Model (ARMA) given as:

$\hat{y}_{t=}\emptyset_1 \hat{y}_{t-1} + \ldots + \emptyset_p \hat{y}_{t-p} + e_t - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q}$ ……(2.16)

Where $\hat{y}_t = y_t - \mu$; $\mu = E[y_t]$ = mean of the series.

Or $\emptyset(B)\hat{y}_t = \theta(B)e_t$; where $\emptyset(B)$ and $\theta(B)$ are polynomial operators in B of degree p and q. B$y_t = y_{t-1}$ hence $B^m y_t = y_{t-m}$; B= backward shift operator. The inverse operation is performed by: F $= B^{-1}$ given as F$y_t = y_{t+1}$

The model employs p+q+2 unknown parameters, $\mu, \emptyset_1 \ldots\ldots \emptyset_p, \theta_1 \ldots\ldots \theta_q, \delta_e^2$, that are estimated from the data. Where δ_e^2 is the variance of the random or white noise. This model may also be written in the form of the linear filter as: $\hat{y}_t = \emptyset^{-1}(B)\theta(B)e_t = \varphi(B)e_t$ with $\varphi(B) = \emptyset^{-1}(B)\theta(B)$.

The general ARMA (p, q) process may be expressed in the equivalent form in terms of the original process y_t as: $\emptyset(B)y_t = \theta_0 + \theta(B)e_t$; where the constant term θ_0 in the model is given as: $\theta_0 = (1 - \emptyset_1 - \emptyset_2 - \ldots - \emptyset_p)\mu$.

In practice, it is often true that adequate representation of actually occurring stationary time series can be obtained with autoregressive-moving average or mixed models in which p and q are not greater than 2 and usually less than 2 (Box, et al, 2008)..

Stationarity and Invertibility Properties of ARMA (p, q) Model

The ARMA (p, q) model given as:

$\hat{y}_{t=}\emptyset_1 \hat{y}_{t-1} + \ldots + \emptyset_p \hat{y}_{t-p} + e_t - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q}$, ……...(2.17)

That is,

$\left(1-\emptyset_1 B-\emptyset_2 B^2-\ldots-\emptyset_p B^p\right)\hat{y}_t = \left(1-\theta_1 B-\theta_2 B^2 \;-..-\theta_q\; B^q\right)$ Or $\emptyset(B)\hat{y}_t =$ $\theta(B)e_t$ may be thought of in two ways:

1. As a pth-order autoregressive process: $\emptyset(B)\hat{y}_t = \alpha_t$,with α_t following the qth-order moving average process, $\alpha_t = \theta(B)e_t$.
2. As a qth-order moving average process: $\hat{y}_t = \theta(B)b_t$ with b_t following the pth-order autoregressive process; $\emptyset(B)b_t = e_t$, so that $\emptyset(B)\hat{y}_t = \theta(B)\emptyset(B)b_t = \theta(B)e_t$.

The expression $\emptyset(B)\hat{y}_t = \theta(B)e_t$, defines a stationary process provided that the characteristic equation $\emptyset(B) = 0$, has all its roots outside the unit circle. Similarly, the roots of $\theta(B) = 0$, must lie outside the unit circle if the process is to be invertible. Thus, the stationary and invertible ARMA (p,q) process has both the infinite moving average representation: $\hat{y}_t = \varphi(B)e_t = \sum_{j=0}^{\infty}\varphi e_{t-j}$, where $\varphi(B) = \emptyset^{-1}(B)\theta(B)$, and the infinite autoregressive representation: $\pi(B)\hat{y}_t = \hat{y}_{t-\sum_{j=0}^{\infty}\pi}\hat{y}_{t-j} = e_t$, where $\pi(B) =$ $\theta^{-1}(B)\emptyset(B)$, with both the φ_j and π_j weights being absolutely sumable. The weights φ_j are determined from the relation: $\emptyset(B)\varphi(B) = \theta(B)$ to satisfy

$\varphi_j = \emptyset_1\varphi_{j-1} + \emptyset_2\varphi_{j-2} + \ldots + \emptyset_p\varphi_{j-p} - \theta_j$; j>0 with $\varphi_0 = 1$; $\varphi_j = 0$ for j< 0 and

$\theta_j = 0$ for j > q .From the relation $\theta(B)\pi(B) = \emptyset(B)$, the π_j are determined to satisfy:

$\pi_j = \theta_1\pi_{j-1} + \theta_2\pi_{j-2} + \ldots + \theta_q\pi_{j-q} + \emptyset_j$; j>0 with $\pi_0 = -1$; $\pi_j = 0$ for j<0 and $\emptyset_j$ for j>p. From these relations, the φ_j and π_j weights can readily be computed recursively in terms of the $\emptyset_j$and θ_j coefficients.

Autocorrelation Function of ARMA (p, q) Process

The autocorrelation function of ARMA process may be derived by multiplying the equation: $\hat{y}_t = \emptyset_1\,\hat{y}_{t-1} + \ldots + \emptyset_p\,\hat{y}_{t-p} + e_t - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q}$ throughout by $\hat{y}_{t-k}$ and taking the expectations. This will yield the autocorrelation function that satisfies the difference equation:

$\gamma_k = \emptyset_1\gamma_{k-1} + \emptyset_2\gamma_{k-2} + \ldots + \emptyset_p\gamma_{k-p} + \gamma_{ye}(k) - \theta_1\gamma_{ye}(k-1) - \ldots - \theta_q\gamma_{ye}(k-q)$(2.18)

Where γ_{ye} = cross covariance function between y and e and is defined as $\gamma_{ye} =$ $E[\hat{y}_{t-k}e_t]$; since y_{t-k} depends only on shocks that have occurred up to the time t-k through the infinite moving average representation:

$\hat{y}_{t-k} = \varphi(B)e_{t-k} = \sum_{j=0}^{\infty}\varphi e_{t-k-j}$, it follows that;

$$\gamma_{ye}(k) = \begin{cases} 0 & k > 0 \\ \varphi_{-k}\,\delta_e^2 & k \leq 0 \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2.19)}$$

Hence the preceding equation for γ_k may be written as:

$\gamma_k = \emptyset_1\gamma_{k-1} + \emptyset_2\gamma_{k-2} + \ldots + \emptyset_p\gamma_{k-p} - \delta_e^2(\theta_k\varphi_0 + \theta_{k+1}\varphi_1 + \ldots + \theta_q\varphi_{q-k})$ with the convention that $\theta_0 = -1$. This implies that, $\gamma_k = \emptyset_1\gamma_{k-1} + \emptyset_2\gamma_{k-2} + \ldots + \emptyset_p\gamma_{k-p}$ $k \geq q + 1$ and hence, $\rho_k = \emptyset_1\rho_{k-1} + \emptyset_2\rho_{k-2} + \ldots + \emptyset_p\rho_{k-p}$ $k \geq q + 1$

Or $\emptyset(B)\rho_k = 0$; $k \geq q + 1$

Thus for ARMA (p, q) process, there will be q autocorrelations $\rho_q, \rho_{q-1}, \ldots \rho_1$ whose values depend directly on the choice of the q moving average parameters θ, as well as on the q autoregressive parameters $\emptyset$. Also, the ρ values, $\rho_q, \rho_{q-1}, \rho_{q-2}$, …….. ρ_{q-p+1}, provide the necessary starting values for the difference equation: $\emptyset(B)\rho_k = 0$;

Where $k \geq q + 1$, which then entirely determines the autocorrelation at higher lags.

If q- p < 0, the whole autocorrelation function ρ_j for j = 0, 1, 2… will consist of a mixture of damped exponentials and/or damped sine waves, whose nature is dictated by the roots of the polynomial $\emptyset(B)$ and the starting values. If, however, q –p ≥ 0, there will be q –p +1 initial values; ρ_0 , ρ_1, …… ρ_{q-p} , which do not follow this general pattern. These facts are useful in identifying mixed series.

The partial autocorrelation function (PACF) of the ARMA process is given as:

$e_t = \theta^{-1}(B)\emptyset(B)\hat{y}_t$ …… (2.20)

Where $\theta^{-1}(B)$ is an infinite series in B. Hence the partial autocorrelation function of a mixed process is infinite in extent. It behaves eventually like the partial autocorrelation function of a pure moving average process, being dominated by mixture of damped exponentials and/or damped sine waves, depending on the order of the moving average and the values of the parameters it contains.

2.5.2 ARIMA Model Building

In time series analysis, there is a fundamental distinction between the process and realization. The actual values in an observed time series are the realization of some underlying process which generated the values. The underlying process is, frequently, stochastic or probabilistic generating process (DeLurgio, 1998; Box, et al, 2008). The purpose of time series analysis is to use the realization of the process (sample) to identify a model of ARIMA process that generated the series.

The procedures used to build the model are generally referred to as Box-Jenkins ARIMA model building methods (Box, et al, 2008).ARIMA model building is an empirically driven methodology of systematically identifying, estimating, diagnosing and forecasting time series. Graphs of actual data, empirically derived statistics and theory are use to decompose a given time series into its ARIMA components. The purpose of this ARIMA analysis is to find a model that reasonably represents the past and future patterns of the series.

The steps of ARIMA model building are as follows:

1.Model identification: this involves using graphs, statistics, Autocorrelation functions (ACF) and Partial Autocorrelation function (PACF) to achieve stationarity and tentatively identify the pattern and model components;

2.Parameter estimation: determine model coefficients through software applications of least square and maximum likelihood methods;

3.Model Diagnosis: Using graphs, statistics, ACF, s and PACF, s of residuals, determine if the model is valid. If valid, then use the model, otherwise, repeat 1-3.

Forecast Verification: Using graphs, simple statistics and confidence intervals, determine the validity of the forecast and track model performance to detect any out-of-control situation.

2.5.2.1 Model Identification: The first task is to appropriately identify subclass of models from the general Autoregressive Integrated Moving Average (ARIMA) model family that will adequately fit the data and can be checked.

The approach will be as follows:

1.To assess the stationarity of the process and if necessary to differencing as many times as possible to achieve stationarity with the aim of reducing the process to the Mixed Autoregressive Moving Average process.

2.To identify the resulting model for the process.

The tools for achieving 1 and 2 above are:

Descriptive statistics: This involves the determination of the vital statistics (mean, variance, standard deviation, mean deviation, skewness, and so forth) of the series and homogeneity test. The results of descriptive statistics may give an indication of the statistical distribution of the data which helps in model identification. Normally distributed series is usually a random process and can be fitted to probability models. Therefore, test for normality of the climatic time series is imperative in model identification. A climate time series is said to be homogeneous when its variations are caused only by fluctuations in weather and climate. Therefore a test for homogeneity is also essential in ARIMA model identification (Wilberforce, 2007)

Time Series Graphs and Plots*:* A time series is a continuous or discrete set of observations that are ordered in equally spaced intervals. When a time series is plotted, common patterns are usually found .Also, outliners, which are non-typical

values of the time series, can be identified and adjusted prior to and during the analysis of the time series. The pattern may be explained by many cause-and-effect relationships. The common patterns are:

Random Pattern: Random time series are the results of many influences that act independently to yield nonsystematic and non repeating patterns about some average value. Purely random series has a constant mean and no systematic pattern (DeLurgio, 1998). Unless other time series are available, simple averaging models are often the most accurate method for predicting them.

Trend: A trend is a general increase or decrease in a time series that lasts for approximately several periods due to constant changes in the condition of the time series. Trends may be period-to-period increase or decrease that follows a straight line, a pattern called a linear trend. Trends may, also, be non linear due to a large number of nonlinear causal influences that produce the series. Capturing typical properties of time series, like trend, is highly relevant for the detection and evaluation of global warming and climate change. It provides indicators for the separation of anthropogenic signals and natural forcing factors by distinguishing between deterministic trend and stochastic variability (Kallache, et al; 2005).

Trends in time series are analyzed using simple linear regression. Regression is a statistical technique that allows decision makers to establish quantitative relationships among variables and also measure the strength of the relationship. The objective is to find the nature of the relationship between x and y from the observational data and use the relationship to predict the response variable y from the input x. Naturally, the first step in such a study is to plot and examine the scatter diagram. If a linear relationship emerges, the computation of the numerical value of R will confirm the strength of the linear relationship. Its value indicates how effectively y can be predicted from x by fitting a straight line to the data. The coefficient of determination or R^2 expresses the strength of the relationship between x and y variables. R^2 varies from zero to 1. The higher the value of, R^2, the better the relationship.

A straight line is determined by two constants: its height above the origin (intercept) and the amount that y increases with increase in x (slope). The best fit line or least square line is close to the points graphed in the scatter plot in terms of minimizing the amount of vertical distance. The basic statistical model for linear trend analysis can be represented by the Equation 2.21 as shown below:

$$y_i = \beta_o + \beta_1 x_i + \varepsilon_i \quad \ldots\ldots (2.21)$$

Where y_i is the ith observation of the response (dependent) variable (temperature, rainfall and evaporation), x_i is the ith observation of the explanatory (independent) variable (year, month); β_0 is the intercept (constant); β_1 is the slope of the regression line which is interpreted as the trend or the Variability of the climatic elements (quantity of interest); ε_i is the random error or residual for the ith observation and n is the sample size. The error ε_i is a random variable which arises from the natural variability inherent in the climate system. The error ε_i has zero mean and constant

variance. Regression is performed by estimating the unknown true interceptβ_0 and slope β_1 with b_0 and b_1 estimates derived from the data.

The assumptions are as follows:

1.The model form is correct: y is linearly related to x;

2.The sampled data used to fit the model are representative of the population;

3.The variance of the residuals is constant and does not depend on x or anything else;

4.The residuals are independent; and

5.The residuals are normally distributed.

The simplest case of linear regression estimation is when ε_i are uncorrelated error terms with zero mean and common variance, in which case the standard ordinary least squares (OLS) formulae are applied to estimate the intercept and slope of the regression line with their standard errors. Usually the slope b_1 is interpreted as the trend which is the measure of Climate Variability in this study.

The procedure involves the estimation of b_0 and b_1 such that: $\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$ is minimized. Where $\hat{y}_i = b_0 + b_1 x_i$ = ordinary least square estimate of y_i. This can be solved for b_0 and b_1 using calculus. The solution is referred to as normal equations from which were derived the following expressions used in regression analysis:

1.Central Tendency (Mean) = $\sum_{i=1}^{n} {x_i}/{n} = \bar{x}$

2.Central Tendency (Mean) = $\sum_{i=1}^{n} {y_i}/{n} = \bar{y}$

3.Sums of Squares $x = \sum_{i=1}^{n}(x_i - \bar{x})^2 = \sum_{i=1}^{n} x_i^2 - n(\bar{x})^2$ = SSx

4.Sums of Squares $y = \sum_{i=1}^{n}(y_i - \bar{y})^2 = \sum_{i=1}^{n} y_i^2 - n(\bar{y})^2$ = SSy

5.Sums of xy Cross Product $= \sum_{i=1}^{n}[(x_i - \bar{x})^2(y_i - \bar{y})^2] = \sum_{i=1}^{n}(x_i y_i) - n\bar{x}\bar{y}$ = Sxy

6.The Estimate of β_1 (slope) = $b_1 = {S_{xy}}/{SSx}$

7.The Estimate of β_o (intercept) = $b_0 = \bar{y} - b_1\bar{x}$

8.The estimate of y given $x_i = \hat{y}_i = b_0 + b_1 x_i$

9.The estimate of residual $\varepsilon_i = y_i - \hat{y}_i$

10.Error sum of squares (SSE) = $\sum_{i=1}^{n} \varepsilon_i$

11.Mean Square Error (MSE) (Variance) $=\delta^2 = {(SSy - b_1 Sxy)}/{n-2} \quad = S^2$

12.Standard Error of Regression (Standard Deviation of residuals) =S $=\sqrt{S^2}$

13.Standard Error of β_1 = SE(β_1) = $\frac{S}{\sqrt{SSx}}$

14.Standard Error of $\beta_o \; = \; SE(\beta_o) = S\sqrt{\left(\frac{1}{n} + \frac{\bar{x}^2}{SS_x}\right)}$

15.The correlation coefficient $\gamma \; = \; \frac{S_{xy}}{\sqrt{SS_x . SS_y}} = b_1\sqrt{{SS_x}/{SS_y}}$

The coefficient of determination (R^2) or fraction of the variance explained by the regression is given as: $R^2 = {[SS_y - S^2(n-2)]}/{SS_y} = 1 - \left({SSE}/{SS_y}\right) = \gamma^2$… (.2.22)

If the assumptions 1 through 4 are all met, then the estimates of b_0 and b_1 are the minimum unbiased estimators of $\beta_o$and β_1 respectively.

Similarly, the mean of the residuals (ε_i) is exactly zero, while the predictions ($\hat{y}_i$) equals the mean of the observed responses (y_i) and thus the regression line passes through the centroid of the data ($\bar{x}, \bar{y}$). Also, the variance of the predictions ($\hat{y}_i$) is less than the variance of the observed responses (y_i) unless$R^2 \; = \; 1.0$. Normality assumption implies that the population from which the sample is drawn is normally distributed. Many statistical procedures rely on population normality. The null hypothesis for normality test is that the population is normal while the alternative hypothesis is that the population is not normal. The test statistic is the p-value which is the probability that determines whether to reject or accept the null hypothesis. The p-value ranges from 0 to 1.The commonly used significant level is $\alpha \; = \; 0.05$. If the p-value is less than α, the null hypothesis is rejected. For trend analysis, the null hypothesis is that there is no significant trend. One advantage of this method is that it is easy to apply to a large number of sites. The disadvantage is that it can fail to detect nonlinear but still monotonic trends.

Seasonal Pattern: This results from events that are periodic and recurrent (yearly, monthly or daily).

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF): The degree of linear dependence between events k time units apart is measured by the auto covariance function, which if positive, is directly related to the strength of storage processes in the atmosphere and within the catchment. It is defined for a continuous series [Xt, tεT] with zero mean by the time average as:

$Ck \; = \; Lim[1/2T \int X(t \, + \, k)Xtdt]$ ……………………………………………. (2.23)

The variable k = lag.
In a second order or weakly stationary process, the auto covariance function is defined as: $Ck = E[X(t + k)X(t)]$..... (2.23a)
Where, E denotes the expected value.
For strictly stationary process in which $E[x^2(t)]$ is finite, both definitions give the same result. Statistically, Ck is consistently estimated by Equation 2.23a.
Autocorrelation function (ACF) is then defined as: $\rho k = Ck/[x^2(t)]$..... (2.23b)
The continuous set of values ρk; k $\geq$ 0 constitute a theoretical correlogram. Estimates of ρk from observed sequences are called serial correlation coefficients (k which is given as:
$(k = [\sum_{t=1}^{N-k}\{(Xt - Xm)(X(t + k) - Xm\}]/$.....(2.24)
A graph of ρk against k is termed a serial correlogram.
Serial correlogram is a very useful tool for investigating the structure of a time series with regard to how observations separated by fixed periods of time are interrelated. In a stationary time series, ρk values decreases as k increases. For a serially independent series, the autocorrelation coefficient equals to zero. This is important in the formulation of linear stochastic models.

Nonstationary series are distinguished by very high, statistically significant ACF, s that decline in a distinctive straight line. For these series, at least, the first 3 ACF, s are statistically significantly different from zero, that is, they are above the two-standard-error limits. In addition, non-seasonal non-stationary series have only one statistically significant peak in the PACF at lag1.

For autoregressive processes, the ACF, s decline at an exponential rate rather than in a straight line. Theoretically, these patterns should persist but in practice, they may only be discernable for two or three lags. Also, for ARIMA (1, 0,0) process, there will be a single statistically significant peak or pike in the PACF at lag1.

For a moving average process-ARIMA (0, 0, 1), the ACF,s are all zero except at lag1 where there is only one significant peak or pike . If $\theta_1 > 0$, the peak is negative and if $\theta_1 < 0$, the peak is positive (DeLurgio, 1998). The number of significant peak or pike determines the order (q) of the moving average (MA) process. The PACF can be used to confirm moving average models. For moving average models, the PACF, s has negative exponential decline when $\theta_1 > 0$, and positive exponential decline when $\theta_1 < 0$. For white noise, the ACF,s and PACF,s have no pattern of decline.

The use of Model Selection Criteria

Another approach to model selection is the use of information criteria such as Akaike Information Criteria (AIC) or Bayesian Information Criteria (BIC). In the case of this approach, a range of potential ARMA models is estimated by maximum likelihood methods and for each, a criterion such as AIC (normalized by sample size n) given as:
$AIC_{p,q} = \frac{-2\ln(maximum\ likelihood)+2r}{n} \cong \ln(\sigma_e^2 + r\frac{2}{n}$ + constant …….. (2.25)
Or BIC, given as: $BIC_{p,q}$ = ln (σ_e^2) +r$\frac{\ln(n)}{n}$ is evaluated…… (2.26)

$where\ \sigma_e^2$ = maximum likelihood estimate of δ_e^2 and r = p+ q +1 =number of parameters estimated in the model including the constant term.

In this approach, the models that yield minimum value for the criteria are preferred and the AIC or BIC values are compared among various models as the basis for selection of model. The disadvantage of this approach is that several models may have to be estimated by maximum likelihood which is computationally time consuming and expensive.

Initial Estimates for ARMA Model Parameters

Although there is a multiplicity of ARMA models possessing the same auto covariance function, there exists only one which expresses the current value of $w_t = \nabla^d y_t$, exclusively in terms of previous history and in stationary invertible form.

$where\ \nabla^d y_t = y_t - y_{t-1} = (1\text{-}B)y_t$ ..... (2.27)

ARMA process is most economically represented by: $\emptyset(B)w_t = \theta(B)e_t$ (Box, et al, 2008). In the general case, calculation of the initial estimates of an ARMA (p, q) process is based on the first p + q +1 sample auto covariances C_j; (j =0, 1, 2… p+ q) of $w_t = \nabla^d y_t$, and proceeds in three stages:

Stage1. The autoregressive parameters $\emptyset_1, \emptyset_2, \ldots\ldots \emptyset_p$, are estimated from the autocovariance, $C_{q-p+1}, \ldots, C_{q+1}, C_{q+2}, \ldots C_{q+p}$.

Stage2.Using the estimates $\acute{\emptyset}$ obtained in stage1, the first q +1 auto covariance C_j of the derived series $w_t' = w_t - \acute{\emptyset} w_{t-1} - \ldots - \acute{\emptyset} w_{t-p}$ are computed.

Stage3.Finally, the auto covariance $C_0', C_1', \ldots\ldots C_q'$ are used in an iterative calculation to compute initial estimates of the moving -average parameters $\theta_1, \theta_2, \ldots, \theta_q$ and the error variance δ_e^2.

Initial Estimates of Autoregressive Parameters

Making use of the equation: $\rho_k = \emptyset_1 \rho_{k-1} + \emptyset_2 \rho_{k-2} + \ldots.. + \emptyset_p \rho_{k-p}$ $\quad k \geq q + 1$ the initial estimates of the autoregressive parameters may be obtained by solving p linear equations:

$C_{q+1} = \acute{\emptyset}_1 C_q + \acute{\emptyset}_2 C_{q-1} + \ldots\ldots.. + \acute{\emptyset}_p C_{q-p+1}$

$C_{q+2} = \acute{\emptyset}_1 C_{q+1} + \acute{\emptyset}_2 C_q + \ldots\ldots.. + \acute{\emptyset}_p C_{q-p+2}$

.

.

$C_{q+p} = \acute{\emptyset}_1 C_{q+p-1} + \acute{\emptyset}_2 C_{q+p-2} + \ldots\ldots.. + \acute{\emptyset}_p C_q$ ..... (.2.28)

Initial Estimates of the Moving Average Parameters

Using the autocovariance estimates;

$C'_j = \sum_{i=0}^{p} \emptyset_i^2 C_j + \sum_{i=0}^{p} (\emptyset_0 \emptyset_i + \emptyset_1 \emptyset_{i+1} + \ldots\ldots + \emptyset_{p-i} \emptyset_p)(C_{j+i} + C_{j-i})$ for j = 0, 1, 2,……, q .Where $\emptyset_0 = 1$, we can obtain initial estimates of the moving average parameters in the derived process ($w_t' = w_t - \acute{\emptyset}_1 w_{t-1} - \ldots.. - \acute{\emptyset}_p w_{t-p}$) by one of the following two procedures:

***1. Linear Convergent Procedure*:**

Using the expressions:

$\gamma_0 = (1 + \theta_1^2 + \theta_2^2 + \ldots\ldots + \theta_q^2)\delta_e^2$

$\gamma_k = (-\theta_k + \theta_1\theta_{k+1} + \ldots\ldots + \theta_{q-k}\theta_q)\,\delta_e^2$ k = 1, 2… q, for the auto covariance function of an MA (q) process, we can compute estimates of the parameters, $\delta_e^2, \theta_q, \theta_{q-1}, \theta_{q-2}, \ldots..\theta_1$, in the following order using iteration:

$\delta_e^2 = \frac{C_0'}{1+\theta_1^2 + \theta_2^2 + \ldots\ldots + \theta_q^2}$ …… (2.29)

$\theta_j = -(\frac{C_j}{\delta_e^2} - \theta_1\theta_{j+1} - \theta_2\theta_{j+2} - \ldots\ldots. - \theta_{q-j}\theta_q)$ with convention that $\theta_0 = 0$

The parameters $\theta_1, \theta_2, \ldots\ldots, \theta_q$ are set equal to zero to start the iteration and the values of θ_j and δ_e^2 to be used in any subsequent calculations are the most up-to-date values available. For example, in a case where q = 2, we will have the following equations:

$\delta_e^2 = C_0'/(1 + \theta_1^2 + \theta_2^2)$; $\theta_1 = -(\frac{C_1'}{\delta_e^2} - \theta_1\theta_2)$ and $\theta_2 = \frac{C_2'}{\delta_e^2}$

2. Quadratically Convergent Procedure:

A Newton-Raphson algorithm which has superior convergence properties to method 1 was given Box, et al, (2008).

Let $\tau' = (\tau_1, \tau_2, \ldots.., \tau_q)$ where $\tau_0^2 = \delta_e^2$; $\theta_j = \frac{-\tau_j}{\tau_0}$; j =1, 2, ….., q

Then, if τ^i is the estimate of τ obtained at the ith iteration, the new values at the (i + 1) iteration is obtained from: $\tau^{i+1} = \tau^i - (T^i)^{-1}\ f_i$ where $f' = (f_0, f_{1,\ldots\ldots..}, f_q)$;

$f_j = \sum_{i=0}^{q-j} \tau_i\,\tau_{i+j} - C_j'$

$$T = \begin{bmatrix} \tau_0 & \cdots & \tau_q \\ \vdots & \ddots & \vdots \\ \tau_q & \cdots & 0 \end{bmatrix} + \begin{bmatrix} \tau_0 & \cdots & \tau_q \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \tau_0 \end{bmatrix} \quad \ldots\ldots (2.30)$$

Given the values of the τ ,s at each iteration, the values of the parameters may be obtained from the above equations.

2.5.2.2 Model Parameters Estimation

The identification process leads to a tentative formulation for the model. The next stage is to obtain efficient estimates of the model parameters, mean, variance, autocovariances and autocorrelation coefficients, the autoregressive coefficient ∅ and the moving average coefficient θ and variance of the random error or white noise, δ_e^2. The main approaches to fitting Box-Jenkins (ARIMA) models are the maximum likelihood (ML) Bayesian methods of estimation.

1. Mean and Variance of a Stationary Process

A stochastic process is strictly stationary if its properties are unaffected by a change of time origin. That is, if the joint probability distribution associated with m observations, $y_{t1}, y_{t2,\ldots\ldots..}, y_{tm}$, made at any set of times $t_1, t_2, \ldots\ldots, t_m$ is the same as that associated with m observations y_{t1+k} , $y_{t2+k}, \ldots\ldots, y_{tm+k}$. Thus for discrete process to be strictly stationary, the joint distribution of any set of observations must be

unaffected by shifting all the times of observation backward or forward by any integer amount k. When m =1, the stationary assumption implies that the probability distribution P(y_t) is the same for all times t and may be written as P(y). Hence, the stochastic process has a constant mean given as:

μ = E[y_t] = $\int_{-\infty}^{\infty} yP(y)dy$ which defines the level about which it fluctuates, and a Variance given as: δ_y^2= E$\left[(y_t-\mu)^2\right]$ = $\int_{-\infty}^{\infty}(y_t-\mu)^2P(y)dy$ which measures the spread about the mean (level). The mean of the stochastic process can be estimated by the sample mean as: $\hat{y}$ = $\frac{1}{N}\sum_{t=1}^{N} y_t$ where N = number of sample.

The variance of the stochastic process can be estimated by the sample variance given as:

$S_y^2 = \frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y})^2$ ..... (2.31)

Auto covariance and Autocorrelation Coefficients

The stationary assumption also implies that the joint probability distribution P (y_{t1}, y_{t2}) is the same for all times t_1, t_2 which are a constant interval apart. It follows that the covariance between y_t and y_{t+k} , separated by k intervals of time or by lagk must be the same for t under stationarity assumption. This auto covariance at lagk and is defined as: $\gamma_{k=}$ COV[y_t, y_{t+k}] = E$\left[(y_t - \mu)(y_{t+k} - \mu)\right]$..... (2.32)

Similarly, the autocorrelation at lagk is $\rho_k = \frac{\mathrm{E}[(y_t-\mu)(y_{t+k}-\mu)]}{\sqrt{E[(y_t-\mu)^2]}\sqrt{E[(y_{t+k}-\mu)^2]}}$ = $\frac{\mathrm{E}[(y_t-\mu)(y_{t+k}-\mu)]}{\delta_y^2}$, since for a stationary process, the variance $\delta_y^2 = \gamma_0$, is the same at time t+k as at time t. Thus autocorrelation at lagk, which is the correlation between y_t and y_{t+k} is $\rho_k = \frac{\gamma_k}{\gamma_0}$. This implies that ρ_0 = 1.

2. *Maximum Likelihood Function and Maximum Likelihood Estimates*

The values of the parameters which maximize the likelihood function are called maximum likelihood estimates. The three parameters concerned in ARIMA process are$\emptyset$, θ , and δ_e^2.

Maximum likelihood estimates ($\hat{\emptyset}$,$\hat{\theta}$) for mixed processes, as for moving average processes may be obtained graphically in simple cases, and more generally by iteration. For moderate and large sample, the covariance matrix may be obtained by evaluating and inverting the information matrix:

$$I(\emptyset, \theta) = n\delta_e^2 \begin{bmatrix} \gamma_{uu(0)} & \gamma_{uu(1)} & & \gamma_{uu(p-1)} & \gamma_{uv(0)} & \gamma_{uv(1)} & & \gamma_{uv(1-q)} \\ \gamma_{uu(1)} & \gamma_{uu(0)} & & \gamma_{uu(p-2)} & \gamma_{uv(1)} & \gamma_{uv(0)} & & \gamma_{uv(2-q)} \\ . & . & & . & . & . & & . \\ . & . & & . & . & . & & . \\ . & . & & . & . & . & & . \\ \gamma_{uu(p-1)} & \gamma_{uu(p-2)} & & \gamma_{uu(0)} & \gamma_{uv(p-1)} & \gamma_{uv(p-2)} & & \gamma_{uv(p-q)} \\ \gamma_{uv(0)} & \gamma_{uv(1)} & .... & \gamma_{vu(p-1)} & \gamma_{vv(0)} & \gamma_{vv(1)} & .... & \gamma_{vv(q-1)} \\ \gamma_{vu(-1)} & \gamma_{uv(0)} & & \gamma_{vu(p-2)} & \gamma_{vv(1)} & \gamma_{vv(0)} & & \gamma_{vv(q-2)} \\ . & . & & . & . & . & & . \\ . & . & & . & . & . & & . \\ . & . & & . & . & . & & . \\ . & . & & . & . & . & & . \\ \gamma_{vu(1-q)} & \gamma_{vu(2-q)} & & \gamma_{vu(p-q)} & \gamma_{vv(q-1)} & \gamma_{vv(q-2)} & & \gamma_{vv(0)} \end{bmatrix}$$

…… (2.33)

$[U:V]$ = nx (p+q) matrix of the time lagged u_t,s and v_t,s; where

$u_{t=} \emptyset_{1,0}u_{t-1} + \ldots\ldots + \emptyset_{p,0}u_{t-p} + e_{t,0}$ and

$v_t = \theta_{1,0}v_{t-1} + \ldots\ldots + \theta_{q,0}v_{t-q} - e_{t,0}$……, (2.34)

$\gamma_{uu(k)\ and}\ \gamma_{vv}$ (k)= autocovariances of u_t,s and v_t,s respectively.

γ_{uv} (k) = the cross covariance defined by γ_{uv} (k) = γ_{uu}(-k) = $E[u_t, v_{t+k}]$ = $E[v_t, u_{t-1}]$

The general problem of fitting the parameters $\emptyset\ and\ \theta$ of the ARIMA model is equivalent to fitting to the w_t,s, the stationary, invertible ARMA (p, q) model given as:

$w_t = \overline{w}_t - \emptyset_1\overline{w}_{t-1} - \emptyset_2\overline{w}_{t-2} - \ldots - \emptyset_p\overline{w}_{t-p} + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_q e_{t-q}$….. (2.35)

Where $w_t = \nabla^d y_t$ and $\overline{w}_t = w_t - \mu$; For d > 0, it would be appropriate to assume that μ = 0. When this is not appropriate, $\overline{w}_t = \sum_{t=1}^{n} {}^{w_t}/_{n}$ is substituted forμ. For the sample size normally considered in time series analysis, this approximation is adequate (Box, et al, 2008). If however, μ is included as additional parameter to be estimated, it can be obtained simultaneously with other parameters.

For any parameters $(\emptyset, \theta)$ and starting values $(w_* a_*)$ a set of values $e_t(\emptyset, \theta | w_* a_* w)$, t =1, 2… n, can be calculated successively. Note that bold character denotes a matrix.

For an ARMA (p, q) model, the likelihood function may be written in matrix form as:

$L_\emptyset w = L_\theta a + F\alpha$. …….. (2.36)

Where $L_\emptyset$ = an nxn lower triangular matrix with 1,s on the leading diagonal;

$-\emptyset_1, on\ the\ first$ Sub diagonal; $-\emptyset_2$ on the second sub diagonal and

so on, with $\emptyset_i$= 0 for I >p

L_θ = an nxn matrix of the same form as $L_\emptyset$ but with θ,s in place of $\emptyset$,s.and a= $(e_{1,} e_{2,\ldots,} e_n)$ is nxn dimensional vector.

$$F = \begin{bmatrix} A_p & B_q \\ 0 & 0 \end{bmatrix} \text{ with } A_p = \begin{bmatrix} \emptyset_p \emptyset_{p-1} & \cdots & \emptyset_1 \\ \vdots & \ddots & \vdots \\ 0\ 0 & \cdots & \emptyset_p \end{bmatrix} \text{ and } B_q = \begin{bmatrix} \theta_q & \cdots & \theta_1 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \theta_q \end{bmatrix} \ldots\ldots\ldots (2.37)$$

$a = (w_{*,} a_*) = (w_{i-p\ ,\ldots\ldots,} w_{0\ ,} e_{i-p}, \ldots\ldots, e_0)$ is the (p+q) dimensional vector of initial values.

Let $\Omega\delta_e^2$ = E (a_*, a'_*) denote the covariance matrix ofa_*. This matrix has the form:

$\Omega\delta_e^2 = \begin{bmatrix} \delta_e^2\Gamma_p & C' \\ C & I_q \end{bmatrix}\delta_e^2$ where Γ_p= E $[w_*{}_, w_*']$ is a pxp matrix with (i ,j)th element γ_{i-j} and $\delta_e^2 C$ = E $[e_{*,} w_*']$ has elements defined by E $[e_{i-q,} w_{j-p}] = \delta_e^2\varphi_{j-i-p+q}$ for j-i-p+q $\geq$ 0 and 0 otherwise. $\varphi =$ Coefficients in the infinite MA operator $\varphi(B)$ = $\emptyset^{-1}(\mathrm{B})\theta(B) = \sum_{k=0}^{\infty}\varphi_k B^k$; $\varphi_{0=}1$, and are easily determined, recursively, through autocorrelation and autocovariance functions earlier discussed.

The autocovariances γ_k in Γ_p can directly be determined in terms of the coefficients $\emptyset_i$,θ_i and δ_e^2 through the use of the first (p+1) equations:

$$\gamma_k = \emptyset_1\gamma_{k-1} + \emptyset_2\gamma_{k-2} + \ldots. + \emptyset_p\gamma_{k-p} - \delta_e^2(\theta_k\varphi_0 + \theta_{k+1}\varphi_1 + \ldots. + \theta_q\varphi_{q-k})$$

with the convention that θ_0 = -1 as earlier discussed.

Similarly, since a = $L_\theta^{-1}(L_\emptyset \mathrm{w} - \mathrm{F}\alpha_*)$ and $\alpha_*$are independent, the joint distribution of w and $\alpha_*$is: P (w, $\alpha_*|\emptyset, \theta, \delta_e^2) = (2\pi\delta_e^2)^{-(n+p+q)/2}\ |\Omega|^{-1/2}\ \exp\left[-\frac{1}{2\delta_e^2}S(\emptyset, \theta, \alpha_*)\right]$...(2.37a)

Where $S(\emptyset, \theta, \alpha_*) = (L_\emptyset \mathrm{w} - \mathrm{F}\alpha_*)' L'^{-1}_\theta L_\theta^{-1}(L_\emptyset \mathrm{w} - \mathrm{F}\alpha_*) + \alpha_*'\,\Omega^{-1}\alpha_*$

By generalized least square theory, $S(\emptyset, \theta, \alpha_*)$ = S ($\emptyset$, θ) + (α_*- $\overline{\alpha_*}$)' D(α_*- $\overline{\alpha_*}$) where S ($\emptyset$, θ)= S($\emptyset$, θ,$\overline{\alpha_*}$) = â'â +$\square_*'\Omega^{-1}\square_*$ is the unconditional sum-of-square function. $\square_*$ =E[$\alpha_*|w, \emptyset, \theta$] = [$\alpha_*$] = $D^{-1}F'L'^{-1}_\theta L_\theta^{-1}L_\emptyset$w, represent the conditional expectation of the preliminary values $\alpha_*$with D = $F'L'^{-1}_\theta L_\theta^{-1}$F = (p+1)(p+1) matrix of symmetric sum-of –squares and product ,and â = [a] = L_θ^{-1}(L$\emptyset w$- F$\square_*$)

By factorization of the joint distribution of w andα_*, we have:

P (w|$\emptyset, \theta, \delta_e^2) = (2\pi\delta_e^2)^{-n/2}\ |\Omega|^{-1/2}|D|^{-1/2}\exp\left[-\frac{1}{2\delta_e^2}S(\emptyset, \theta)\right]$ as the unconditional likelihood function. It follows that the maximum likelihood estimate of $\delta_e^2$is given as: $\widehat{\delta_e^2}$ = S ($\widehat{\emptyset}$,$\widehat{\theta}$)/n where $\widehat{\emptyset}$ and $\widehat{\theta}$ are the maximum likelihood estimates of$\emptyset$, and θ.

Again, it should be noted that S ($\emptyset, \theta$) = $\sum_{t=1}^{n}|e_t|^2 + \widehat{e'_*}\Omega^{-1}\widehat{e_*}$ and the elements$[e_1]$, $[e_2]$, ……., $[e_n]$ of â =[a] are computed recursively from the relation L_θ[a] = $L_\emptyset$w – F[e_*] as

[e_*] = w_t - $\emptyset_1[w_{t-1}]$ - ……… - $\emptyset_p[w_{t-p}] + \theta_1[e_{t-1}]$ + …….+ $\theta_q[e_{t-q}]$ for t = 1, 2,………,n using the back-forecast values [α_*] for the preliminary values with [w_t] = w_t for t = 1,2,…, n. In addition, the back-forecast $\widehat{\alpha_*}$ = [α_*] can be calculated from $\widehat{\alpha_*}$ = $D^{-1}F'U$ where, U = $L'^{-1}_\theta L_\theta^{-1}L_\emptyset$w = L'^{-1}_θa^0 and the elements u of U is calculated through the backward recursion as: $u_{t=}\ e_t^0 + \theta_1 u_{t+1}$ + ……..+ $\theta_q u_{t+q}$ with starting values u_{n+1} = …… = u_{n+q} = 0 and e_t^0 are the elements of a$_o$ = $L_\theta^{-1}L_\emptyset$w and denotes the estimates of e_t conditional on zero starting values α_*= 0. Also the vector h = F'U consists of p+q elements:

$$h_j = \begin{cases} \sum_{i=1}^{j} u_i\emptyset_{p-j+i} \\ -\sum \mathrm{u_i}\theta_{\mathrm{q-j+p+i}} \end{cases} \quad \text{j= 1, …. P} \quad \ldots\ldots\ldots\ldots\ldots\ldots (2.38)$$

J = p+1 ...p+q. Using equations: l_* ($\emptyset, \theta, \delta_e^2$) = $\frac{n}{2}$ln (δ_e^2) $- \frac{S_*(\emptyset,\theta)}{2\delta_e^2}$ and

$\mathrm{e_t} = \overline{\mathrm{w}}_\mathrm{t} - \emptyset_1\overline{w}_{t-1} - \emptyset_2\overline{w}_{t-2} - \ldots. - \emptyset_p\overline{w}_{t-p} + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots. + \theta_q e_{t-q}$. We may write; $\square_*'\Omega^{-1}\square_*$ = â'$_*$â$_*$+ ($\widehat{w}_*$⊾- C'â$_*$)'K^{-1}($\widehat{w}_*$⊾- C'â$_*$), so that we have

S ($\emptyset$, θ) = $\sum_{\mathrm{t=1-q}}^{\mathrm{n}}|e_t|^2$ + ($\widehat{w}_*$⊾- C'â$_*$)'K^{-1}($\widehat{w}_*$⊾- C'â$_*$), where

K $= \delta_e^{-2}\Gamma_p$ -C'C = $\delta_e^{-2}\gamma_o$ - 1 = $(\emptyset - \theta)^2$ / (1 - $\emptyset^2$). And $|\Omega| = |K|$

In general, the likelihood associated with a series y of n+d values generated by any ARIMA process is given by:

$$L(\emptyset, \theta, \delta_e^2|y) = (2\pi\delta_e^2)^{-n/2}|M_n^{(p,q)}|^{1/2} \exp\left[-\frac{S(\emptyset,\theta)}{2\delta_e^2}\right] \quad \text{.....(2.39)}$$

Where $|M_n^{(p,q)}| = |\Omega|^{-1}|D|^{-1} = |K|^{-1}|D|^{-1}$

By considering the mixed ARMA model as an infinite moving average, the unconditional sum-of-squares function for the mixed model will have the relation $\widehat{e'_*}\Omega^{-1}\widehat{e_*} = \sum_{t=1}^{n}[e_t]^2$, hence we have $S(\emptyset, \theta) = \sum_{t=1}^{n}[e_t]^2$ and in practice the values $[e_t]$ may be computed recursively with the summation proceeding from some point t =1 – Q , beyond which $[e_t]$,s are negligible.

As an example for the mixed model, consider the ARMA (1, 1) model:

$w_t - \emptyset w_{t-1} = e_t - \theta e_{t-1}$ Then we will have $\alpha'_* = (w_o, e_o)$, $A_1 = \emptyset$; $B_1 = -\theta$ and $\delta_e^2\Omega = \delta_e^2\begin{bmatrix}\delta_e^{-2}\gamma_o & 1\\ 1 & 1\end{bmatrix}$ with $\delta_e^{-2}\gamma_o = (1+\theta^2 - 2\emptyset\theta)/(1- \emptyset^2)$.

Thus we have;

$$D = \Omega^{-1} + F'L'^{-1}_{\theta}L^{-1}_{\theta}F = \frac{1}{\delta_e^{-2}\gamma_o - 1}\begin{bmatrix}1 & -1\\ -1 & \delta_e^{-2}\gamma_o\end{bmatrix} + \frac{1-\theta^{2n}}{1-\theta^2}\begin{bmatrix}\emptyset^2 & -\emptyset\theta\\ -\emptyset\theta & \theta^2\end{bmatrix} \quad \text{..... (2.40)}$$

The back-forecasts are obtained as $\widehat{\alpha_*} = D^{-1}h$. where h' = $(h_1, h_2) = (\emptyset, -\theta)u_1$, $u_1$are obtained from the backward recursion $u_1 = e_t^o + \theta u_{t+1}$; u_{t+1} =0 and $e_t^o = w_t - \emptyset w_{t-1}^o + e_t^o$; t = 1, 2,…..n, are obtained using zero initial values $w_{0=}^0$ $e_0^0 = 0$, with $w_t^0 = w_t$ for $1 \leq t \leq n$. Thus the exact sum –of-squares is obtained as:

$S(\emptyset, \theta) = \sum_{t=0}^{n}[e_t]^2 + \frac{\widehat{w}_o - \hat{e}_o)^2}{\delta_e^{-2}\gamma_o - 1}$ with $[e_t] = w_t - \emptyset[w_{t-1}] + \theta[e_{t-1}]$; t = 1, 2,….,n and $\delta_e^{-2}\gamma_o - 1$ =K = $(\emptyset - \theta)^2$/ (1 - $\emptyset^2$). In addition, we $|M_n^{1,1}| = \{|K||D|\}^{-1}$; with

$$|K||D| = 1 + \frac{1-\theta^{2n}}{1-\theta^2}\frac{(\emptyset-\theta)^2}{1-\emptyset^2}.$$

2.5.2.3 Model Diagnostic Checking

No model forms ever represent the true observations absolutely. It follows that given sufficient data; statistical tests can discredit models that could be adequate for the purpose at hand. Model, having been identified and parameters estimated needs to be checked for "goodness-of-fit". The principal focus of the diagnostic stage of Box-Jenkins ARIMA model building is the analysis of the residuals. In statistical terms, white noise is normally and independently distributed with zero mean, a constant variance, zero autocovariances, zero autocorrelations and zero partial autocorrelations. A number of important properties result from these characteristics:

Given that e_t is normally distributed, the mean of e_t is zero or E $(e_t) = 0$……. (2.41)

The varianceδ_e^2 is constant and equals: $\delta_e^2 = E(e_t^2) = \frac{\sum(e_t - (e_t^2))^2}{n-1} = \frac{\sum(e_t - 0)^2}{n-1} = \frac{\sum e_t^2}{n-1}$.(2.42)

Since they are statistically independent of each other, the autocorrelations equal to zero:

That is $E(e_{t,}e_{t-k}) = \frac{\sum(e_t - E(e_t))(e_{t-k} - E(e_{t-k}))}{n-k} = \frac{\sum(e_t, e_{t-k})}{n-k} = 0$ for k ≠0..... (2.43)

As result of the independence, the autocovariances and therefore, the autocorrelations equal zero. ACF (k) $= \frac{E(e_t, e_{t-k})}{E(e_t^2)} = \frac{COV(e_t, e_{t-k})}{VAR(e_t^2)} = \frac{\sum(e_t, e_{t-k})}{\sum e_t^2} = \frac{0}{\sum e_t^2} = 0$…… (2.44)

Given that a time series is white noise, the Standard Error S_e of the autocorrelation function can be shown to be: $S_e\ [ACF(k)] \approx {}^{1}/_{\sqrt{n}}$

When plotted, the residuals will be normally distributed, that is, they are completely random, stationary, and independent: ACF (k) = PACF (k) = 0 for k ≠ 0.
The following algorithms represent the different measures of the performance of ARMA models:

1. Pearson's Product Moment Correlation Coefficient(R): This is a measure of the linear association between individual pairs of forecasts and observations. The correlation coefficient does not vary under any shift or re-scaling of the forecast or observed values and is defined as:

$$R = \frac{\sum(y_f - \bar{y}_f)(y_o - \bar{y}_o)}{\sqrt{\sum(y_f - \bar{y}_f)^2} \times \sqrt{(y_o - \bar{y}_o)^2}} \quad ; \ldots\ldots\ldots (2.45)$$

Where y_f = forecast value; y_o = station observed value and $\overline{y_f}$ and $\overline{y_o}$ = mean values. For a perfect fit R^2 = 1.0; $0 \leq R^2 \leq 1$.

2. Mean Squared Error (MSE) and Root Mean Squared Error (RMSE)

These are two of the most widely used forecasting skill scores (Wilks, 1995; and Jolliffe & Stephenso, 2003 as cited by Idowu, 2008) and are given as:

$$MSE = \frac{1}{n}\sum_{i=0}^{n}(y_{fi} - y_{oi})^2 \text{ and } RMSE = \sqrt{\frac{1}{n}\sum_{i=0}^{n}(y_{fi} - y_{oi})^2} \ \ldots\ldots\ldots (2.46)$$

These are widely used to measure the accuracy of the forecast which depend on bias, resolution and uncertainty. Both MSE and RMSE have the same unit as forecast variable. The RMSE measures the average magnitude of forecast errors. The average errors are weighted according to the square of the error and as such become more sensitive to large forecast error than smaller errors. A perfect score is 0.

3. Mean Absolute Error (MAE): This defines the average of differences between the forecasts and observations, and is given as:

$$MAE = \frac{1}{n}\sum_{i=0}^{n}|y_{fi} - y_{oi}| \ \ldots\ldots\ldots (2.47)$$

4. Q-statistic

Q-statistic is an objective diagnostic measure of white noise for a time series that assesses whether, as a group, there are patterns in the autocorrelations or autocorrelations are statistically different from those expected from white noise. It is given as:

$$Q = n\,(n+2)\sum[ACF(i)^2/(n-i)] \text{ for I = 1, 2… k} \ldots\ldots\ldots (2.48)$$

It is also known as Box-Ljung statistic (DeLurgio, 1998).

This statistic is distributed as a chi-square distribution with k – c degree of freedom (df), where c equals the number of coefficients in the model. It can, thus, be seen that Q is proportionate to the sum of autocorrelations through lag k.

Q-statistic is used to perform the following hypothesis tests:

Null Hypothesis; H_o: ACF,s are not statistically significantly different from white noise ACF,s; Alternative Hypothesis; H_1: ACF,s are statistically significantly different from white noise ACF,s; If $Q \leq$ Chi-square from table at 0.05 level of significance: then infer ACF patterns are not statistically significantly different from white noise ACF, that is, the null hypothesis is not rejected. If Q > Chi-square from table at 0.05 level of significance: then infer ACF patterns are statistically significantly different from white noise ACF, that is, the null hypothesis is rejected and the alternative hypothesis is not rejected. For ARMA models, the degree of freedom, df = k-p-q. If a model has a high R^2 (that is, low sum-of-squares), statistically significant coefficients, non-redundant coefficients, and no pattern left in the ACF' s, PACF,s , and residual plots, we conclude that a good ARIMA model has been identified.

Generally a good model should have the following statistical characteristics:

(i) Statistically significant coefficients.

(ii) Stationary and invertible coefficients.

(iii) Low Residual sum of errors (RSE) compared to the standard deviation of the original series.

(iv) High R^2.

(v) Low BIC or AIC in comparison to other models.

(vi) Q or Box-Ljung statistics indicate that there is no pattern in ACF's for the first 20 to 30 lags.

(vii) The ACF's and PACF's confirm that no significant correlations exist at lower order lags and also, no significant correlations exist at or adjacent to seasonal lags.

(viii). Plots of residuals show no outliners or nonstationarlty If significant outliners exist, then the model may not be as efficient as possible and the analysis may be flawed.

(ix) The model is parsimonious, simple. Stationary and invertible but effective, that is, not having g too many coefficients.

2.6 MEASURES AND COMPONENTS OF CLIMATE VARIABILITY

While it is a common practice to focus on measures of central tendency, such as the mean, it is equally as important to understand dispersion or variability. For extremely

heterogeneous samples, small differences in the mean values would be of little practical significance. The following section will first describe several different measures of variability, how they are computed, how they are interpreted, and when they are useful. It will then describe the components of variance. Both explained and unexplained sources of variation will be defined and put into context.

2.6.1 Measures of Climate Variability

There are several measures used to describe variability each with its own disadvantages and advantages. These include Range, Interquartile Range, Mean Deviation, Variance, Standard Deviation, Root Mean Square Anomaly, Coefficient of Variation, and Time series methods (trend and ARIMA model analyses).

2.6.1.1 Range: The simplest measure of variability is the range, which is the difference between the highest and lowest values within a sample. However, it is based on only the two most extreme values. Since the extremes of any distribution of values are by definition rare or unlikely, it is simply a matter of chance whether or not any given range correctly describes the sample's variability.

2.6.1.2 Interquartile Range (IQR): Another measure of variability is the Interquartile Range (IQR). It is computed by taking the difference between the upper and the lower quartile (the 25^{th} percentile subtracted from the 75^{th} percentile). It is relatively easy and a good indicator of the spread in the centre region of the data. It is more resistant to extreme than the range but does not incorporate all the data in the sample.

2.6.1.3 Quartile Deviation: This is defined as half the difference between the first and third quartiles. In other words, it represents half of the range covered by the middle 50% of the cases in a sample or the middle 25% of the sample. Since the first and third quartiles vary less across samples than the extreme values, the quartile deviation is a more stable and reliable measure of variability than the range.

2.6.1.4 Mean Deviation*:* This a more precise way of describing variability which relates the individuals' values to the mean. The mean deviation is defined as the arithmetic mean of the absolute differences of the values from the mean. It is computed as*: Mean Deviation* $=\sum_{i=1}^{n}\frac{(|x_i-\bar{x}|)}{n}$ ……. *(2.49)*

Where x_i =each sample value, $\bar{x}$ = sample mean, n = number of sample points. It provides a good descriptive measure of how large a deviation is expected, on average.

2.6.1.5 Variance: Variance is another measure of variability closely related to the mean deviation which is calculated as:

Variance = Σdeviations^2*/n* …… *(2.50)*

Deviation refers to the differences between the individual values and the overall mean and n refers to the sample size. Because the deviations are squared, individuals with extreme values have a much greater influence on estimates of variation than individuals with small deviations from the mean. The fact that the deviations are squared also makes the variance statistic hard to interpret meaningfully. In order to change the variance statistic back to meaningful units, standard deviations are typically used to describe variability (Fleming, 2007).

2.6.1.6 Standard Deviation (SD): The most useful and frequently used measure of variability is the standard deviation (SD), which is defined as the square root of the arithmetic mean of the squared deviations from the mean. It is also the square root of the variance. Standard deviations are calculated as:

S.D. = $\sqrt{}$ *deviations*^{2}*/n* …… *(2.51)*

Standard deviations have several l important properties that should be emphasized. First, they describe the dispersion of values around the mean; the larger the standard deviation, the larger the spread of values. More importantly, the standard deviation makes it possible to apply probabilities associated with the normal curve, a special type

of symmetrical curve (a bell shape) that makes it possible to estimate the likelihood of any value within a normally distributed sample.

Regardless of the mean and standard deviation, the normal curve will always have the same proportion of values that fall between the mean and any given number of standard deviation units. Knowing the standard deviation makes it possible to predict the probability of any measure relative to the mean. Normal tables, which can be found at the back of any statistics book, provide the exact probability associated with any standard deviation score. For example, approximately 68.3% of the individuals in a sample are distributed within ± 1SD of the mean, 95.5% are distributed within ± 2SD of the mean and 99.7% are distributed within $\pm\ 3SD$. As such, standard deviations provide probabilities for all possible values around the mean (Fleming, 2007). On that basis, the distribution of values for a sample with a mean of 10 with a standard deviation of 2 will look entirely different than the distribution for a sample with a mean of 10 with a standard deviation of 4. Climatologists often use standard deviations to help classify abnormal climatic conditions. The Table below describes the abnormality of a data value by how many standard deviations it is located away from the mean. The probabilities in the third column assume the data is normally distributed.

Table 2.1: Data Abnormality Relative to the Standard Deviation

Standard Deviation Away From Mean	Abnormality	Probability of Occurrence
Beyond -3SD	Extremely Subnormal	0.15%
-3 to .2 SD	Greatly Subnormal	2.35%
-2 to -1SD	Subnormal	13.5%

-1 to +1SD	Normal	68.0%
+1 to +2SD	Above Normal	13.5%
+2 to +3SD	Greatly Above Normal	2.35%
Beyond +3SD	Extremely Above Normal	0.15%

Source: Oliver (1981).

2.6.1.7 Standard Error (SE): Statistics provide parameter estimates (e.g. means) of a population's true value. A standard error, another measure closely related to the standard deviation, provides the probabilities of the distribution of values associated with parameter estimates. It is based on a theorem that if repeated random samples of a given size are drawn from a normal population, with a given mean and variance, the sampling distribution of sample means will be normal and their variance will be described by the standard error. In other words, assuming an unlimited number of samples, each with a sample size of n, drawn from one population, the standard error of the mean of any one of those samples provides the theoretical distribution of all of the other mean values about that mean. For example, given a mean of 5 with a standard error of 2, the mean might be expected to actually range between 3 and 7 approximately 68% of the time and between 1 and 9 approximately 95% of the time. Standard errors can therefore be used to determine when an estimate derived for a sample differs significantly from zero. The standard error is closely related to the standard deviation because it provides the standard deviation of the normal distribution of sample means. It is calculated as:

$$Standard\ Error = SD/\sqrt{n} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (.2.52)$$

2.6.1.8 Coefficients of Variations (CV): Coefficients of variations (CV) are used to compare the variability of measures that have different means. Since measures with larger means typically have larger standard deviations, it might be misleading to

directly compare the absolute values of the standard deviations. The CV measures the size of the standard deviation relative to the mean. CVs are especially useful for measures that differ in the types of units recorded (for example. mm, kg, deg, etc.). Coefficient of variation (CV) is calculated as*: CV = SD/Mean* ………………. (.2.53)

Coefficient of Variation had been used by Adejuwon (2006) to evaluate climate variability in Sub Saharan West Africa.

2.6.1.9 Root Mean Square Anomaly (RMSA): This is similar to standard deviation except that it is used for large sample sizes. It is calculated as:

$$RMSA = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad \ldots\ldots (2.54)$$

The term $x_i - \bar{x}$ is the anomaly. It provides similar information as the standard deviation. It is more commonly used than standard deviation in statistical analyses of climate related data as they are generally large in size.

2.6.1.10 Standardized Anomaly Index (SAI): This is a measure of distance, in standard units, between a data value and its mean. It removes the influences of location and spread from the data and easier to discern normal against unusual values. It is computed as: $SAI = \frac{x_i - \bar{x}}{SD}$ …………………………………………………………………...... (2.55)

It is dimensionless and there is no assumption of any distribution.. The standardized anomaly index (SAI) exhibit a mean of zero and standard deviation of one. Grumm, R.H. (2011) used SAI to analyze and understand the historic Tornadic event of 27-28 April in 2011 in the eastern United States of America. SAI information is helpful in predicting historic events.

***2.6.1.11 Time Series Methods (Trend and ARIMA Models Analyses*)**:** These have been extensively used in literature to analyze climate variability since climate variability can be regarded as the variability inherent in the stationary stochastic

process approximating the climate on a scale of a few decades and adequately discussed in section 2.5.

2.6.2 Components of Climate Variability: It is important to understand that there are components of variance that combine to make up total variance. At the simplest level, variance can be divided into explained and unexplained variation. The explained component is the factors that have been shown to account for the variance. Homogeneous groups that differ considerable from each other might be expected to explain a high proportion of the total variance. For example, a sample composed of males and females might be expected to show substantially higher variance than separate samples of males and females. Unexplained sources of variation refer to variation that is left unaccounted for by the explained sources. Unexplained variation is sometimes referred to as residual or error variance. Unexplained or residual variation is what remains after all of the explained sources of variability have been accounted for. It pertains to random variation without any pattern (that is, it has not or cannot be related to other variables)

Variation can be explained by all types of measures, including variables measured on dichotomous, nominal, ordinal and interval scales. T-test and analyses of variance are typically used to determine the significance of dichotomous and nominal sources of variation. Variables measured on interval scales can also be used to explain variation, using correlation, regression or analyses of covariance.

2.7 IMPACT OF CLIMATE VARIABILITY ON WATER RESOURCES OF WEST AFRICA REGION

Climate variability is having a multitude of immediate and long-term impacts on water resources worldwide. These include flooding, drought, sea-level rise in the estuaries,

drying up of rivers, poor water quality in surface and groundwater systems, precipitation and water vapour pattern distortions and snow and land ice mal-distributions (Urama and Ozor, 2010). West Africa sub region has experienced a significant decline in rainfall in recent decades. A noticeable decline in rainfall series was observed around the year 1968 to 1972 with the year 1970 as a transitional year. The drop in average rainfall, before and after 1970, ranges from 15% to over 30% depending on the area. This situation has resulted in about 200 kilometres southwards shift in isohyets. In the whole region, the decline in rainfall results from reduced number of rainy days and events (Niasse et al (Eds.), 2004).

As in the case of the annual rainfall series, a significant variation in the annual average discharge has, also, been observed since the 1970's in most rivers within the region. Across the major basins in the region, the variation in discharge time is generally similar to that of the rainfall. However, the decline in discharge is more significant than that of the rainfall: 40% to 60% average decline in discharge since the early 1970s as against 15% to 30% decline in rainfall (Niasse et al, 2004). About 60% decline had been observed in the discharges of rivers Senegal and Gambia within the Northern guinea Savannah (NGS) over the period 1971 t0 1989 compared to the period 1951 to 1989 against a drop of 25% in the average annual rainfall across the same basin and for the same reference period (Niasse et al (Eds.), 2004). In the region's large basins, the reduction in discharge ranges from 25 to 50% for the same period. In the region's largest river, the river Niger, in addition to a drop in discharge, severe low flow conditions that resulted in the stoppage of flows were observed in 1983, 1984 and 1987 over the Bani tributary at Douna, Mali and in 1985 in Niamey (Niasse et al (Eds.), 2004). In 2002, the volume of water discharged at Koulikoro (upper reaches of river

Niger in Mali) was 29.7billion cubic metres, that is, a 14% decrease in relation to the average for the period 1971 to 2001, which was 34.4 billion cubic metres. In the same year, there was a drop of 40% in the discharge compared to the average for the period before 1970 (over 49billion cubic metres per annum)(Niasse et al ,2004).

The decrease in discharge recorded in the region's largest water courses since the early 1970s gave rise to significant reduction in the areas of the major natural wetlands. The shrinkage in the average area of the Hadejia Nguru Floodplain (on the Komadugu Yobe river system in northern Nigeria) ranges from 2,350 square kilometers in 1969 to less than 1,000square kilometers in 1995 (Niasse et al (Eds.), 2004). A similar trend was observed over river Niger Inland Delta, which is the second largest wetland in Africa after the Okavango floodplain in South Africa. The maximum area flooded in the Inland Delta has decreased significantly from 37,000 square kilometers in the early 1950's to about 15,000square kilometers since 1990. The area of Lake Chad estimated at more than 20,000 square kilometers during the wet years before 1970, shrunk to less than 7,000 square kilometers in the 1990's (Niasse et al (Eds.), 2004).

Another consequence of climate variability on water resource in the West Africa sub region is proliferation of invasive weeds such as water lettuce, water hyacinth, typha and so forth. The decline in discharges, global warming, and eutrophication, which reduces the velocity of flood propagation and causes virtual stagnation of water in some places, create favourable conditions for these weeds to grow. Floating weeds hinder fishing, navigation, proper functioning of irrigation schemes and hydroelectric power development. In addition, the weeds create an environment conducive to the breeding of vectors of water borne and water related diseases such as malaria. In recent years, water hyacinth has been growing on the Otti sub catchment across the Volta and typha

and has been significantly expanding over Komadugu Yobe basin (Northern Nigeria) including Lake Nguru. Upstream of the Diama dam at the mouth of the Senegal River, on the edges of the Djoudj and Diawling Ramsar site, the expansion of typha was compared to giant carpet spread over the rivers (Niasse et al (Eds.), 2004).

The decline in rainfall and surface runoff due to climate variability has significantly reduced the recharge areas of aquifers which, as a consequence, reduce the input of groundwater into major water courses (Niasse et al (Eds.), 2004). The recurrent drought resulting from climate variability accelerates desertification and deforestation which in turn contributes to the persistent drought.

2.8 MEASURES OF IMPACT OF CLIMATE VARIABILITY ON WATER RESOURCES:

The impact of climate variability on water resources variables (stream flows) may be defined as the responses of the water resources variables to the variations in climatic elements (temperature and rainfall). There are several approaches, in literature, for the evaluation of the impact of climate variability on stream flows but the commonly used techniques includes the following:

2.8.1 Comparative Analysis: A comparison is made of the differences between the statistical parameters of the hydrological and the climatic variables for various equal-length periods. For this purpose, the time series records for the hydrological and climatic variables are divided into n periods, each of m number of years. The statistics normally computed are; mean, standard deviation, coefficient of variations, coefficient of skewness, coefficient of kurtosis, trend in mean, trend in the variance , among others (WMO, 1988). Impact is achieved or established when the differences in the statistical parameters of the hydrological variables vary in responses to the changes in the differences in the statistical parameters of the climatic variables.

2.8.2 Trend Characterization: Simple Linear Regression analysis provides a primary indication of trends in time series data. In order to detect trends that are monotonic but non-linear, non-parametric methods such as Mann-Kendall test is commonly used, especially, for the analysis of hydrologic data (Helsel and Hirsch, 2002; McBean and Motice, 2006). The Mann-Kendall test (tau) measures the strength of the monotonic relationship between two variables x and y..It does not require the assumption of normality and only indicates the direction and not the magnitude of significant trends. It is a ranked based procedure and therefore resistant to the effect of small number of outliers and measures all monotonic correlations (linear and non-linear). Its large

sample approximation produces p-values that are very close to the exact values, even for small sample size (Helsel and Hirsch, 2002).

Mann-Kendall (tau) test is most easily computed by first ordering all data pairs by increasing x. If a positive correlation exists, the y's will increase more often than decrease as x increases, while the reverse is true for negative correlation. The two-sided test for correlation evaluates the hypotheses: $The\ null\ (H_{0)}$: No correlation exists between x and y. and H_1: Correlation exists between x and y. Reject the null hypothesis when the p-value is less the significant level (α) which is usually 0.05 or 0.10.

The Mann-Kendall test statistic S is computed by subtracting the number of "discordant" pairs, M (number of (x,y) pairs where y decreases as x increases) from the number of "concordant" pairs, P (number of (x,y) pairs where y increases as x increases). That is S= P- M. Where P = the number of times the y's increases as the x's increases (number of pluses)($y_i < y_{j\ for\ all\ i} < j$); M=the number of times the y's decreases as the x's increases (number of minuses) ($y_i < y_{j\ for\ all\ i} < j$); $i = 1,2,3 \ldots.(n - i)\ and\ j = (i + 1), (i + 2), (i + 3) \ldots \ldots, n$. n = sample size. If all y values increases along with x values, $S = n(n - 1)/2$ and the correlation coefficient = +1. When all y values decreases with increasing x, then $S = -n(n - 1)/n$ and the correlation coefficient =-1. Tau $(\tau) = \frac{S}{n(n-1)/2}$. Impact is established when trends in the climatic variables corresponds with the trends in hydrologic variables. It is also established if the value of tau is significantly different from zero.

2.8.3 Rainfall-Runoff Relationship: Another way to estimate the impact of climate variability on stream flow is to use Rainfall-Runoff models (Li, et al, 2007). The annual stream flow for a catchment can be estimated by equation 2.53 as:

$Q_1 = a + bP_1(\delta_1^2)^c$ …………………………………………………………….... (2.56)

Where Q_1=computed annual stream flow; P_1 =annual rainfall and δ_1^2 =variance of the monthly rainfall; $a, b, and\ c$ are constants calibrated for the baseline period. The subscript "1" represents the baseline period when the catchment is under stable conditions, that is, no changes in catchment properties such as land use and land cover. In applying equation 2.53, the total stream flow record is divided into two periods. The first period represents the baseline and the second period represents the changed stream flow. Equation 2.54 is then applied to estimate the annual stream flow during the first period as the baseline conditions. Similarly, the same equation is used to calculate the annual stream flow that would occur in the second period. The effect of climate variability, in this case, rainfall, on the stream flow can be estimated by equation 2.55 as: $\Delta Q^p = Q_2 - Q_1$ ………………………………………………………….. (2.57)

Where, $Q_2\ and\ Q_1$ are the computed annual stream flows during the first and second periods of the record respectively.

2.8.4 Hydrological Sensitivity Method: Hydrological sensitivity can be defined as the percentage change in mean annual stream flow occurring in response to a change in mean precipitation P and potential evapotranspiration E_o. The water balance for a catchment can be expressed as: $P = E + Q + \Delta S$……..… (2.58)

Where E= evapotranspiration; Q = stream flow; ΔS =change in catchment water storage. Over a long period of time (10years), it is reasonable to assume that ΔS is zero (Li, et al, 2007). The long-term average evapotranspiration can be estimate by equation 2.56 (Zhang et al, 2001 as cited by Li, et al 2007) as:

$$\frac{E}{P} = \frac{1+w\left(E_0/P\right)}{1+w\left(E_0/P\right)+\left(E_0/P\right)^{-1}} \quad \text{……..…… (2.59)}$$

Where w = a model parameter relating to vegetation type

The change in the mean annual runoff can be determined using equation 2.57 (Li, et al, 2007) as: $\Delta Q^{clim} = \beta\Delta P + \gamma\Delta E_0$ ……(.2.60)

Where ΔQ^{clim} , ΔP and ΔE_0 are changes in stream flow, precipitation, and potential evapotranspiration respectively, β is the sensitivity of stream flow to precipitation and γ is the sensitivity to potential evapotranspiration (Li, et al, 2007)

The sensitivity coefficients can be expressed as:$\beta = \frac{1+2x+3wx}{(1+x+wx^2)^2}$……..…….. (2.61)

$$\gamma = \frac{1+2wx}{(1+x+wx^2)^2} \quad \text{……..…. (.2.62)}$$

Where x is the index of dryness which is equal to E_0/P and w as previous defined.

2.8.5 Flow –Duration Curve (FDC): A flow – duration curve (FDC) represents the relationship between the magnitude and frequency of stream flow. FDC is constructed from daily stream flow data over a time interval of interest and provides a measure of the percentage of time a given stream flow is equalled or exceeded over that time interval. Each value of discharge Q, has a corresponding exceedence probability p, and a flow-duration curve is simply a plot of Q_p, the pth quantile or percentile of stream flow versus exceedence probability p, where p is defined by equation 2.60 as:

$$p = 1 - p\left(Q_p \leq q\right) \quad \text{……..…… (2.63)}$$

The quantile Q_p, is a function of the observed stream flow, and since this function depends on observations, it is often termed the empirical quantile function (Li et al, 2007).

CHAPTER THREE

MATERIALS AND METHODS

3.1 PREAMBLE

This section discusses the type of data that were collected and the checks and preliminary analysis performed on the data and the methods and procedures for the analysis of the data based on the study objectives. It includes of the following subsections:

1..Data collection and preliminary analysis;

2..Analytical methods for the evaluation of climate variability; and

3..Evaluation of the impact of climate change and variability on water resources of the study area.

3.2 DATA COLLECTION AND PRELIMINARY ANALYSIS

Data must be available in order to accurately determine meaningful climate variability within the Kaduna State of Nigeria and the impacts on the water resources of the Lower Kaduna River Catchment for periods of decades (Wilberforce, 2007). It is also important that each data series under consideration possesses a complete or near complete set of high quality values. Often, time series, both in physical and behavioural dataset, tend to have contiguous missing values, that is , runs of values, all missing (Pyle, 1999). This can easily happen if the collection mechanism either fails or is intermittent in operation. Also, there may be runs of data with periods of no data in between. Filling in these gaps with self-similar patterns from other parts of the series reinforces the apparent self-similarity (Pyle, 1999).

Apart from missing values, outliners (values that lie far outside the bulk of the range) also occur in time series. These can come as individual occurrences and sometimes in runs, that is, clusters of consecutive values of the same order of magnitude but as a group lying well outside the range of other values. Outliners need to be replaced if no rationale can account for them. Missing values and outliners, if present in a dataset, introduce bias, that is, the sampled data are no longer representative of the population from which they were taken (Merson and McHale, 2010).

3.2.1 Data Collection

The data for this study were obtained from Kaduna State Water Board, Hydro meteorological section and they include daily minimum and maximum temperatures in degrees Celsius and daily rainfall and evaporation depths in millimeters and daily stream flows in cubic metres per second (cu.m/sec.) for the period 1960 to 2006 (Table 3.1 and as indicated in Figure 3.1). The data were from the 12 available meteorological

stations scattered over the state and located as indicated in Table 3.1 below. The River gauging station is located at the lower part of River Kaduna at Kaduna South station within the Lower Kaduna River Catchment.

3.2.2 Missing Data Analysis

The missing values and the outliers were replaced by the method of mean substitution as suggested by Dahabiah et al, 2010 and Merson & McHale, (2010). The computed mean values from the available data were substituted for the missing values and outliers

Table 3.1 Information on Meteorological Stations in the Study Area

S/N	Meteorological Station	Year Established	Location (Coordinates)		Available Data
			Latitude	Longitude	
1.	Ikara	1977	11.18°	8 .25°	Temperature, Rainfall and Evaporation
2.	Zaria	1977	11 .15°	7 .78°	“
3.	Kangimi	1977	10 .77°	7 .58°	“
4.	Kauru	1975	10 .58°	8.15°	“
5.	Birnin Gwari	1969	10 .58°	6 .57°	“
6.	Kaduna North	1981	10 .55°	7 .48°	“
7.	Kaduna South	1944	10 .50°	7 .43°	Temperature, Rainfall ,Evaporation, and Discharge
8.	Saminaka	1977	10.38°	8 .70°	Temperature, Rainfall and Evaporation
9.	Kachia	1978	9 .90°	7 .97°	“
10.	Zonkwa	1987	9 .75°	8 .32°	“
11.	Kafanchan	1973	9.60°	8.30°	“
12.	Kagarko	1981	9 .48°	7 .68°	“

Source: Kaduna State Water Board, Kaduna.

3.2.3 Preliminary Statistical Analyses

From the daily minimum and maximum temperatures, monthly minimum and maximum temperatures were selected from which the annual minimum and maximum temperatures were obtained.. The annual rainfall and the annual evaporation depths are the summation of the daily rainfall and evaporation depths respectively for the year.

For the ARMA model development, the moving average (MA) values of these data were used. One of the simplest methods of forecasting is to assume that a future value will be equal to an average of past values. This is the essential assumption of the moving average (MA) model. A simple moving average is useful in modelling a random series (series without trend or seasonality) because; it averages the most recent

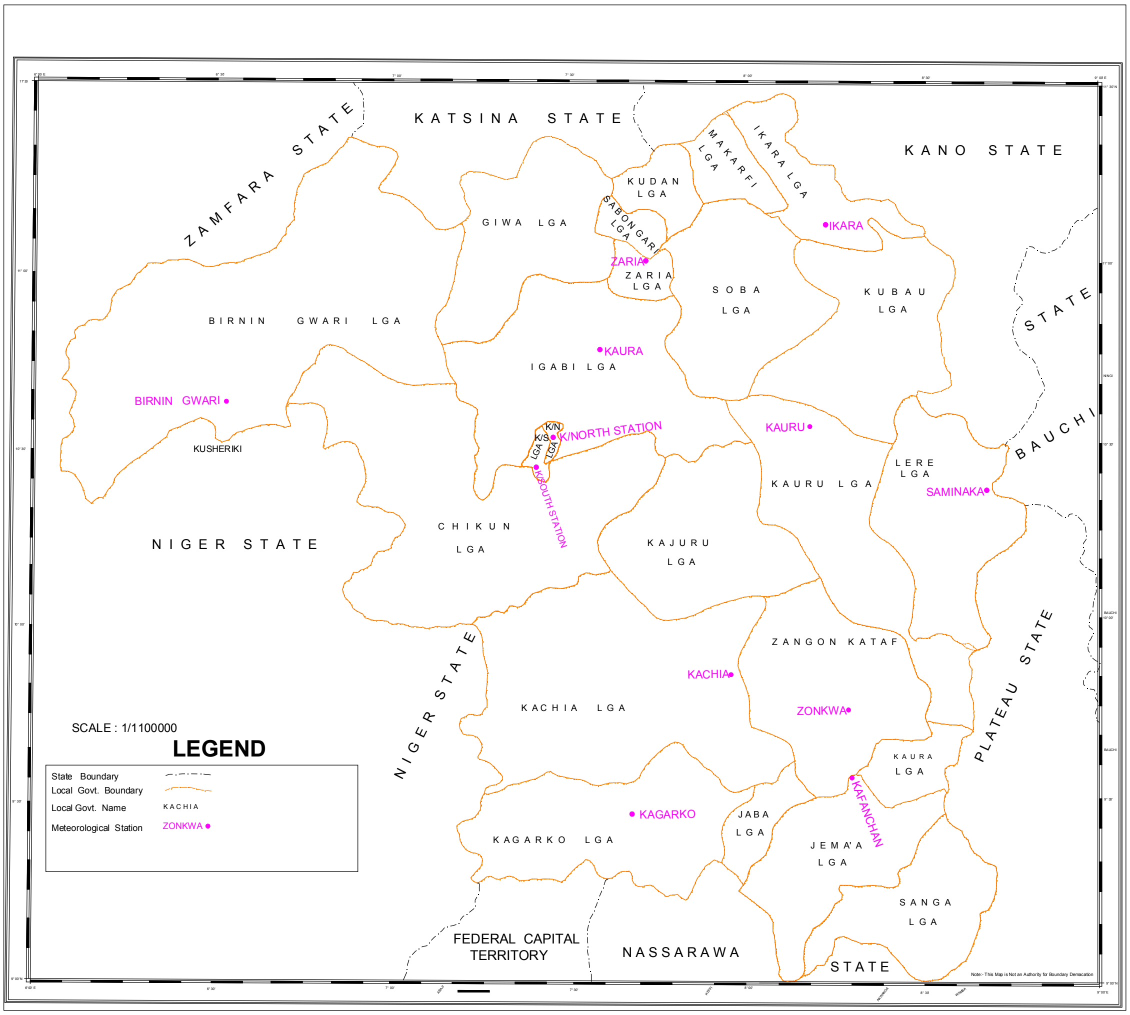


FIG. 3.1: THE METEOROLOGICAL STATIONS OF KADUNA STATE

actual values to remove the unwanted randomness (DeLurgio, 1998). In general, an N-period moving average denotes that each new forecast moves ahead one period by adding the newest actual value and dropping the oldest actual value. The accuracy of the different models is compared using the error statistics defined as follows:

$$Mean\ Error(ME) = \frac{\sum(A_t - F_t)}{n} = \bar{e}_t \quad \ldots\ldots (3.1)$$

$$Sum\ of\ Squared\ Error(SSE) = \sum(A_t - F_t)^2 = \sum e_t^2 \quad \ldots\ldots (3.2)$$

$$Residdual\ Standard\ Error\ (RSE) = \sqrt{\frac{\sum e_t^2}{n-k}} \quad \text{..... (3.3)}$$

Where A_t = actual value at time t; F_t = forecast value at time t; n = number of errors and k =1 for estimating one coefficient of the moving average.

The optimal number of periods for a simple moving average is the number that minimizes the RSE. A long-period moving average yields the lowest RSE when the series is very random and erratic, that is, possessing low levels of autocorrelation. However, if the series is random and moves up and down smoothly, that is, highly correlated, a short-period moving average will yield lower RSE (DeLurgio, 1998). Moving average is appropriate for pattern less series (series without deterministic trend or seasonality) (DeLurgio, 1998).

In the study reported herein, a 10-year period (decade) was used to compute the moving average for the annual minimum, maximum and mean temperatures and the annual rainfall and evaporation depths which were used in the ARMA modelling of meteorological variables as suggested by Li,Xier, (2009).

The annual stream flows were the summation of the daily stream flows. The series of annual maximum flow (Q_{max}), the annual minimum flow (Q_{min}) and the mean annual discharge (Q_{mean}) during the period 1960 to 2006 were extracted from the daily discharge records and used to represent the long-term discharge characteristics of the Lower Kaduna catchment in relation to temperature and rainfall variations. The annual maximum and minimum stream flows were the maximum and minimum daily stream flows respectively for the year. The processed data for the evaluation of climate variability/ change in the study area are, therefore, the annual minimum, maximum and mean temperatures and annual rainfall and evaporation depths and annual stream flows, annual maximum , minimum stream and mean streamflows. Descriptive statistical analysis, homogeneity test using Run Test and normality test using Anderson-Darling approach were then performed on these data to verify their integrity using Minitab Software.

3.2.3.1. Homogeneity Test: A climate time series is said to be homogeneous when its variations are caused only by fluctuations in weather and climate. There are several methods for testing homogeneity in literature (Wilberforce, 2007) but the method of "Run Test" was used in this study. The Run Test is a non-parametric statistical test of hypotheses that does not require the assumption of any known distribution. Inferences drawn from tests based on parametric tests such t-test, chi-square test etc may be seriously affected when the parent population distribution is not normal. Run test is used to examine whether or not a set of data constitute a random sample from an infinite population. Test for randomness is very important because the assumption of randomness underlies statistical inferences. In addition, test for randomness is important in time series analyses. The hypotheses for Run test are:

Null (H_0): Sample values come from random sequence;

Alternative (H_1): Sample values come from non- random sequence.

The number of times that the category changes; that is, where x_i belongs to one category and x_{i+1} belongs to the other, as well as the number of records in category one ($n_{1,f}$) and category two ($n_{2,f}$), are determined. The number of Runs, R, is the number of sign changes plus one. The simplest distribution of the number of Runs is approximately normal with:

$$\mu_R = \frac{2n_{1,f}n_{2,f}}{n_{1,f}+n_{2,f}} + 1 \quad \text{(3.4)}$$

$$\delta_R = \sqrt{\frac{2n_{1,f}n_{2,f}(2n_{1,f}n_{2,f}-n_{1,f}-n_{2,f}}{(n_{1,f}+n_{2,f})^2(n_{1,f}+n_{2,f}-1)}} \quad \text{(3.5)}$$

The test statistic is $Z = \frac{R-\mu_R}{\delta_R}$ $(if\ n_f \geq 50)$ (3.6)

Otherwise,

$$Z = \begin{cases} \frac{(R-\mu_R+0.5)}{\delta_R} & if\ R-\mu_R \leq -0.5 \\ \frac{(R-\mu_R-0.5)}{\delta_R} & if\ R-\mu_R \geq 0.5 \\ 0\ if\ |R-\mu_R| < 0.5 \end{cases} \quad \text{(3.7)}$$

The one sided p-value $p_1 = \Pr(Z \geq |Z|) = 1-\alpha(|Z|)$ and the two sided p-value is $P_2 = 2P_1$. Reject the null hypothesis when $P_2$is less than alpha level which is usually 0.05 and 0.10.

***3.2.3.2 Normality Test*:** The normality test is a test to determine whether the hydro-climatic data follow normal distribution. Normally distributed data are easily analyzed using empirical probability distributions. The commonly used test of normality is the Anderson-Darling (A-D) statistic, A_n^2, defined as:

$$A_n^2 = \int_{-\infty}^{\infty} |F_n(x) - F(x)|^2\, \Psi(x) f(x)\, dx \text{ (Vose Software, 2007)} \quad \text{(3.8)}$$

Where $\Psi(x) = {}^{n}/_{F(x)\{1-F(x)\}}$; n = Total number of data points; F(x) = distribution function of the fitted distribution; f(x) =density function of the fitted distribution; $F_n(x) = \frac{i}{n}$; i= the cumulative rank of the data point.

The Anderson-Darling statistic is a sophisticated version of Kolmogorov-Smirnoff (K-S) statistic. It is more powerful for the follow reasons:

1.$\Psi(x)$ Compensates for the increased variance of the vertical distances between distributions'δ_{k-s^2};

2. $f(x)$ weighs the observed distances by the probability that a value will be generated at that x-values; and

3. The vertical distances are integrated over all values of x to make maximum use of the observed data (the K-S statistic only looks at the maximum vertical distance).

The A-D statistic is therefore, a generally more useful measure of fit than the K-S statistic, especially where it is important to place equal emphasis on fitting a distribution at the tails as well as the main body. The hypotheses for the Anderson-Darling normality test are:

H_0 : Data are from a normally distributed population;

H_1: Data are not from a normally distributed population;

The p-value from the Anderson-Darling test assesses the probability that the data are from a normally distributed population. If the distribution fits the data, the A-D statistic will be small and the associated p-value will be greater than the chosen alpha-level (0.05 and 0.10). In this study, Anderson-Darling Normality test procedure was used and the analysis was performed by MINITAB software.

3.3 METHODS OF CLIMATE VARIABILITY ANALYSIS

This section outlines the approaches that were used to analyze or evaluate or quantify climate variability and their effects on the water resources of the Lower Kaduna River catchment. These approaches include computation of coefficient of variation for the quantification of the climate variability, trend and time series analysis for the evaluation of characteristics of the variations and correlation analysis for the evaluation of the effects of the annual mean temperature on rainfall and streamflows of the Lower Kaduna River catchment area.

Climate variability includes the extremes and differences of monthly, seasonal, and annual values of the climatically expected value (temporal mean), while climate change is the difference between long-term mean values of a climate parameter or statistics, where the mean is taken over a specified interval of time, usually, a number of decades such as 30years. These imply that the terms climate variability and climate change refer to two different concepts of the climate process, in particular to climate represented by a stationary process and non-stationary process respectively. It further implies that climate is viewed as a process which can be approximated by a stationary process on a short time scale but is non-stationary on a long time scale. Within this shorter time scale, it is therefore considered appropriate to talk about “climate normals” representing central tendencies around which the climate fluctuates. These fluctuations constitute climate variability (WMO, 1998).

The long-term non-stationarity implies that no long-term climate normals exist or that climate normals (mean) exhibit irregular fluctuations. These fluctuations can be approximated as changes in the quasi-constant central tendencies or climate normals in the successive periods of a few decades within which the stationary representation is acceptable (WMO, 1998). In summary, climate variability can be regarded as the variability inherent in the stationary stochastic process approximating the climate on a scale of few decades while climate change can be regarded as the difference between the stationary processes representing climate in successive periods of several decades.

There are several methods of evaluating variability as discussed in section 2.6 but in this study, the variability of the climate within Kaduna State and Lower Kaduna River Catchment was investigated using the following techniques:

3.3.1 Simple Approach: The simplest measures of Climate Variability is by dividing the time series data into two equal-length periods and compute the difference between the means (E) and standard deviations (SD) of the time series in the two time scales as stated, mathematically in Equations 3.9 and 3.10. The statistics (mean and standard deviation) were computed for the two periods in each station of record.

$$Climate\ Variability\ =\ E1 - E2 \quad \ldots\ldots (3.9)$$

Also, $$Climate\ Variability\ =\ SD1 - SD2 \quad \ldots\ldots (3.10)$$

The percentage Variability is given in equations 3.11 and 3.12 as follows;

Percentage Variability = $\frac{E1-E2}{E1} \text{x} \frac{100}{1}$ ..... (3.11)

Also, Percentage Variability = $\frac{SD1-SD2}{SD1} x \frac{100}{1}$ ..... (3.12)

Where E1 and E2 = means of the time series in the time periods 1 and 2 respectively, while SD1 and SD2 are the standard deviations of the time series in the time periods 1 and 2 respectively. The two time scales used were 1961- 1990 as recommended by WMO (1988) and 1971 – 2000. The differences between these statistics in the two time scales were used to quantify climate variability within the region and in the study area. These statistics were computed as follows:

$Mean\ E = \sum_{i=1}^{n} X_i / n$ $and\ Standard\ Deviation : SD = \sqrt{\sum_{i=1}^{n} \frac{(X_i - E)}{n-1}}$, In which

$X_i =$ $each\ variable\ in\ the\ time\ series$ and n = number of the series.

3.3.2The coefficient of variation (CV*):* The coefficient of variability (CV) is another measure of Climate Variability. This has extensively been used in literature to evaluate climate variability (Adejuwon, 2006 and Fleming, 2007). It measures the size of the standard deviation (which is the most frequently used measure of variability) relative to the mean. It was computed as shown in Equation 2.53 given as:

Coefficient of variation (CV) = $SD/\bar{X}$ ..... (2.53)

The CV less than 0.1or 10% indicates low variability while CV greater than 0.9 or 90% indicates high variability (Durdu, 2009). Threshold CV is 0.4 or 40%, that is, the climate state is stable if the CV is less or equal to 0.4 or 40% above which the climate state becomes increasingly unstable (Zuming, 1987 , Lane et al, 1999).

3.3.3Time Series Methods: The Time series methods include smoothing, exponential smoothing, decomposition, Fourier analysis, Autoregressive Integrated Moving Average (ARIMA), linear trends and nonlinear growth models. The purpose of these methods is to model the pattern of past values in order to project them into the future as well as to determine the variability in the time series. In this study, linear trend analysis and ARIMA models, which have been extensively used in literature to evaluate climate variability (section 2.5), were used to evaluate the Climate Variability as follows:

3.3.3.1Trend Analysis: The objective of trend analysis is to identify if the values of the random variable generally increase or decrease over some period of time in statistical terms. The general trend of the hydro-meteorological series can be ascribed to climate change or the influence of man's activities such as agriculture, deforestation and urbanization (Haidu et al, 1987) on the climate system. In this study, an attempt was made to estimate the magnitudes and statistical significance of trends that is Climate Variability, in the annual maximum, annual minimum and annual mean temperatures, annual rainfall and evaporation and annual series of streamflows using Equation 2.21 in section 2.5 which was given as:

$y_i = \beta_o + \beta_1 x_i + \varepsilon_i$ ..... (2.21)

Climate Variability = slope of the regression line, β_1

Analyses of trends were performed for individual stations on the annual maximum, annual minimum and annual mean temperatures, annual rainfall and evaporation using MINTAB Software..

***3.3.3.2. Autoregressive Integrated Moving Average (ARIMA) Model Approach*:**

The major complication with the use of linear regression models in the analysis of climate data is that climate data are usually autocorrelated, that is, the terms cannot be taken as independent. Autocorrelated data are appropriately analyzed within the field of statistics called time series analysis (Richard et al, 2007). One common approach to time series analysis is to assume that the climate state values form an autoregressive integrated moving average process ARIMA). The standard ARIMA (p, d, q) process is given in Equation 2.8 while the ARMA (p,q) process is as given in Equation 2.17:

$Y_t - \emptyset_1 Y_{t-1} - \emptyset_2 Y_{t-2} - \ldots - \emptyset_p Y_{t-p} = e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots \ldots + \theta_q e_{t-q} \ldots$ (2.17)

Where $\emptyset_1 \ldots \ldots \ldots \emptyset_p$ are autoregressive coefficients; $\theta_1 \ldots \ldots \ldots \ldots \theta_q$ are moving average coefficients and e_t are the residuals which are independent with zero mean and

common variance. The ARIMA building process is had been summarized in the flow chart in Figure 3.2 and detailed in section 2.4.1.The autoregressive coefficient is the measure of the slope which is interpreted, in this study, to be the measure of Climate Variability. That is Climate Variability = Autoregressive Coefficient.

The first task is to appropriately identify subclass of models from the general Autoregressive Integrated Moving Average (ARIMA) model family that will adequately fit the data and can be checked. The approach will be as follows:

1.To assess the stationarity of the process and if necessary to differencing as many times as possible to achieve stationarity with the aim of reducing the process to the Mixed Autoregressive Moving Average process.

2.To identify the resulting model for the process.

The tools for achieving (1) and (2) above are the Autocorrelation function (ACF) and Partial autocorrelation function (PACF) described as follows:

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF):
Autocorrelation measures the degree of association between two sets of values of a time series which are separated by some lag k. It can be computed in several ways, one of which is the autocorrelation function (ACF), defined mathematically in Equations 2.23 and 2.24 as:

$$\text{ACF(k)} = \frac{\sum_{t=1+k}^{n}(Y_t-\bar{Y})(Y_{t-k}-\bar{Y})}{\sum_{t=1}^{n}(Y_t-\bar{Y})^2} \quad \text{.....(2.23)}$$

Where Y_t = time series; $\bar{Y}$ = mean value; Y_{t-k} = lagged time series.
ACF's are so important because they assist in the identificantion, parameter estimation and diagnosis of forecasting models such ARIMA models.

Partial correlation coefficients measure the degree of association or influence that eexists between two variables after their shared mutual influence with a common variable, X_1 ,has been removed. That is the degree of association between the residuals. It is define mathematically as in Equation 2.20.For example the Partial Correlation coefficient between $X_2$and X_3can be derived as follows:
Step 1: Regress X_2as a function of X_1 and save the residual as $X_{2.1}$; that is,

$$X_2 = a + b\,X_1 + e = a + b\,X_1 + X_{2.1} \quad \text{.....(3.12)}$$

Step 2 : Regress X_3 as a function of X_1 and save the residual as$X_{3.1}$; that is,

$$X_3 = a + bX_1 + e1 = a + bX_1 + X_{3.1} \quad \text{.....(3.13)}$$

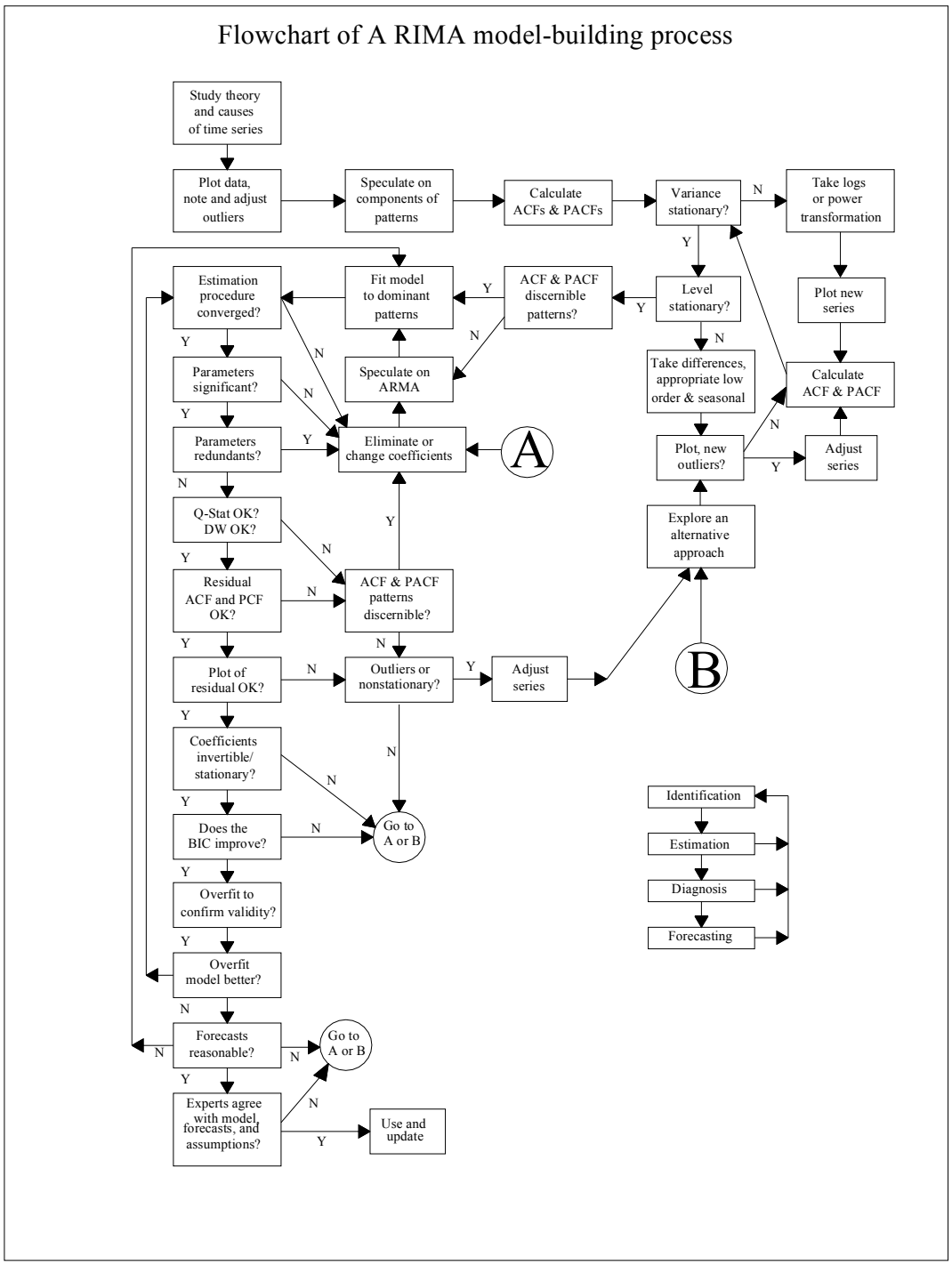


Figure 3.2 Flow Chart of ARIMA Building Process

The correlation between $X_{2.1}$and $X_{3.1}$is called the partial correlation coefficient. It is measured by the Partial Autocorrelation Function (PACF) in the case of autocorrelated time series. PACF plays an important role in building good structured models. ACF and PACF were determined using SPSS statistical software and were used to identify

the model. The number of statistically significant ACF and PACF determines the model order. Estimation of model coefficients was achieved through software applications of least square and maximum likelihood methods. The values of the Autoregressive parameters were used as measures of Climate Variability.

The following algorithm represents the measure of the performance of ARMA models:

$$R = \frac{\Sigma(y_f - \bar{y}_f)(y_o - \bar{y}_o)}{\sqrt{\Sigma(y_f - \bar{y}_f)^2 \times \sqrt{(y_o - \bar{y}_o)^2}}} \quad ; \ldots\ldots (3.14)$$

Where R = Pearson's Product Moment Correlation Coefficient; y_f = forecast value; y_o = station observed value and $\overline{y_f}$ and $\overline{y_o}$ = mean values.

For a perfect fit R^2 =1.0;0≤ R^2 ≤ 1.This is a measure of the linear association between individual pairs of forecasts and observations. The model was validated by the R^2

3.3.4. Anomaly Approach: Another approach to the evaluation of Climate Variability was the use of Anomaly. The average annual values of the climatic time series were computed for each station over the 1961 – 1990 baseline periods. For each station, the value of each climatic variable was subtracted from the 30-year (1961-1990) average value of the climatic variable for each year to obtain the Anomaly.

That is, the Anomaly = $\bar{X}_{30} - X_i$ ……………………………………………… (3.15)

Where, $\bar{X}_{30}$ is the 30-year average of the variable X over the baseline year and X_i is current value of the variable in year i at any station. The Percentage Anomaly was computed using Equation 3.16.

The Percentage Anomaly = $\frac{\bar{X}_{30} - X_i}{\bar{X}_{30}} x \frac{100}{1}$. …………………………………… (3.16)

The 47-year series of yearly average anomalies of maximum, minimum, and mean temperatures, rainfall and evaporation trends in the time series were analyzed with MINITAB software. The values of the Anomalies were used as measures of Climate Variability.

The unbiased estimate of the Climate Variability was obtained by the use of Standardized Anomaly Index (SAI). It provides an area-average index of the climatic variables (maximum, minimum, and mean temperatures, rainfall and evaporation) yields based on the standardization of the annual values. It was computed using Equation 2.55 as :

SAI=Z = $\frac{X_i - \bar{X}}{S}$……………………………………………….. …………… (2.55)

Where $\bar{X}$ and S is the mean and standard deviation respectively. For the annual rainfall time series, this statistic enables us to determine the dry/cool (negative value) and wet/hot (positive value) years in the record.

3.4 ESTIMATING CLIMATE VARIABILITY IMPACTS ON WATER RESOURCES OF THE STUDY AREA

The impacts of climate variability on water resources may be defined as the measure of the degree of influence of Climate variables on the Water resources variables. The estimation of the impacts of climate variability on water resources of the study area is achieved when it can be established as follows:

1. The values of climate variables increase as the values of water resources variables increase;- Positive Impact.
2. The values of climate variables decrease as the values of water resources variables decrease;-Positive Impact.
3. The values of climate variables increase as the values of water resources variables decrease;- Negative Impact
4. The values of climate variables decrease as the values of water resources variables increase;-Negative Impact.
5. The values of climate variables are not related to the values of water resources variables;No Impact. That is, the two sets of variables are statistically independent.

The terms positive and negative are the attributes of the relationship, they do not denote the strength or the degree of the association between the two sets of variables or time series. The consequent of positive impact is the tendency for flooding while that of negative impact is the tendency for drought.

There are several measures of the correlation or the degree of association between the climate variables and water resources variables but the approach used in this study includes the following:

1. Comparative Analysis; and
2. Correlation Analysis.

3.4.1 Comparative Analysis;

Comparative Analyses involve the comparison of the behaviours of certain parameters of climatic variables with the behaviours of similar parameters of water resources variables with a view of determining the influence of climatic variables on water resources variables. This approach has been used by World Meteorological

Organization (WMO, 1988) to evaluate the impact of climate variability on water resources. The parameters considered in this study were Descriptive Statistics, Trends and Anomalies. The approaches used are as described below:

3.4.1.1 Comparison of the Descriptive Statistical Parameters of the Hydro-Climatic Variables

The Climate and water resources time series were divided into two equal-length time periods; 1961- 1990 and 1971-2000. The descriptive statistics of climate and water resources time series were computed for the two time periods. The differences in the values of the statistics between the two time periods were computed for both the climatic time series and water resources time series as follows:

$$\text{Difference (\%)} = \frac{Stat_1 - Stat_2}{Stat_1} \; x \; \frac{100}{1} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.17)$$

Where $Stat_1$ = Descriptive statistic for the first time period; $Stat_2$ =Descriptive statistic for the second time period.

The Impact of climate variability on the water resources variables is achieved when one of the five scenarios in section 3.3 is true in relation to the differences in the statistics of the climate variables and water resources variables. The results were presented in Table 4.8.

3.4.1. 2 Comparison of the Trend Characteristics of the Hydro-climatic Variables

The long-term trends analyses of the climate time series and water resources time series were determined using the linear regression model as described in section 3.2.3.1. The Impact of climate variability on the water resources variables is achieved when one of the five scenarios in section 3.3 is true in relation to the trends of the climate time series and water resources time series. The results are presented in Table 4.8.

The detection of trend in measured time series data can also be posed as a hypothesis testing problem in which the null hypothesis (H_o) is that there is no trend in the data and the alternative hypothesis (H_1) is that there is trend in the data (McCabe et al, 1997). The reality will be that either the null or alternative hypothesis is true or a statistical test will indicate that either the null or alternative hypothesis is true. The power of the statistical test is the probability of accepting the alternative hypothesis when it is true based on the p-value. The p-value indicates the level of probability of accepting or rejecting either the null or the alternative hypothesis. Generally, reject H_o if p-value ≤ 0.05.

In order to test the null hypothesis (H_o) of no significant trends in the climatic and water resources time series, the Mann-Kendall's test was used. Mann- Kendall's test was used as a statistical tool of choice because the model works for non-normal distributions involving seasonality, missing values, censored or unusual data and has a

high asymptotic efficiency (Berryman et al, 1988; Gan, 1998 and Fu, 2008). The Mann-Kendall's test was applied to the annual data series. The test statistic Z was estimated by equation 3.23 as stated below.

$$Z = \begin{cases} \frac{S-1}{var(s)^{1/2}} & if\ S > 0 \\ 0 & if\ S = 0 \\ \frac{S+1}{var(s)^{1/2}} & if\ S < 0 \end{cases} \qquad \text{.......................................} \ (3.18)$$

Where $var\ (s) = n(n-1)(2n+5) - \sum t(t-1)(2t+5)/18$ and

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} Sign(x_j - x_k)$$

$$Sign(x_j - x_k) = \begin{cases} 1\ if\ x_j - x_k > 0 \\ 0\ if\ x_j - x_k = 0 \\ -1\ if\ x_j - x_k < 0 \end{cases}$$

Where x is the observed variable (annual mean temperature, rainfall and stream flow series), k=1, 2, 3… n-1and j = k+1, k+2, k+3……,n; n is the number of independent and random samples; t is the event of any given tie and α is the significant level which ranges from 0.01 to 0.05 (1% to 5%).

The null hypothesis, H_0, was that there was no significant warming/cooling or wetting/drying trend and was accepted if :$-Z_{\alpha/2} < Z < Z_{\alpha/2}$ where $Z_{\alpha/2}$ are the standard normal deviates ($Z_{\alpha/2} = 1.96\ f$or $\alpha = 0.05\ and\ Z_{\alpha/2} = 1.65\ for\ \alpha = 0.01$). the alternative hypothesis , $H_{1,}$ that trend existed was accepted if $Z < -Z_{\alpha/2}$ or if $Z > Z_{\alpha/2}$ (Gan, 1998, as cited by Wang et al, 2008).

The Impact of climate variability on water resources variables is attained when one of the five scenarios in section 3.3 is true in relation to the magnitude and significance of the trends in both climatic and water resources time series or whether or not the null hypotheses are true in both cases. The results are presented in Table 4.8.

3.4.1.3 Comparison of the Anomalies of the Hydro-climatic Variables

The Anomalies of the climatic time series and water resources time series were determined as described in section 3.3.4 using Equations 3.15, 3.16, and 2.55. The Impact of climate variability on water resources variables is attained when one of the five scenarios in section 3.4 is true in relation to the anomalies of the Climate time series and water resources time series. The results are presented in Figures 4.21-4.23

3.4.2 Correlation Analyses of Hydro-climatic Variables: Correlation coefficients measure the strength of association between two continuous variables. Generally, they measure whether one variable increases as the second increases, whether it decreases as the second increases, whether it decreases as the second decreases or whether the

pattern of variation are totally unrelated. Measures of correlation coefficients are dimensionless and range from -1 to +1.When there is no relationship or correlation between the two variables, the correlation coefficient equals zero. When one variable increases as the second increases, the correlation coefficient is positive and when they vary in opposite directions, the correlation coefficient is negative. When y, generally increases or decreases as x increases, the two variables are said to possess a monotonic correlation (Helsel and Hirsch, 2002).

The strength or degree of association between two sets of time series is a measure of the impact of one upon the other, in this case, the impact of climate variability on the water resources variables. The higher values of the correlation coefficient, means higher degree or level of impact.

The two measures of correlation used in this study were Kendall's tau (τ) and Pearson's r. Tau is a ranked-based procedure and is therefore resistant to the effect of a small number of unusual values (outliners). It is well suited for variables which exhibit skewness around the general relationship. Tau (τ) correlation coefficient is given by:

$$\tau = {}^{S}/_{n(n-1)/2} \quad \text{..... (3.19)}$$

Where S = the test statistic which measures the monotonic dependence of y on x or

P-M; where P = "number of pluses", the number of times the y's increase as the x's increase or the Number of $y_i < y_j$,for all $i < j$.n = $total\ number\ of\ variables$

M = "number of minuses", the number of times y's decrease as the x's increase or

The number of $y_i > y_j$, for all $i < j$. $i = 1, \dots \dots (n-1)$, And $j = (i+1), \dots \dots n$

To test for the significance of tau, S is compared to the expected value when the null hypothesis is true. For large sample size, S is modified to be closely approximated by a normal distribution Z_s which is given by equation 3.23.

The Pearson's r correlation coefficient is the most commonly used measure of correlation. It is called linear correlation coefficient and is given by:

$$r = \frac{1}{n-1}\sum_{i=1}^{n}\left(\frac{x_i-\bar{x}}{S_x}\right)\left(\frac{y_i-\bar{y}}{S_y}\right) \quad \text{..... (3.20)}$$

Where;S_x = standard deviation of x's; $S_{y=}$ standard deviation of y's; $\bar{x}$ = mean of x's and $\bar{y}$=mean of y's. The significance of r was tested by determining whether r differs from zero. The test statistic t_r was computed by:

$$t_r = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \quad \text{..... (3.21)}$$

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 RESULTS

The results of the assessment of climate variability, in particular, fluctuations or variations in the annual temperatures (maximum, minimum, and mean temperatures), annual rainfall and evaporation, within Kaduna State of Nigeria and the estimation of the impact of these variability on the water resources, in particular the stream flow, of Lower Kaduna River Catchment are presented and discussed in this chapter under the following sub-headings:

1..Preliminary Statistical Analyses

2..Climate variability in Kaduna State of Nigeria, and

3.Estimation of Impacts of climate variability on the water resources of Lower Kaduna River catchment.

4.1.1 Preliminary Statistical Analyses

The results of descriptive statistical analysis of the climate variables, temperatures, rainfall and evaporation, are presented in Table 4.1 while the results of homogeneity test are presented in Tables 4.2 and 4.2a. Decision rule: Reject null (H_0) hypothesis when the p-value is less than the alpha (α) level of 0.05. .From the results, 75% of the temperature data, about 50% of the annual rainfall data and 35% of the annual evaporation data have p-values greater than alpha level. Using an alpha level of 0.05, it can be concluded that there is insufficient evidence to suggest that the meteorological data are not from a random sequence.

Table 4.1: Descriptive Statistics of the Climatic Variables

Statistic	Station												Zonal Mean
	Ikara	Zaria	Kangimi	Kauru	Birnin Gwari	Kaduna North	Kaduna South	Saminaka	Kachia	Zonkwa	Kafanchan	Kagarko	
	Annual Maximum Temperature												
Mean	38.103	38.538	37.462	38.750	39.429	39.385	38.447	39.100	39.429	38.300	37.939	37.625	38.54
Median	38.000	38.000	38.000	38.000	39.000	39.000	38.000	39.000	39.000	37.500	38.000	37.000	38.17
Standard Deviation	1.472	2.005	2.387	2.768	3.071	3.623	1.119	1.583	2.168	2.849	1.676	1.974	2.225
Maximum	40.000	46.000	40.000	47.000	50.000	54.000	41.000	42.000	48.000	47.000	38.000	46.000	44.92
Minimum	36.000	36.000	30.000	36.000	36.000	36.000	35.000	35.000	37.000	34.000	36.000	36.000	35.25
Skewness	-0.119	2.021	-1.955	2.719	1.877	2.916	-0.104	-1.181	2.4454	1.454	3.536	3.5000	1.426
Kurtosis	-1.304	6.992	3.681	8.618	4.162	10.542	2.029	1.842	8.601	3.523	17.139	15.010	6.736
	Annual Minimum Temperature												
Mean	12.931	8.885	12.808	9.083	10.000	12.500	10.745	8.333	10.857	11.750	10.909	14.208	11.08
Median	13.000	8.000	12.000	9.500	10.000	12.500	11.000	8.000	11.000	11.500	11.000	14.000	10.96
Standard Deviation	1.963	3.410	2.530	1.165	2.339	1.273	2.600	1.729	1.325	1.333	1.958	1.103	1.894
Maximum	17.000	15.000	20.000	10.000	14.000	15.000	19.000	12.000	14.000	15.000	13.000	17.000	15.08
Minimum	9.000	4.000	10.000	7.000	4.000	10.000	2.000	5.000	8.000	10.000	2.000	12.000	6.917
Skewness	-0.110	0.323	2.000	-1.018	-0.483	-0.189	-0.296	0.087	0.178	0.806	-3.293	0.613	-1.38
Kurtosis	-0.371	-1.379	3.848	-0.324	0.185	-0.322	3.719	-0.585	0.056	0.465	13.620	0.969	1.657
	Annual Mean Temperature												
Mean	25.483	23.712	25.135	23.917	24.714	25.942	24.650	23.717	25.143	25.025	24.409	25.917	24.81
Median	25.500	24.000	25.000	24.000	24.000	25.750	24.500	23.750	25.000	25.000	24.500	25.750	24.73
Standard Deviation	0.921	1.524	1.082	1.428	1.800	1.867	1.281	0.868	1.169	1.560	1.320	1.070	1.324
Maximum	27.000	27.000	27.500	28.000	28.500	33.000	28.500	25.000	29.000	29.000	28.500	30.000	28.42
Minimum	24.000	21.500	21.500	22.000	22.000	23.500	21.500	22.000	23.500	22.500	19.500	24.500	22.33
Skewness	0.054	0.444	-1.095	2.226	0.287	2.265	0.350	-0.219	1.274	0.931	-0.822	2.501	0.683
Kurtosis	-0.951	-0.613	4.577	7.083	-0.938	7.737	1.077	-1.097	2.971	1.402	7.684	8.973	3.159

Table 4.1: Continued

Statistic	Station												Zonal Mean
	Ikara	Zaria	Kangimi	Kauru	Birnin Gwari	Kaduna North	Kaduna South	Saminaka	Kachia	Zonkwa	Kafanchan	Kagarko	
	Annual Rainfall												
Mean	1118	1102	1301.7	11760	1240.	1322.5	1385.2	1383.0	1527.7	1722.4	1777.5	1761.1	1402
Median	1094.0	1020.	1242.0	1214	1244	1346.0	1320.0	1361.5	1483.0	1687.0	1793.0	1592.0	1366
Standard Deviation	275.9	277.8	356.9	275.9	165.2	262.9	313.8	307.7	320.6	424.7	359.2	580.3	326.7
Maximum	1747.0	1686.0	2219.0	1732.0	1704.0	1686.0	2333.0	1940.0	2333.0	2471.0	2333.0	3466.0	2138
Minimum	702.0	702.0	777.0	731.0	862.0	602.0	926.0	838.0	968.0	898.0	1152.0	1081.0	853.0
Skewness	0.614	0.674	0.976	0.187	0.317	-0.795	0.953	0.106	0.607	0.157	-0.078	1.621	0.444
Kurtosis	-0.113	-0.515	0.237	-0.450	0.869	0.651	0.687	-0.946	0.223	-0.845	-1.272	2.095	0.052
	Annual Evaporation												
Mean	3065.3	3003.2	2939.8	3011.1	2829.9	2351.6	2452.6	2551.6	2581.8	2884.5	2333.8	2461.8	2704
Median	3017.0	2966.5	3014.0	2999.5	2702.5	2390.5	2454.0	2638.0	2656.0	2948.0	2346.0	2443.0	2715
Standard Deviation	379.0	305.6	394.8	168.9	637.7	265.2	335.1	394.8	275.4	562.0	288.3	247.3	354.5
Maximum	3882.0	3623.0	3441.0	3383.0	4299.0	2814.0	3336.0	3236.0	3004.0	3887.0	2755.0	3117.0	3398
Minimum	2272.0	2330.0	1957.0	2759.0	1084.0	1849.0	1892.0	1774.0	1957.0	1957.0	1493.0	2011.0	1945
Skewness	0.130	-0.011	-1.509	0.991	0.377	-0.236	0.647	-0.584	-1.125	-0.268	-0.942	0.767	-0.15
Kurtosis	-0.232	-0.294	1.851	1.205	1.324	-0.694	0.131	-0.448	0.917	-0.535	1.303	1.846	0.531

Table 4.2: Homogeneity Test Results of Climatic Variables

	Station

	Ikara	Zaria	Kangimi	Kauru	Birnin Gwari	Kaduna North	Kaduna South	Saminaka	Kachia	Zonkwa	Kafanchan	Kagarko
	Annual Maximum Temperature											
Test Value K (mean)	38.04	38.44	37.536	38.714	39.429	39.385	38.468	39.10	39.429	38.30	37.939	37.625
Observed Number of Runs	5	10	8	4	10	9	24	13	16	6	18	9
Expected Number of Runs	15.07	16.75	11.5	7.8571	16.771	12.077	24.404	15.933	13.857	10.10	16.273	12.917
Cases ≥ Test Value	12	14	21	6	12	8	22	14	10	7	21	11
Cases < Test Value	17	18	7	8	23	18	25	16	18	13	12	13
p- Value	0.00	0.022	0.119	0.056	0.017	0.223	0.905	0.384	0.489	0.068	0.638	0.151
	Annual Minimum Temperature											
Test Value K (mean)	12.93	9.594	12.75	9.143	10.00	12.50	10.75	8.333	10.86	11.75	10.91	14.21
Observed Number of Runs	10	6	10	4	7	15	13	11	11	8	11	8
Expected Number of Runs	14.10	16.94	13.21	8	18.14	14	24.49	15.93	14.93	11	10.82	10.92
Cases ≥ Test Value	19	17	9	7	15	13	24	14	15	10	27	7
Cases < Test Value	10	15	19	7	20	13	23	16	13	10	6	17
p- Value	0.130	0.000	0.228	0.052	0.009	0.841	0.001	0.098	0.184	0.253	0.912	0.218
	Annual Mean Temperature											
Test Value K (mean)	25.48	24.02	25.143	23.929	24.714	25.942	24.606	23.717	25.143	25.025	24.424	25.917
Observed Number of Runs	12	12	14	9	6	10	14	10	15	6	16	11
Expected Number of Runs	15.07	17	14.929	7.4286	18.486	14	24.234	16	14.357	8.5	16.758	13
Cases ≥ Test Value	17	16	13	9	17	13	21	15	11	5	20	12
Cases < Test Value	12	16	15	5	18	13	26	15	17	15	13	12
p- Value	0.316	0.106	0.868	0.513	0.000	0.161	0.004	0.041	0.954	0.212	0.920	0.531

Table4.2: Continued.

	Station											
	Ikara	Zaria	Kangimi	Kauru	Birnin Gwari	Kaduna North	Kaduna South	Saminaka	Kachia	Zonkwa	Kafanchan	Kagarko
	Annual Rainfall											
Test Value K (mean)	1118	1115	1301.7	1188	1240.3	1322.5	1385.2	1383.0	1527.7	1703.9	1777.5	1761.2
Observed Number of Runs	8	16	5	6	17	14	11	8	10	16	12	8
Expected Number of Runs	15.35	24.23	14.103	9.2353	19.947	13.692	22.702	15.733	17.364	16.938	18	12.259
Cases ≥ Test Value	13	21	10	10	20	15	17	13	15	15	17	8
Cases < Test Value	16	26	19	7	18	11	30	17	18	17	17	19
p- Value	0.009	0.021	0.000	0.156	0.420	0.900	0.000	0.006	0.014	0.875	0.055	0.075
	Annual Evaporation											
Test Value K (mean)	3065	3020	2951.0	2999.1	2829.9	2351.6	2431.5	2551.6	2519.5	2887.5	2333.8	2408.0
Observed Number of Runs	9	8	10	11	8	4	9	8	6	5	13	9
Expected Number of Runs	15.48	17	12.586	7.8571	16.278	14	24.489	14.333	13.414	9.4	17.485	12.917
Cases ≥ Test Value	14	16	21	6	11	13	24	20	20	14	17	11
Cases < Test Value	15	16	8	8	25	13	23	10	9	6	16	13
p- Value	0.023	0.002	0.319	0.133	0.002	0.000	0.000	0.014	0.002	0.031	0.158	0.156

It is generally recognized that ideal consistent homogeneous time series are difficult to obtain. Therefore, quasi-consistent time series (time series for which adequate corrections have been made for change in measuring equipment and technique, sampling interval and data processing techniques) are considered acceptable for analyses (WMO, 1988). However, homogeneous time series are to be preferred.

Table 4.2a Homogeneity Test Results of Hydro- Climatic Variables

Station		Hydro-Climatic Variables					
		Tmean	Rtotal	Qtotal	Qmax	Qmin	Qmean
Kaduna South	Test Value K (Mean)	24.564	1385.2	55908	1688.	0.770	4637.1
	Observed Number of Runs	15	11	9	10	10	9
	Expected Number of Runs	23.979	22.702	18.69	18.11	19.79	19.158
	Cases ≥ Test Value	20	17	14	13	21	15
	Cases < Test Value	27	30	24	25	17	23
	p-Value	0.007	0.000	0.001	0.003	0.001	0.000

A typical result of probability plot and Anderson-Darling test is presented in Figures 4.1 and 4.1a while the summary of the test results are presented in Table 4.3.The hypotheses for the Anderson-Darling normality test are: H_0 : Sample values come from a normally distributed population and H_1 : Sample values come from a non- normally distributed population. If the normal distribution fits the data, the Anderson –Darling (AD) statistic will be small and the p-value will be greater than the chosen alpha-level. From the results of Anderson-Darling (AD) normality test, there is insufficient evidence to suggest that majority of the meteorological data are from a normally distributed population. Generally, water resources data are non-normal (Figure 4.2) due to the presence of right skewness and outliers and also, the fact that they have a lower bound of zero (that is, negative values are not possible) (Helsel and Hirsch, 2002). Based on the plot and normality test, assume that majority of the data are not from a normally distributed population.

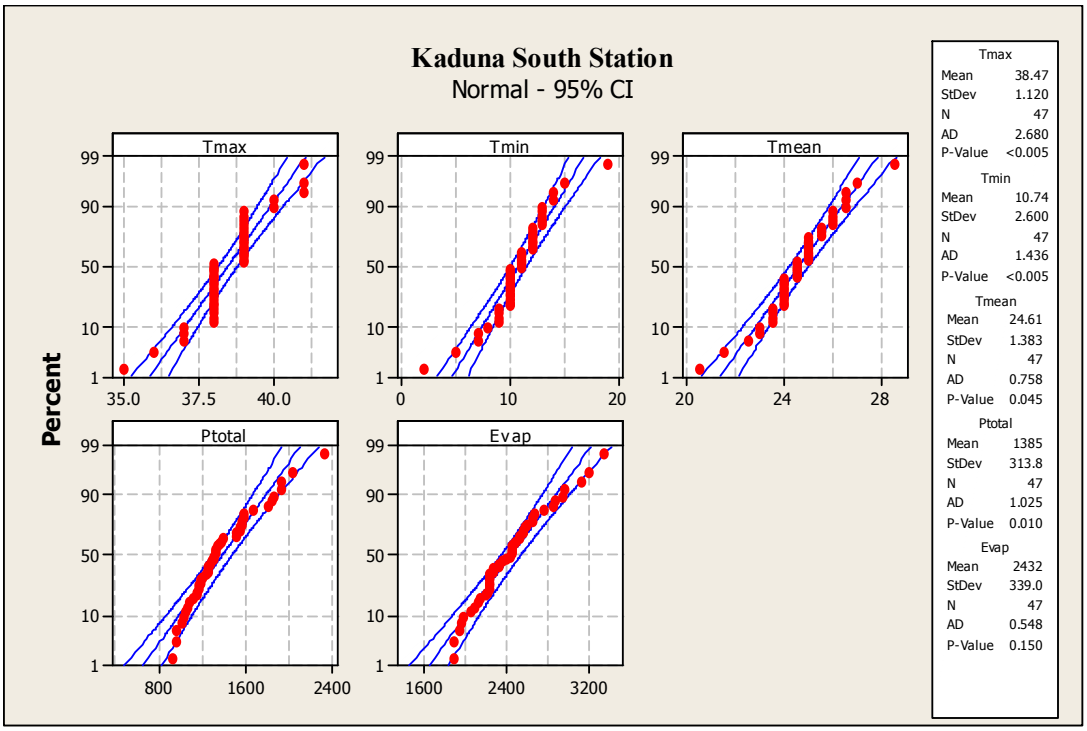


Figure 4.1: Probability Plots and Anderson-Darling (AD) Normality Test Results of Climatic Variables in Kaduna South Station

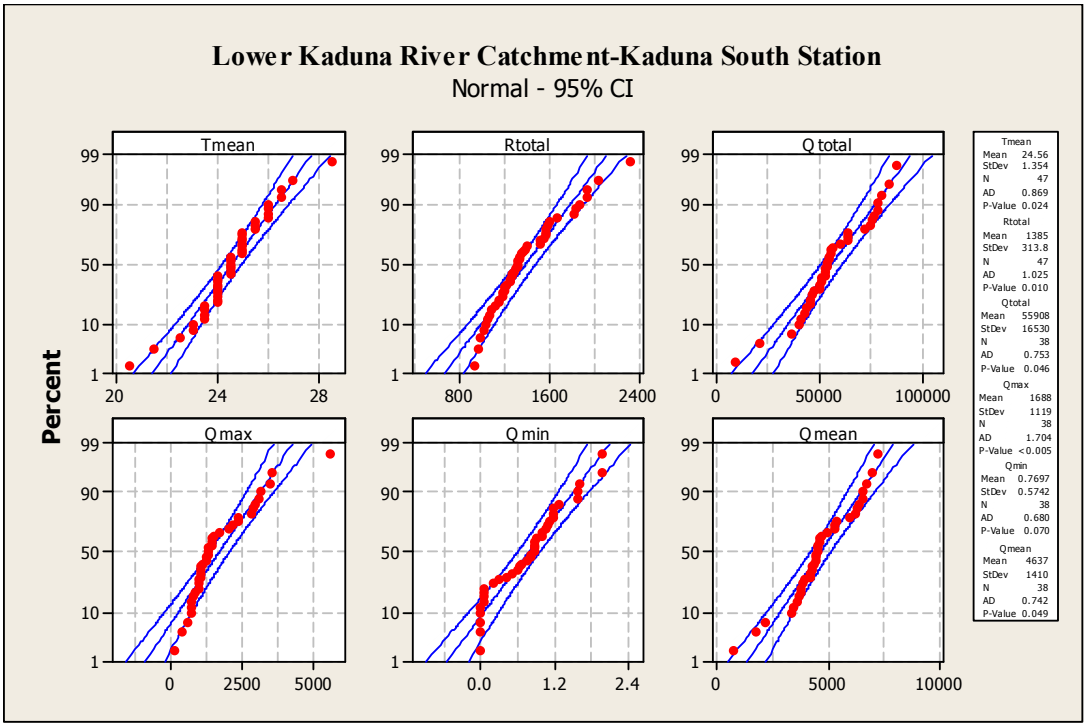


Figure 4.1a: Probability Plots and Anderson-Darling (AD) Normality Test Results of Hydro-Climatic Variables in Kaduna South Station

Table 4.3: Summary of Anderson-Darling (AD) Normality Test Results of Climatic Variables

Statistic	Station											
	Ikara	Zaria	Kangimi	Kauru	Birnin Gwari	Kaduna North	Kaduna South	Saminaka	Kachia	Zonkwa	Kafanchan	Kagarko
	Annual Maximum Temperature											
AD-Statistic	1.19	1.521	2.906	1.977	2.059	2.405	2.680	1.750	1.784	0.802	3.365	2.897
p-Value	<0.005	<0.005	<0.005	<0.005	<0.005	<0.005	<0.005	<0.005	<0.005	0.031	<0.005	<0.005
	Annual Minimum Temperature											
AD-Statistic	0.732	1.197	3.195	1.353	0.469	0.716	1.436	0.459	1.027	0.750	3.804	1.347
p-Value	0.050	<0.005	<0.005	<0.005	0.234	0.054	<0.005	0.245	0.009	0.042	<0.005	<0.005
	Annual Mean Temperature											
AD-Statistic	0.491	0.682	1.050	1.951	0.653	1.960	0.758	0.838	0.694	0.796	2.107	1.638
p-Value	0.202	0.068	0.008	<0.005	0.081	<0.005	0.110	0.027	0.062	0.032	<0.005	<0.005
	Annual Rainfall											
AD-Statistic	0.346	0.861	1.108	0.270	0.270	0.358	1.025	0.365	0.319	0.347	0.720	1.060
p-Value	0.458	0.025	0.006	0.632	0.659	0.426	0.010	0.415	0.519	0.459	0.055	<0.005
	Annual Evaporation											
AD-Statistic	0.111	0.292	1.786	0.720	1.914	0.253	0.548	0.783	1.195	0.580	0.504	0.450
p-Value	0.992	0.585	<0.005	0.046	<0.005	0.708	0.150	0.037	<0.005	0.116	0.190	0.253

Table 4.4: Summary of Results of Climate Variability Analyses

Parameter Measured	Period	Station												Zonal Mean
		Ikara	**Zaria**	**Kangimi**	**Kauru**	**Birnin Gwari**	**Kaduna North**	**Kaduna South**	**Saminaka**	**Kachia**	**Zonkwa**	**Kafanchan**	**Kagarko**	
Annual Maximum Temperature														
Mean	1961-1990	39.385	39.4	38.417	39.30	37.84	38.70	38.40	38.714	39.75	37.50	38.118	37.125	38.55
	1971-2000	38.304	38.6	38.227	38.71	38.76	39.35	38.70	39.167	39.68	38.50	37.926	37.667	38.63
	Diff.	-1.081	-0.80	-0.19	-0.59	0.917	0.65	0.300	0.453	-0.07	1.00	-0.192	0.542	0.080
	% Diff.	-2.75	-2.03	-0.50	-1.50	2.40	1.70	0.78	1.20	-0.17	2.70	-0.50	1.50	0.20
Standard Deviation	1961-1990	0.768	2.03	0.793	2.791	1.573	2.452	1.003	2.128	3.049	0.577	2.233	0.641	1.67
	1971-2000	1.550	1.98	1.066	2.555	2.064	4.056	1.149	1.736	2.297	3.299	1.838	2.249	2.15
	Diff.	0.782	-0.05	0.273	-0.24	0.491	1.604	0.146	-0.392	-0.75	2.722	-0.395	1.608	0.48
	% Diff.	102	-2.27	34.4	-8.50	31.20	65.40	14.60	-18.40	-24.7	471.80	-17.70	250.90	28.74
Trend per Decade	1960-2006	-1.17	-0.99	-1.22	-3.16	1.70	0.610	0.120	0.50	-0.60	0.270	0.010	0.42	-0.29
	p-Value	0.000	0.04	0.033	0.092	0.000	0.532	0.274	0.136	0.247	0.814	0.975	0.481	0.302
C.V.	1960-2006	0.04	0.05	0.062	0.066	0.078	0.092	0.030	0.041	0.055	0.074	0.044	0.053	0.057
Annual Minimum Temperature														
Mean	1961-1990	12.077	6.81	12.000	8.800	9.000	12.700	9.833	9.071	10.17	12.750	11.059	14.250	10.71
	1971-2000	12.609	9.12	12.182	9.143	9.897	12.350	10.533	8.375	10.73	11.857	10.778	14.056	10.97
	Diff.	0.532	2.31	0.182	0.343	0.897	-0.350	0.700	-0.696	0.560	-0.893	-0.281	-0.194	0.26
	% Diff.	4.41	33.8	1.50	3.900	10.00	-2.800	7.100	-7.700	5.500	-7.000	-2.540	-1.400	2.43
Standard Deviation	1961-1990	1.553	2.40	1.809	1.135	1.795	1.494	2.718	1.385	0.718	0.957	1.197	1.282	1.537
	1971-2000	1.901	3.66	1.468	1.099	2.006	1.348	2.945	1.583	1.202	1.460	2.100	1.056	1.819
	Diff.	0.348	1.26	-0.341	-0.04	0.211	-0.146	0.227	0.198	0.484	0.503	0.903	-0.226	0.282
	% Diff.	22.40	52.4	-18.90	-3.20	11.80	-9.800	8.400	14.30	67.41	52.60	75.400	-17.60	18.35
Trend per Decade	1960-2006	1.11	2.92	1.42	0.99	0.790	0.070	0.880	-0.64	0.650	-0.680	0.190	0.400	0.675
	p-Value	0.008	0.00	0.020	0.296	0.042	0.834	0.001	0.078	0.035	0.193	0.596	0.201	0.192
C.V.	1960-2006	0.152	0.36	0.192	0.120	0.234	0.102	0.242	0.210	0.122	0.113	0.018	0.078	0.162

Table 4.4: Continued.

Parameter Measured	Period	Station												Zonal Mean
		Ikara	**Zaria**	**Kangimi**	**Kauru**	**Birnin Gwari**	**Kaduna North**	**Kaduna South**	**Saminaka**	**Kachia**	**Zonkwa**	**Kafanchan**	**Kagarko**	
Annual Mean Temperature														
Mean	1961-1990	25.731	23.1	25.208	24.05	23.42	25.700	24.117	23.893	24.96	25.125	24.588	25.688	24.63
	1971-2000	25.457	23.9	25.205	23.93	24.33	25.850	24.617	23.771	25.21	25.179	24.352	25.861	24.81
	Diff.	-0.274	0.80	-0.003	-0.12	0.91	0.150	0.500	-0.122	0.25	0.054	-0.236	0.173	0.180
	% Diff.	-1.100	3.46	-0.010	-0.50	3.90	0.600	2.100	-0.500	1.000	0.220	-0.960	0.670	0.731
Standard Deviation	1961-1990	1.033	1.56	0.964	1.54	1.017	1.252	1.381	0.881	1.469	0.629	1.228	0.458	1.118
	1971-2000	0.952	1.63	0.766	1.31	1.681	2.046	1.574	0.794	1.250	1.836	1.433	1.148	1.368
	Diff.	-0.081	0.07	-0.198	-0.23	0.664	0.794	0.193	-0.087	-0.22	1.207	0.205	0.690	0.250
	% Diff.	-7.840	4.40	-20.50	-14.5	65.30	63.40	14.000	-9.900	-14.9	191.90	16.700	150.70	22.36
Trend per Decade	1960-2006	-0.040	0.97	0.100	-1.09	1.250	0.340	0.480	-0.070	0.03	-0.210	0.080	0.420	0.188
	p-Value	0.833	0.00	0.752	0.251	0.000	0.497	0.000	0.709	0.930	0.742	0.712	0.187	0.468
C.V.	1960-2006	0.036	0.06	0.042	0.055	-0.07	0.072	0.056	0.040	0.047	0.062	0.054	0.041	0.041
Annual Rainfall														
Mean	1961-1990	934.50	980	1084.7	1285	1198	1142.9	1260.6	1133.90	1424	1499.8	1568.70	1642.0	1263
	1971-2000	1022.8	1104	1196.7	1188	1227	1305.1	1298.5	1306.4	1449	1619.2	1720.20	1751.0	1349
	Diff.	88.300	124	112.00	-97.0	29.0	162.20	37.90	172.50	25.00	119.40	151.50	109.00	86.00
	% Diff.	9.500	12.7	10.30	-7.50	2.400	14.20	3.00	15.20	1.800	8.00	9.700	6.60	6.81
Standard Deviation	1961-1990	157.10	281	170.40	225.3	146.4	281.4	189.20	180.40	201.5	267.40	308.10	644.00	254.4
	1971-2000	198.70	311	247.80	272.0	168.5	296.7	275.70	278.30	285.5	400.20	369.00	594.00	308.1
	Diff.	41.60	30.0	77.40	46.70	22.10	14.30	86.50	97.90	84.00	132.80	60.90	-50.00	53.70
	% Diff.	26.50	10.4	45.40	20.73	15.10	5.10	45.70	54.30	41.70	49.70	19.80	-7.800	21.11
Trend per Decade	1960-2006	225.56	55.9	266.60	-199	35.02	154.13	100.00	284.02	152.1	208.55	168.80	89.22	128.4
	p-Value	0.000	0.05	0.000	0.122	0.155	0.022	0.002	0.000	0.007	0.005	0.005	0.544	0.076
C.V.	1960-2006	0.247	0.28	0.274	0.227	0.133	0.200	0.229	0.223	0.210	0.246	0.202	0.330	0.233

Table 4.4: Continued.

Parameter Measured	Period	Station												Zonal Mean
		Ikara	**Zaria**	**Kangimi**	**Kauru**	**Birnin Gwari**	**Kaduna North**	**Kaduna South**	**Saminaka**	**Kachia**	**Zonkwa**	**Kafanchan**	**Kagarko**	
Annual Evaporation														
Mean	1961-1990	3294.8	2925	3160.4	2954	2573	2563.8	2300.7	2821.6	2643	2863.5	2414.10	2460.0	2748
	1971-2000	3062.6	2952	2919.4	2999	2598	2406.2	2332.3	2671.5	2493	2714.0	2325.70	2370.4	2654
	Diff.	-232.2	27.0	-241.00	45.00	25.00	-157.6	31.60	-150.10	-150	-149.50	-88.40	-89.60	-94.0
	% Diff.	-7.050	0.92	-7.60	1.53	0.97	-6.20	1.40	-5.30	-5.70	-5.20	-3.70	-3.60	-3.42
Standard Deviation	1961-1990	333.50	243	170.40	93.90	422.1	138.60	206.60	242.20	139.2	159.10	195.80	153.70	208.2
	1971-2000	414.40	288	423.80	158.6	389.5	264.30	338.90	313.60	275.5	490.00	313.80	218.00	324.0
	Diff.	80.90	45.0	253.10	64.70	-32.6	125.70	132.30	71.40	136.3	330.90	118.00	64.30	115.8
	% Diff.	24.30	18.6	148.30	68.9	-7.70	90.70	64.00	29.50	97.90	208.00	60.30	41.80	55.62
Trend per Decade	1960-2006	-108.5	86.8	-55.00	146.8	397.2	181.97	99.27	268.00	14.37	642.49	-49.88	57.21	140.1
	p-Value	0.203	0.08	0.464	0.152	0.000	0.006	0.002	0.000	0.823	0.005	0.352	0.413	0.208
C.V.	1960-2006	0.124	0.10	0.133	0.053	0.225	0.113	0.139	0.155	0.111	0.190	0.124	0.102	0.131

4.1.2 Climate Variability over the Kaduna State of Nigeria

The variability of the climatic elements, temperatures, rainfall and evaporation, were assessed using the following approaches:

1. Comparison of the means and standard deviations of the climate variables between two time scales, 1961-1990 (current climate) and 1971-2000 in all the stations to determine the change in the statistics of the climatic vriables.
2. Computation of the annual coefficient of variations (CV) of the climate variables for the time period 1960- 2006 for all the stations.
3. The Time Series analyses which include the trends variations of the climate variables to estimate the annual or decadal trends or variations in the climatic time series and Time series analyses of the climatic variables (temperatures, rainfall and evaporation) to identify the Auto regressive Moving Average (ARMA) models appropriate for the forecast of the climate variables
4. The analyses of the annual anomalies of the climatic time series.

The results of the climate variability analyses using approaches (1) and (2) and that of trends analyses are presented in Table 4.4 while the time series plots and linear trend models for Kaduna South gauging station are presented graphically in Figures 4.2a to 4.2e.

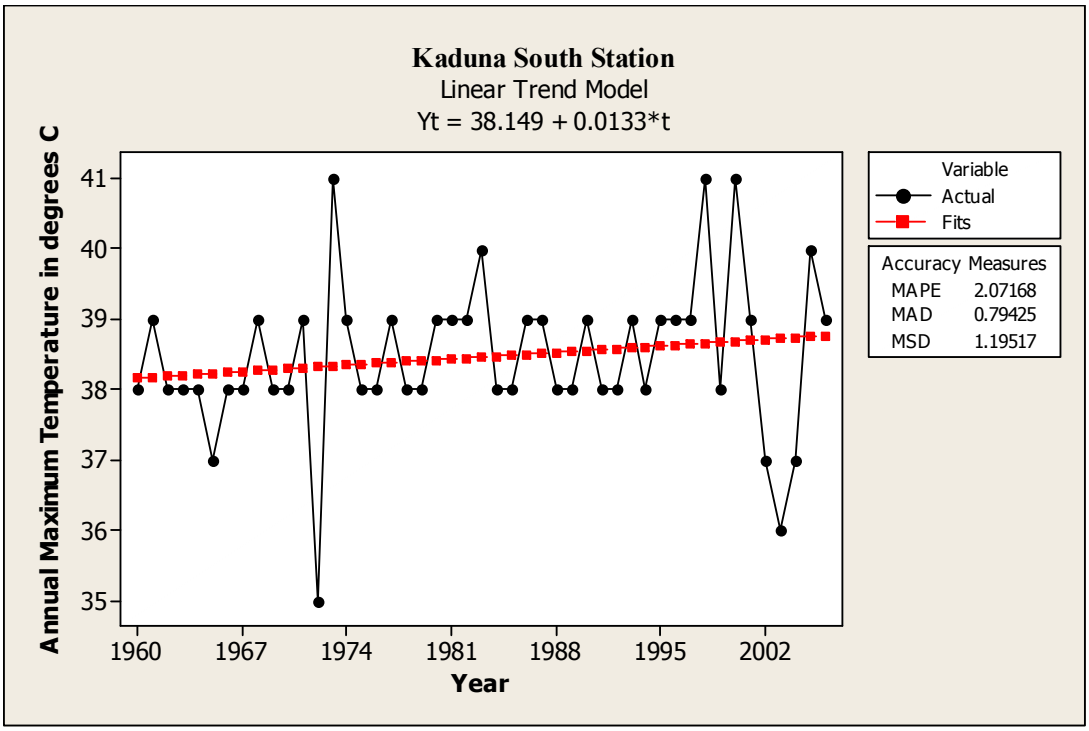


Figure 4.2a: Trend Analysis Plot for Annual Maximum Temperature

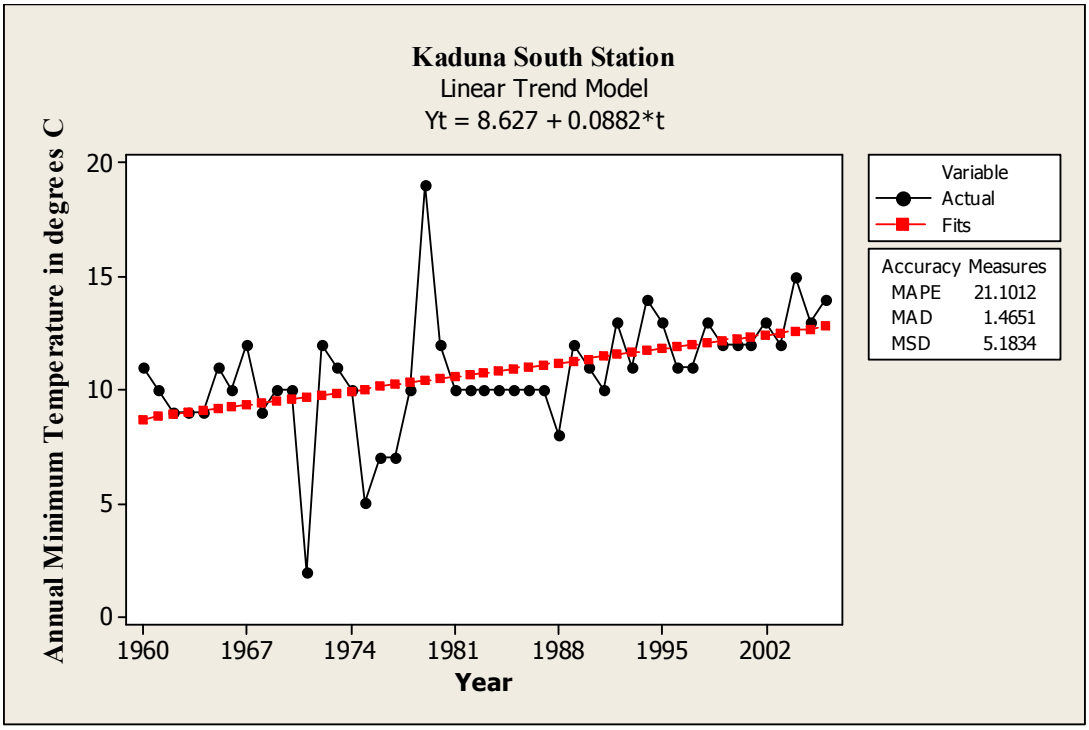


Figure 4.2b: Trend Analysis Plot for Annual Minimum Temperature

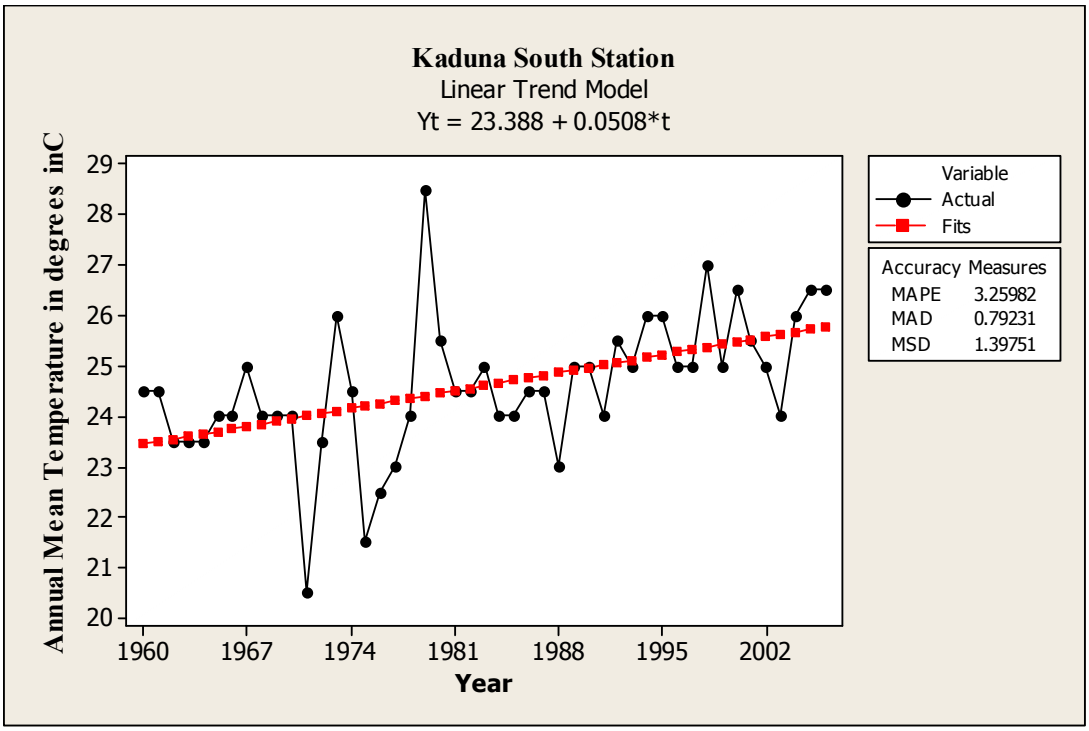


Figure 4.2c: Trend Analysis Plot for Annual Mean Temperature

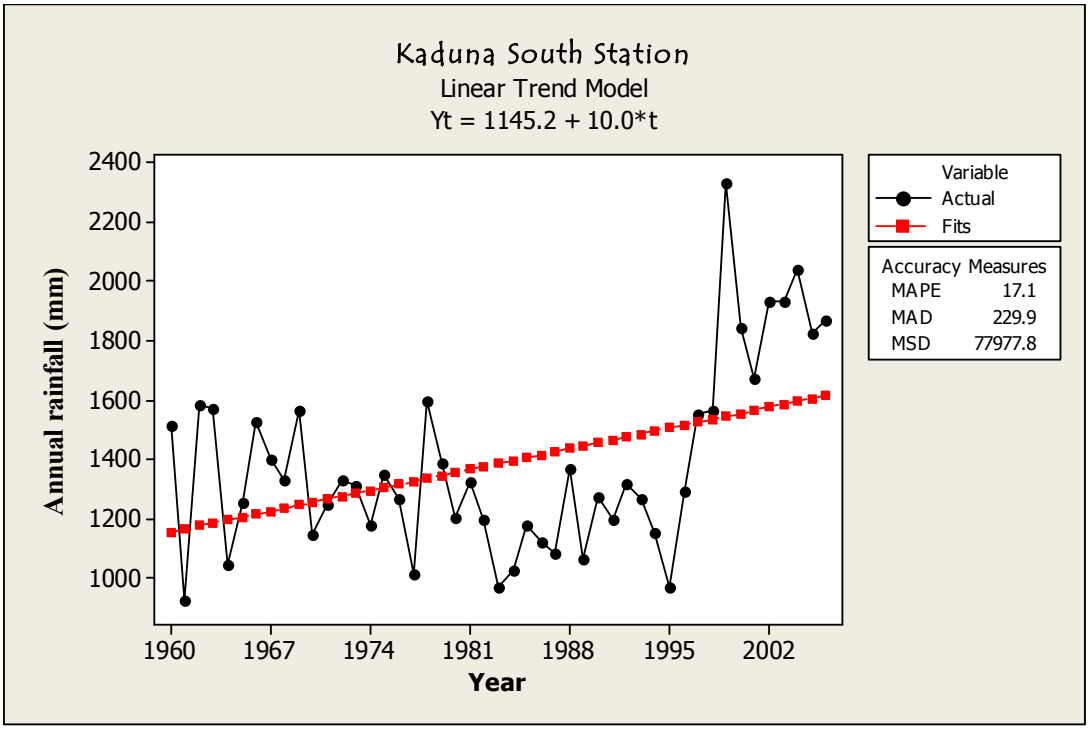


Figure 4.2d: Trend Analysis Plot for Annual Rainfall

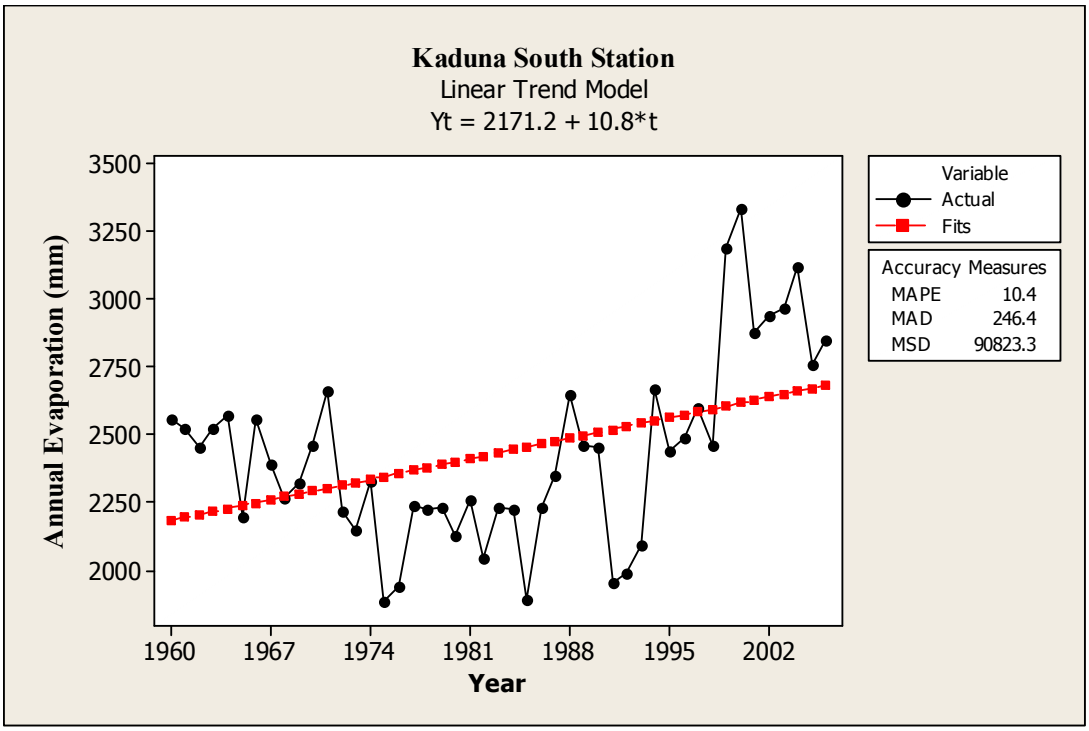


Figure 4.2e: Trend Analysis Plot for Annual Evaporation

4.1.2.1. Times Series Analysis of the Climate Variables

The major problem with the use of linear regression models in the analysis of climate data is that climate data are usually autocorrelated, that is, the terms cannot be taken as independent. Autocorrelated data are appropriately analyzed using time series models (Richard et al, 2007). The approach used in this study was to assume that the climate variables (temperature, rainfall and evaporation) form an autoregressive moving average (ARMA) process. Using Equations 2.17, 2.20 and 2.23, the appropriate ARMA models were obtained through the process of model identification, model parameter estimation and model validation or diagnosis as follows:

1. The Autocorrelation functions (ACF) and the Partial Autocorrelation functions (PACF) of the climate data from Kaduna South station (temperature, rainfall and evaporation) were ploted and presented in Figures 4.3 to 4.7.
2. The ACF and PACF plots (Figures 4.3 – 4.7) indicate that the annual maximum temperature, annual minimum temperature, annual mean temperature, annual rainfall and annual evaporation time series are stationary and serially independent and therefore do not require differencing (that is d = 0, Equation 2.7).

3. Also, from Figures 4.3 to 4.7, it can be observed that there is only one significant pike in each of the PACF plots, indicating that the autoregressive process would be of the order one (p =1) with the moving average process of the same order one, that is , d is zero.

The appropriate ARMA model to fit the climate states is ARMA (1, 1) or its equivalent ARIMA (1, 0, 1).

1. The identified ARMA model parameters were estimated through SPSS software application of the least-square and maximum likelihood methods baesd on Equations 2.31 and 2.32 and the results are presented in Tables 4.5 and 4.6.
2. The model parameters in Table 4.5 are all significant except the moving average process parameter in annual maximum and minimum temperatures.
3. The models were validated by the Pearson Product Moment Coefficient (R).

From Table 4.6, the stationary R-squared ranged from 0.794 to 0.962 (79.4% to 96.2% of the variance explained) which are high enough to consider the models as adequate for the forecast of the climate variables within the Study area in Kaduna State of Nigeria.

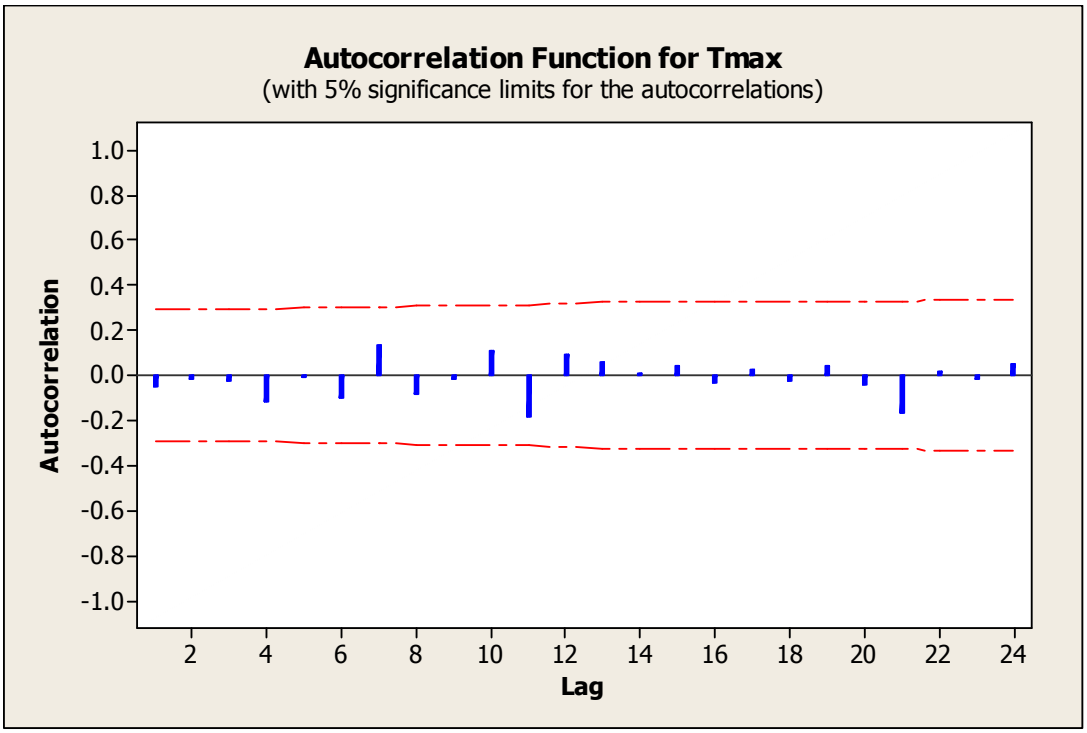


Figure 4.3a: ACF Plot of Annual Maximum Temperature from Kaduna South Station

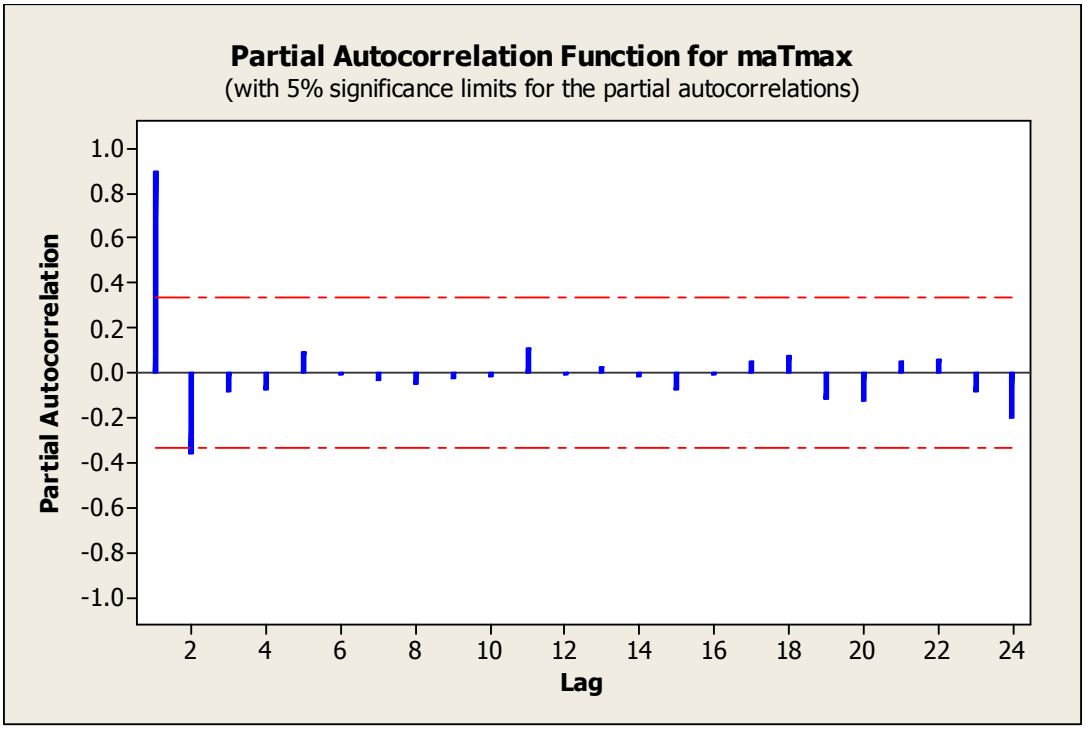


Figure 4.3b: PACF Plot of Annual Maximum Temperature from Kaduna South Station

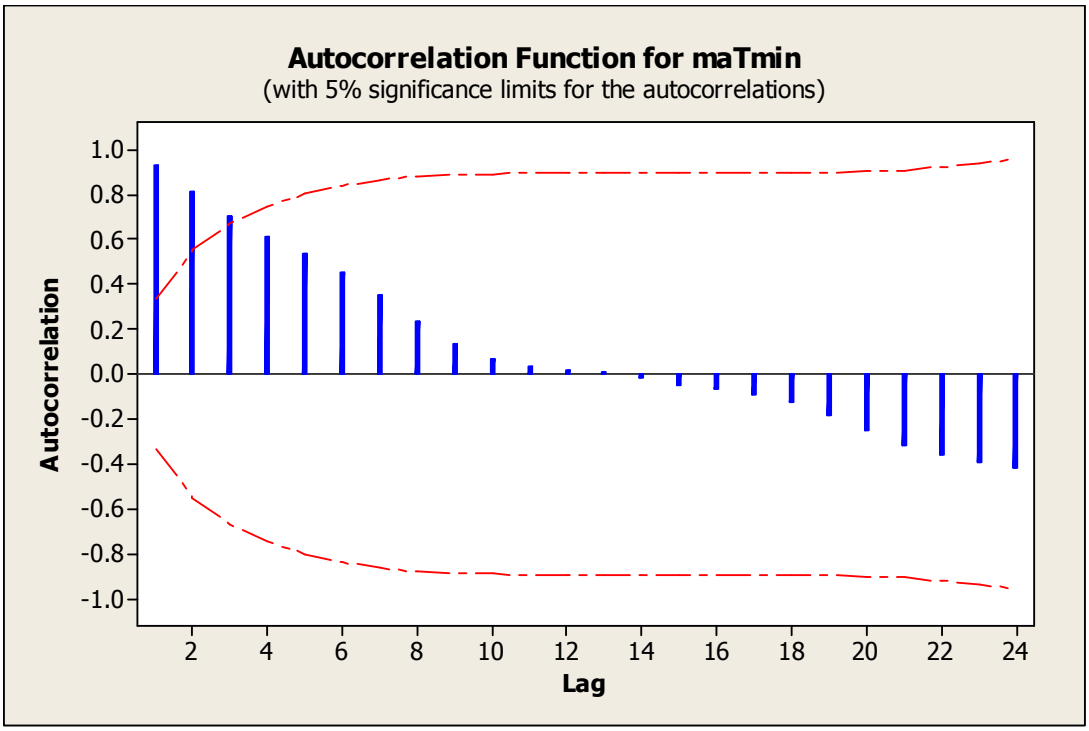


Figure 4.4a: ACF Plot of the Annual Minimum Temperature from Kaduna South Station

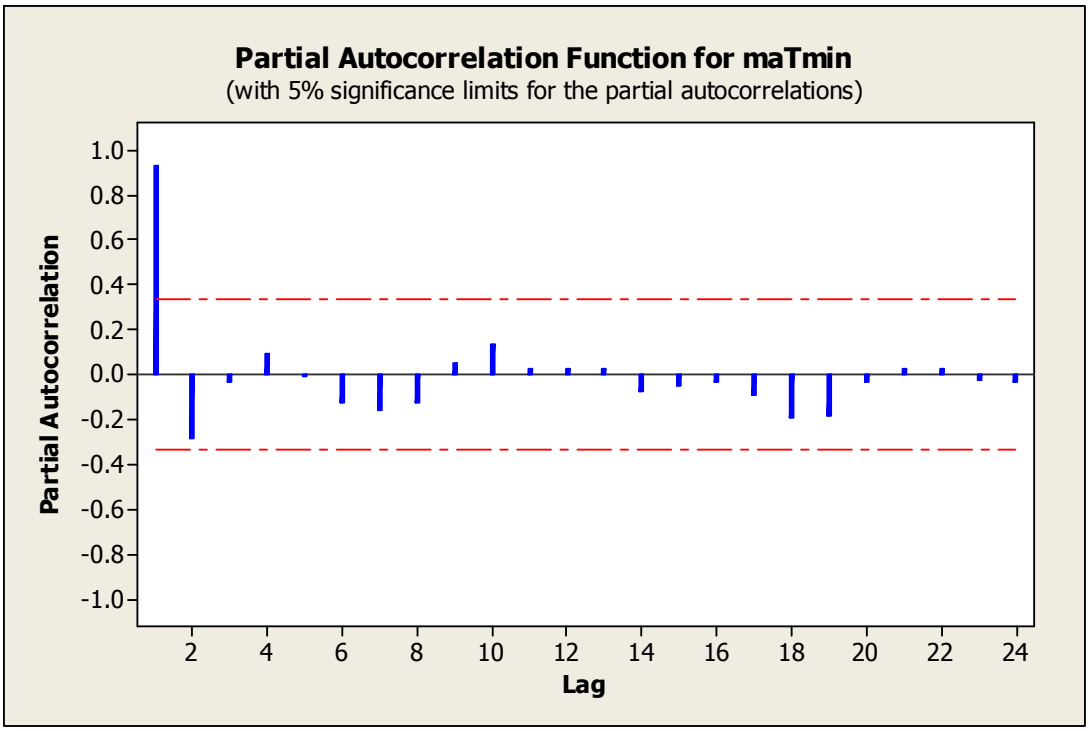


Figure 4.4b: PACF Plot of Annual Minimum Temperature from Kaduna South Station

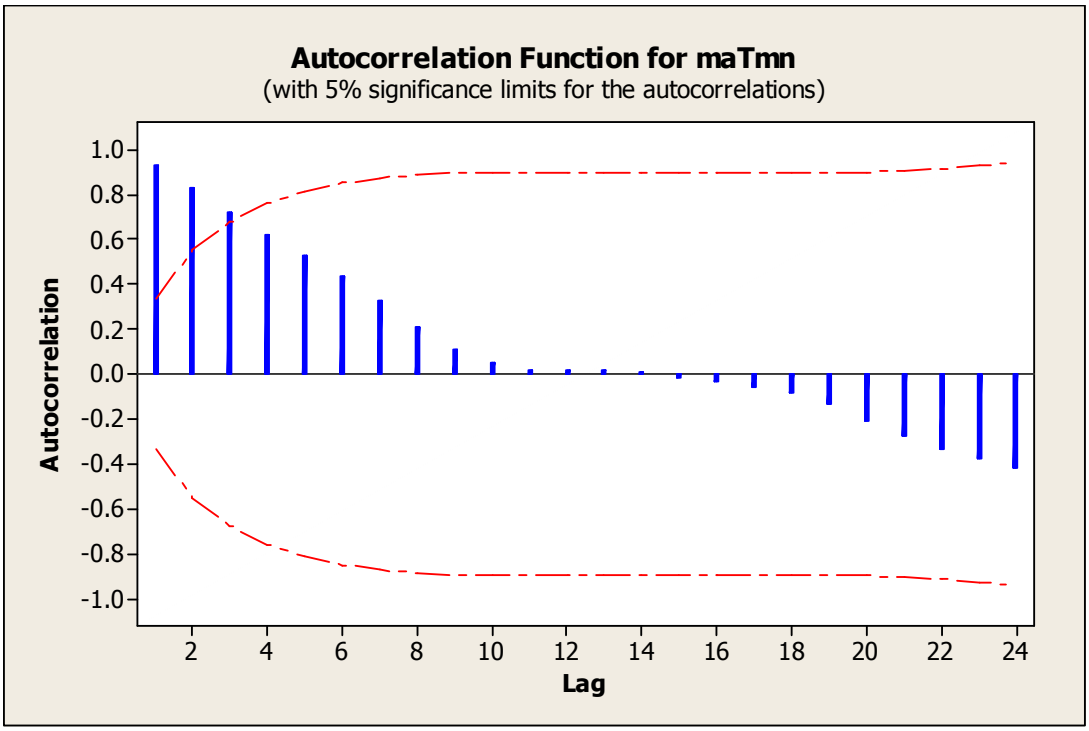


Figure 4.5a: ACF Plot of Annual Mean Temperature from Kaduna South Station

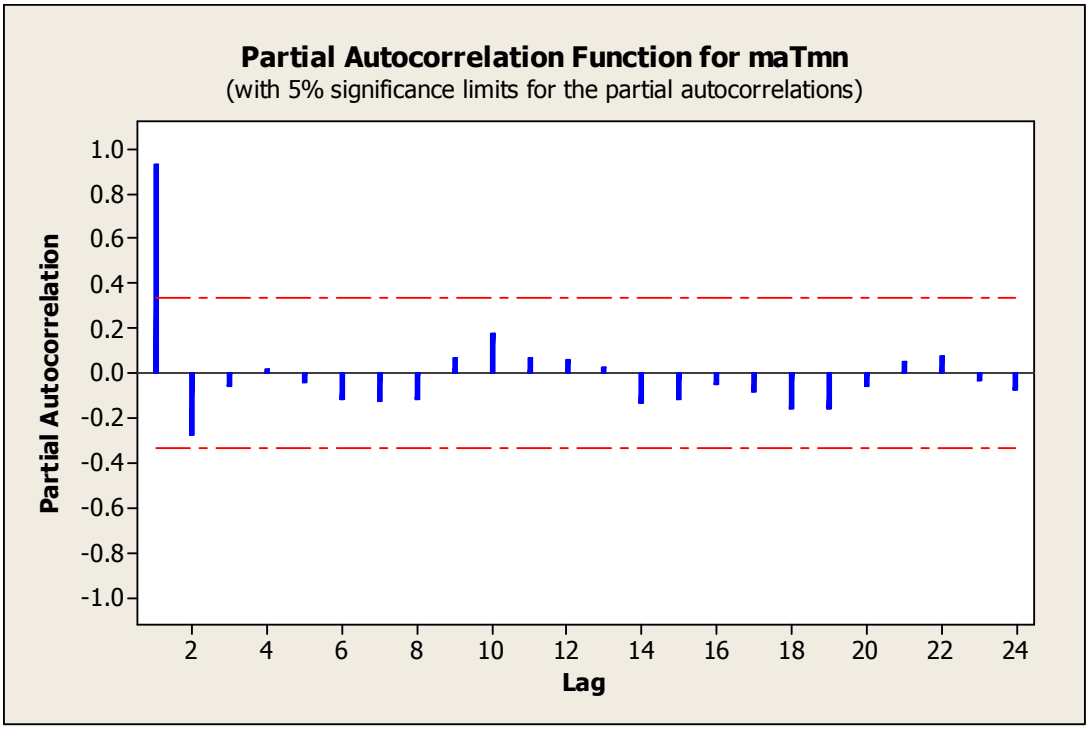


Figure 4.5b: PACF Plot of Annual Mean Temperature from Kaduna South Station

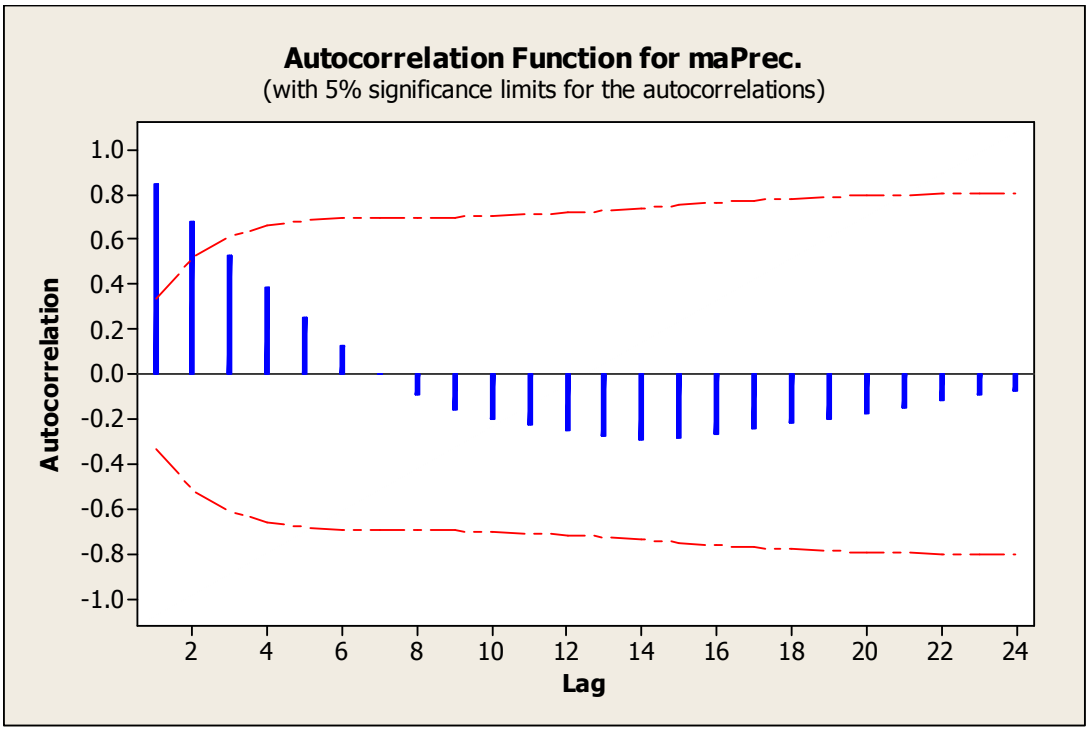


Figure 4.6a :ACF Plot of Annual Rainfall from Kaduna South Station

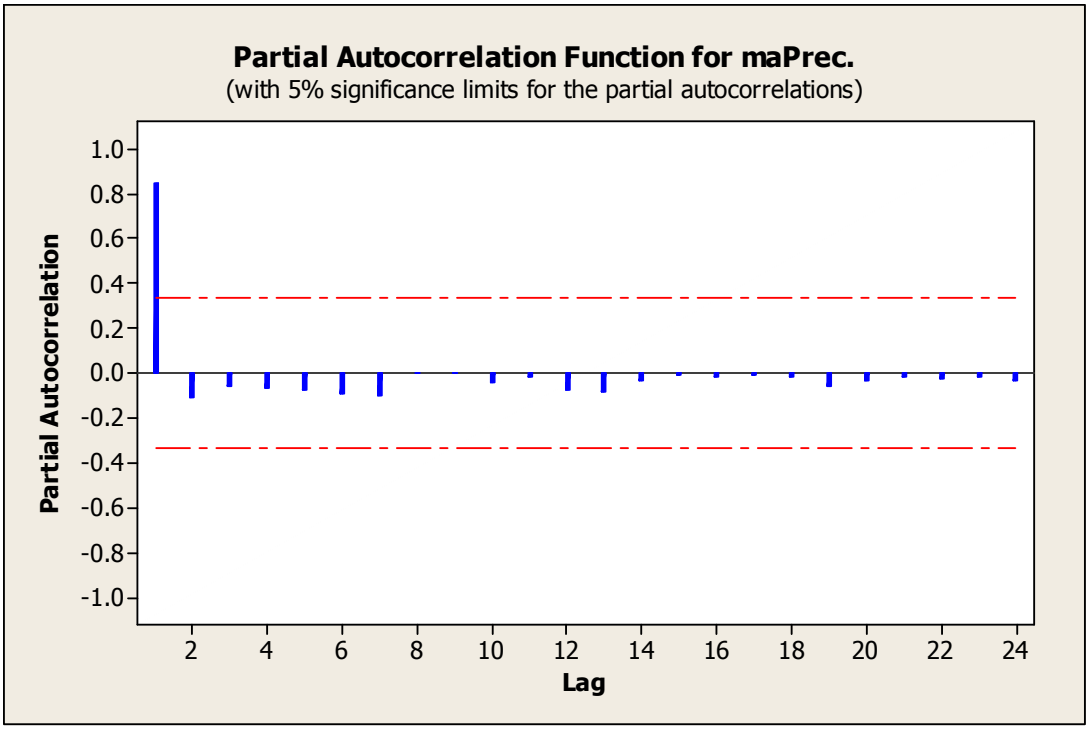


Figure 4.6b :PACF Plot of Annual Rainfall from Kaduna South Station

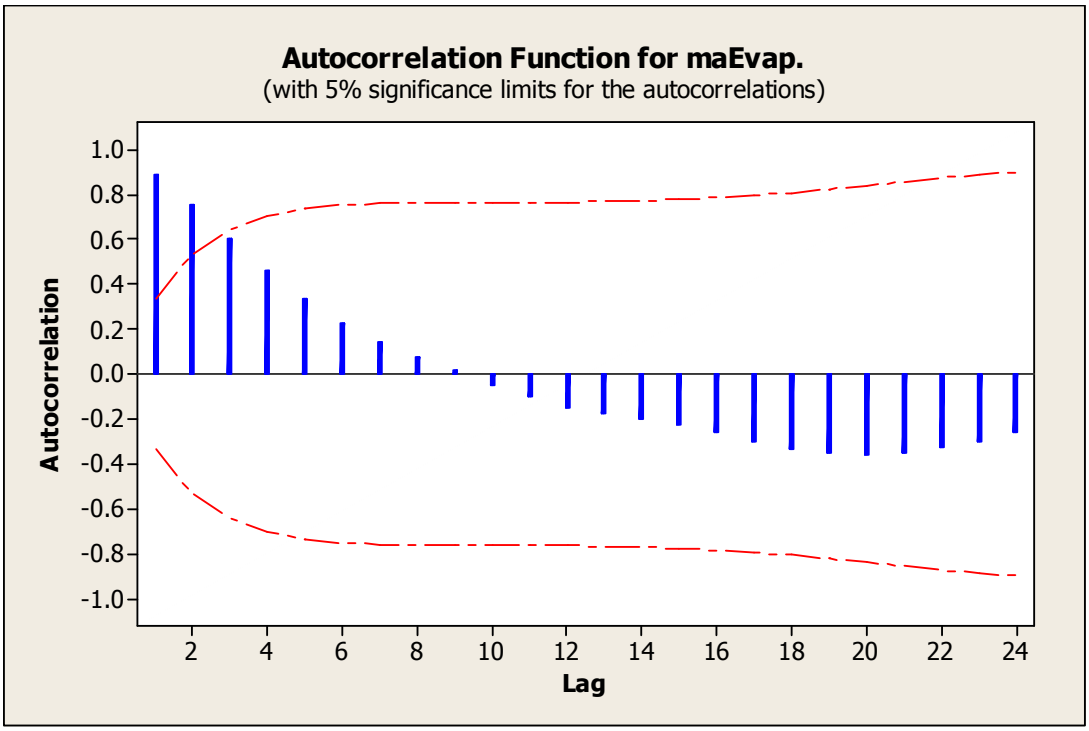


Figure 4.7a :ACF Plot of Annual Evaporation from Kaduna South Station

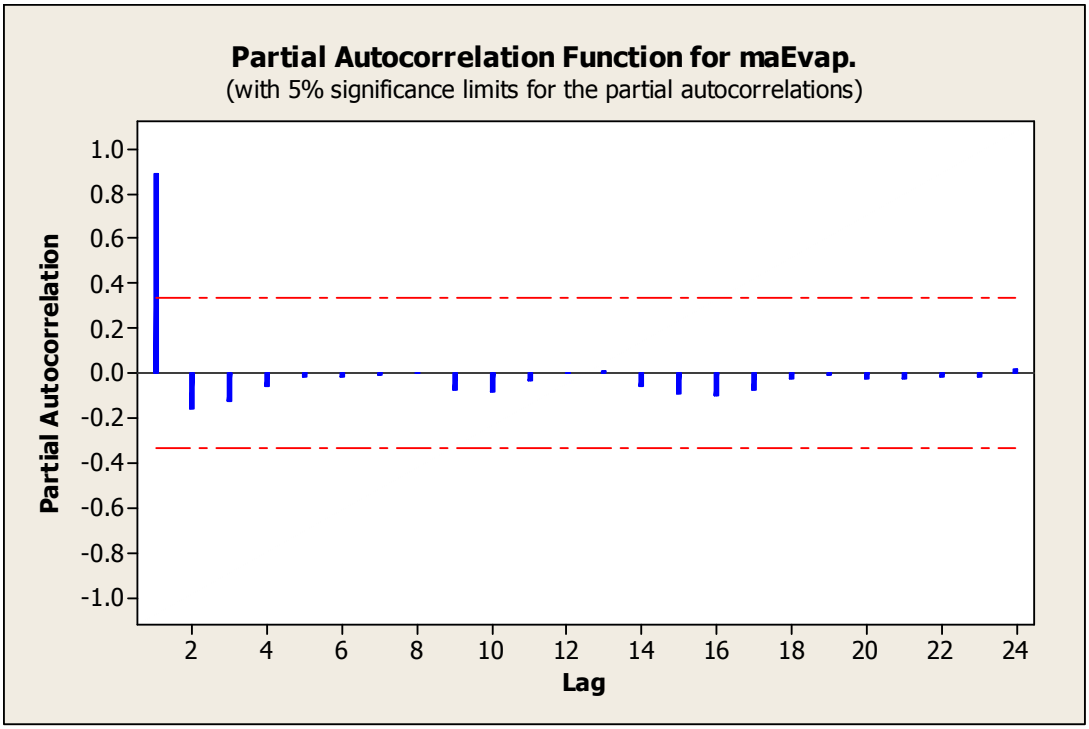


Figure 4.7b: PACF Plot of Annual Evaporation from Kaduna South Station

Table 4.5 ARMA Model Parameter Estimates

S/N		Parameter	Estimate	Standard	t	Sig.

				Error		
1	Annual Maximum Temperature (Tmax)	∅	0.625	0.189	3.298	0.002
		θ	-0.138	0.242	-0.571	0.572
2	Annual Minimum Temperature (Tmin)	∅	0.941	0.069	13.585	0.000
		θ	-0.210	0.180	-1.169	0.250
3	Annual Mean Temperature (Tmn)	∅	0.921	0.076	12.167	0.000
		θ	-0.365	0.170	-2.149	0.039
4	Annual Rainfall (Rt)	∅	0.979	0.047	20.678	0.000
		θ	-0.506	0.156	-3.245	0.003
5	Annual Evaporation (Evapo)	∅	0.982	0.036	26.954	0.000
		θ	-0.529	0.150	-3.537	0.001

Table 4.6 Models Fit Statistics

Model	Number of Predictors	Stationary R-squared	Ljung.Box Q			Number of Outliners
			Statistics	DF	Sig.	
Tmax	1	0.794	8.846	16	0.920	0
Tmin	1	0.902	32.042	16	0.010	0
Tmn	1	0.928	22.252	16	0.135	0
Pt	1	0.935	15.113	16	0.516	0
Evapo.	1	0.962	23.934	16	0.091	0

4.1.2.2. Anomalies of the Climate Variables

Based on the computation of the standardized anomaly indices (SAI) and anomalies (Equations 3.15, 3.16 and 2.55) relative to 1961-1990 baseline climate variables, the results of the variability of the climatic elements, annual maximum temperature in degrees Celsius (T_{max}), annual minimum temperature in degrees Celsius (T_{min}) and annual mean temperature in degrees Celsius (T_{mn}), annual rainfall in millimeters (Pt) and annual evaporation in millimeters (Evapo) in terms of the Anomalies (TmaxA,TminA, TmnA, PtA and EvapA) for the Study Area are presented graphically in Figures 4.8a to 4.8d.

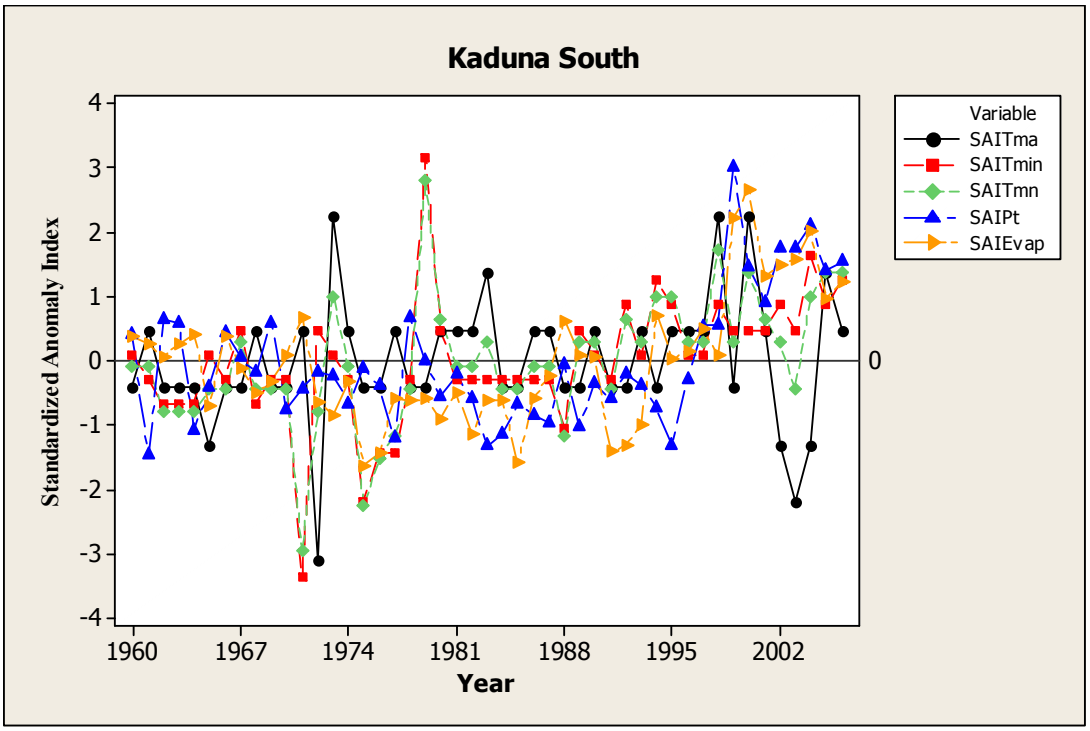


Figure 4.8a: Standardized Anomaly Index for Temperatures, Rainfall and Evaporation

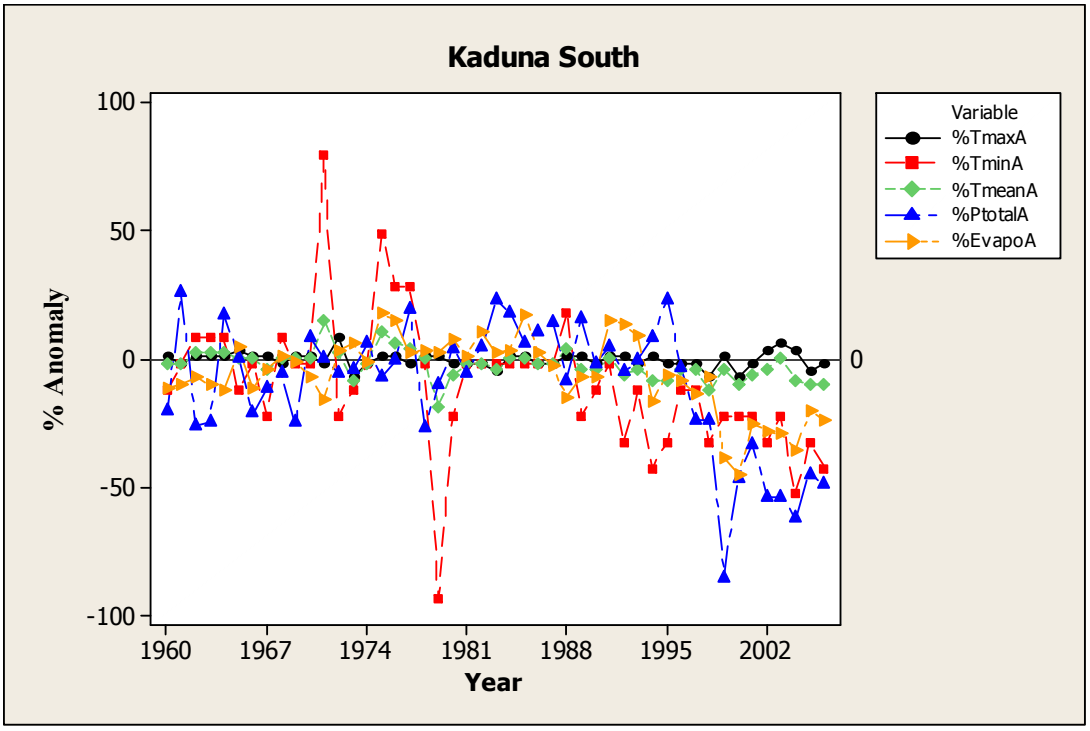


Figure 4.8b :%Anomalies of Temperatures, Rainfall and Evaporation relative to 1961-1990

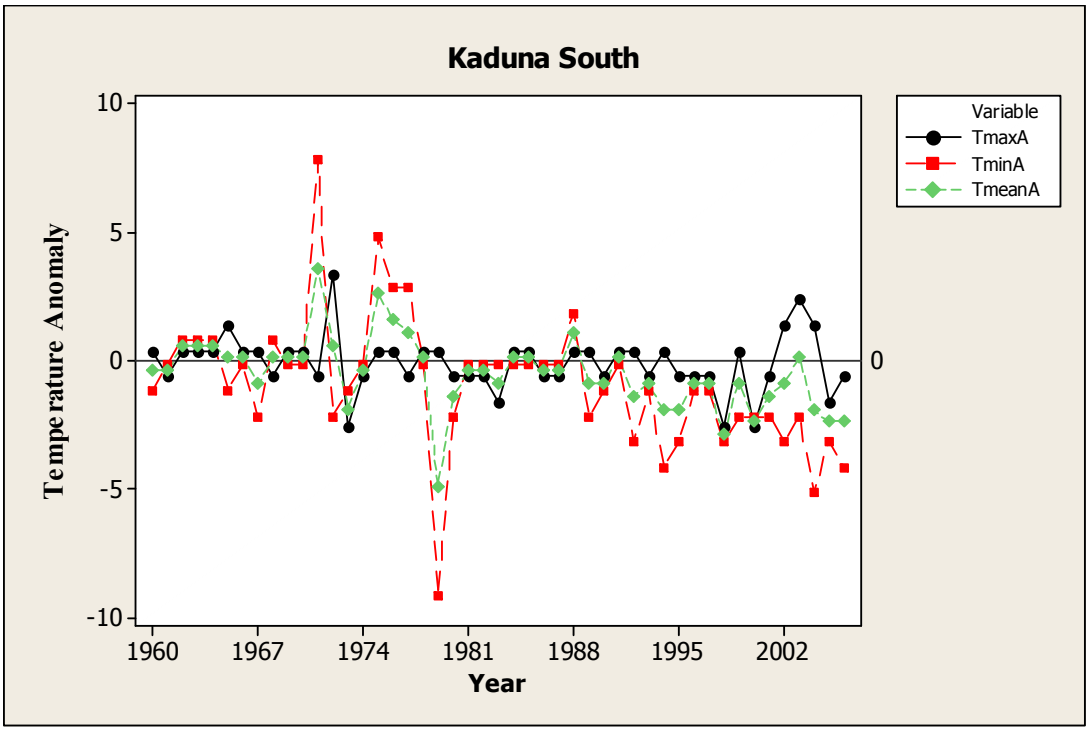


Figure 4.8c: Temperature Anomalies relative to 1961-1990

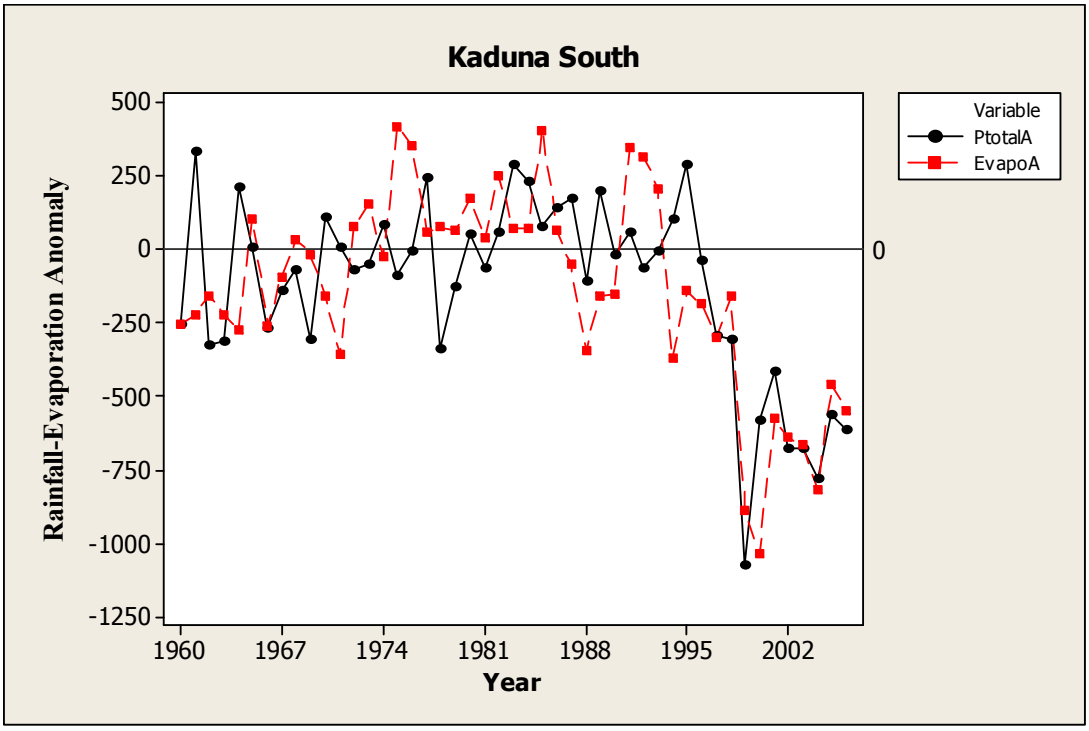


Figure 4.8d: Rainfall and Evaporation Anomalies relative to 1961-1990

4.2.1 Discussion of Results of Climate Variability Analyses

Climate variability is a function of the variability of climate elements, temperatures, rainfall and evaporation, the variability of which are discussed below

4.2.1.1 Annual Maximum Temperature (T_{max}) Variability and Trend

From Table 4.1, the mean annual maximum temperature (Tmax) ranged from 37.5℃ in Kangimi to 39.4℃ in Birnin Gwari with the average for Kaduna State of 38.54℃ . The standard deviation, ranged from 1.12℃ in Kaduna South station to 3.62℃ in Kaduna North station with a zonal average of 2.23℃ . The maximum values ranged from 38℃ to 54℃ with a state average of 44.92℃ while the minimum values ranged from 30℃ to 37℃ with a State average of 35.25℃. The annual maximum temperature exhibited right skew ness (Table 4.1) except in Ikara, Kangimi, Kaduna South and Saminaka stations. Kurtosis is a measure of data peakness or flatness relative to normal distribution. Normal distribution has zero kurtosis. Positive kurtosis indicates peaked distribution while negative kurtosis indicates flat distribution. From the results in Table4.1, T_{max} exhibited peaked distribution except in Ikara.

From Table 4.4, the differences in the mean value of the annual maximum temperature (Tmax) between the two time scales 1961-1990 and 1971- 2000 were positive in Birnin Gwari, Kaduna North, Kaduna South, Saminaka, Zonkwa and Kagarko, indicating increase in the mean value of T_{max} relative to the 1961-1990 mean value. The increase ranged from 0.3℃ (0.8%) in Kaduna South to 0.92℃ (2.4%) in Birnin Gwari. The declines in the mean of Tmax were indicated in Ikara (-1.08℃ or -2.75%), Zaria (-0.8℃ or -2.0%), Kangimi (-0.2℃ or -0.5%), Kauru (-0.6℃ or -1.5%), Kachia (-0.07℃ or -0.2%), and Kafanchan (-0.2℃ or -0.5%). The State average increase in the mean annual maximum temperature (T_{max}) was 0.08℃ , indicating warming, though, low. This has implication for global warming

The differences in the standard deviation between the two time scales, 1961-1990 and 1971-2000, were positive except in Zaria (-0.05℃ or -2.3%), Kauru (-0.24℃ or -8.5%), Saminaka (-0.4℃ or-18.4%), Kachia (-0.75℃ or -24.7%) and Kafanchan (-0.4℃ or -17.7%). The positive value indicates increase in the variability of the annual maximum temperature (Tmax) relative to the 1961-1990 value. The increase ranged from 0.2℃(15%) in Kaduna South to 2.72℃ (472%) in Zonkwa with the state average of 0.5℃ . The trends per decade were positive except in Ikara (-1.17℃), Zaria (-0.99℃), Kangimi (-1.22℃), Kauru (-3.16℃), and Kachia (-0.6℃) (Table 4.4) but statistically significant only in Ikara, Birnin Gwari, Kangimi and Zaria. The positive trends indicate increase in the T_{max} while negative trends indicate decline in the Tmax. The average state trend per decade was -0.3℃ which is cooling. The coefficient of variations which measure the variability of the climate elements, range from 0.03 to 0.092 (3% to 9%) with the state average of 0.06 (6%), indicating low variability (CV < 0.1or 10%)(Durdu, 2009).

From Figures 4.8 and A1 to A11(Appendix), the annual maximum temperature increased by more than 20% in Birnin Gwari (12.2℃ or 32%), Kaduna North (15.3℃

or 40%), Kachia (8.3℃ or 21%), Zonkwa (9.5℃ or 25%), Kafanchan (7.88℃ or 21%) and Kagarko (8.88℃ or 24%) relative to 1961-1990 mean value. These increases were recorded in Kaduna State, respectively, in 2006, 1993, 1980, 1999, 1985, and 1998.In Birnin Gwari, there was a general increase in Tmax from 1992 to 2006 while in Saminaka, the increase was steady from 1982 to 2006. The hottest year within the state was 1993 with day time maximum temperature increase of 15.3℃. The decline in the Tmax ranges from -0.12℃ (-0.31%) in Kafanchan to -8.42℃ (-22%) in Kangimi relative to the 1961-1990 period.

4.2.1.2 Annual Minimum Temperature (T_{min}) Variability and Trend

From Table 4.1, the mean annual minimum temperature ranged from 8.3℃ to 14.2℃ with the State average of 11.1℃. The standard deviation ranged from 1.1℃ to 3.41℃ with the State average of 1.89℃. The maximum values of Tmin range from 10℃ to 20℃ with the state average of 15.1℃ while the minimum values ranged from 2℃ to 12℃ with the state average of 6.75℃ and state range of 8.35℃. From the values of the median and skew ness in Table 4.4, the annual minimum temperature was right skewed except in Ikara, Kauru, Birnin Gwari, Kaduna South and Kafanchan and exhibits peaked distribution except in Ikara, Kaduna North and Saminaka which were flat.

From Table 4.4, the differences in the mean value of the annual minimum temperature (T_{min}) between the two time scales, 1961-1990 and 1971-2000 were negative in Kaduna North (-0.35℃ or -2.8%), Saminaka (-0.7℃or -7.7%), Zonkwa (-0.9℃or -7%), Kafanchan (-0.3℃ or -2.5%) and Kagarko (-0.2℃ or -1.4%) indicating a decline in the mean value of Tmin relative to 1961-1990 mean value. The decline ranged from -0.9℃ (-7%) to -0.2℃ (-1.4%).Positive variability (increase in the T_{min}) were indicated in Ikara (0.53℃ or 4.4%), Zaria (2.3℃ or 34%), Kangimi (0.2℃ or 1.5%), Kauru (0.34℃ or 3.9%), Birnin Gwari (0.9℃ or 10%), Kaduna South (0.7℃ or 7.1%) and Kachia (0.56℃ or 5.5%). The range of the increase was from 0.2℃ (1.5%) to 2.3℃ (34%). The increase in the annual minimum temperature over the state averaged 0.26℃ which is warming.

The differences in the standard deviation between the two time scales, 1961-1990 and 1971-2000 mean value were positive except in Kangimi (-0.34℃ or -19%), Kauru (-0.04℃ or -3.2%), Kaduna North (-0.15℃ or -9.8%) and Kagarko (-0.23℃ or -18%) (Table 4.4). The increase ranged from 0.21℃ (12%) to 0.9℃ (75.4%) relative to 1961-1990 baseline standard deviation with the state increase of 0.28℃, indicating increase in the variability of the Tmin relative to 1961-1990 mean value. The trends per decade of T_{min} varied from -0.68℃ to 2.92℃ which were statistically significant except in Kafanchan, Kaduna North, Kauru, Kagarko, Zonkwa and Saminaka with state average of 0.68℃ per decade indicating warmer climate in the state . Negative trends were indicated in Saminaka (-0.64℃) and Zonkwa (-0.68℃). The coefficient of variation ranged from 0.08 in Kagarko to 0.36 in Zaria with a state average of 0.2 indicating moderate variability of the annual minimum temperature in the state.

From Figures 4.8 and A1 to A11 (Appendix), the annual minimum temperature exhibited general increase from 1994 - 2006 in Ikara, 1991-2006 in Zaria, 1981-1994 in Kauru, 1991-2004 in Birnin Gwari, 1978-2006 in Kaduna South and 1993-2006 in Kachia except in 2003 relative to 1961-1990 baseline period. The increases in the annual minimum temperature indicate that night times are getting hotter from the 1990s. The major cause of global warming is the increase in the minimum temperature rather than the maximum or mean temperatures. It is the increase in the minimum temperature that melts the polar ice and increase the sea volume and sea level rise. The warmest years were 1998 in Zaria with an increase of 8.2°C (120.2%) and 2004 and 2005 in Kangimi with an increase of 8.0°C (67%) over the 1961-1990 baseline mean value. The overall increase ranged from 0.2°C (2.3%) in Kauru to 8.2°C (120.2%) in Zaria. The coolest year was 1993 in Kafanchan with a minimum temperature decline of 9.1°C (82%) below the 1961-1990 baselines mean value. The maximum increase of 8.2°C and the maximum decline of 9.1°C in the annual minimum temperature indicated in the state were exceedingly higher than the 1.4 – 5.8°C estimated by IPCC (2007) and other researchers (IPCC, 2001 and Odjugo, 2010).

4.2.1.3 Annual Mean Temperature (T_{mn}) Variability and Trend

From Table 4.1, the mean of the annual mean temperature (T_{mn}) ranges from 23.71°C to 25.94°C with the state average of 24.82°C while the standard deviation ranged from 0.87°C to 1.87°C with a state average of 1.34°C. The distribution of Tmn was right skewed except in Saminaka and peaked except in Ikara, Birnin Gwari, and Saminaka. The maximum values of Tmn ranged from 25°C to 33°C with the state average of 28.42°C while the minimum values ranged from 19.5°C to 24.5°C with the state average of 22.3°C.

The differences in the mean of T_{mn} (Table 4.4) between the two time scales 1961-1990 and 1971-2000 were positive except in Ikara (-0.27°C or -1.1%), Kangimi (-0.003°C or -0.01%), Kauru and Saminaka (-0.12°C or -0.5%) and Kafanchan (-0.24°C or -1%). The overall variability ranged from -0.27°C (-1.1%) to 0.91°C (3.9%) with the state average of 0.17°C which was warming, indicating increase in the variability of the annual mean temperature relative to 1961-1990 period and consequently the climate..

The declines in the standard deviation (Table 4.4) relative to 1961-1990 period were indicated in Ikara (-0.08°C or -7.8%), Kangimi (-0.2°C or -20.5%), Kauru (-0.22°C or -14.4%), Saminaka (-0.09°C or -10%) and Kachia (-0.22°C or 15%) while increases were in indicated in Zaria (0.07°C or 4.4%), Birnin Gwari (0.66°C or 65.3%), Kaduna North (0.8°C or 63.4%), Kaduna South (0.2°C or 14%), Zonkwa (1.21°C or 192%), Kafanchan (0.21°C or 16.7%) and Kagarko (0.7°C or 151%). The state average increase in annual mean temperature variability was 0.25°C.

Negative trends (Table 4.4) were indicated in Ikara, Kauru, Saminaka and Zonkwa which are not statistically significant. The positive trends were, also, not significant except in Zaria, Birnin Gwari, and Kaduna South stations. The state average trend is

0.20°C/decade. From the values of the coefficient of variation (Table 4.4), the variability of the annual mean temperature was low with the state average of 0.054 or 5.4%.

From Figures 4.8 and A1 to A11 (Appendix), the T_{mn} anomalies relative to 1961-1990 period varied from 0.08°C (0.34%) in Birnin Gwari to 7.3°C (28.4%) in Kaduna North. Generally, the increase in the annual mean temperature relative to 1961-1990 periods was consistent from the 1990s particularly, in Zaria, Birnin Gwari, Kaduna South, and Kachia. The decline in the annual mean temperature ranged from 0.1°C (0.4 %) to 5.1°C (21%) in Kafanchan. The coolest year was 1993 in Kafanchan.

4.2.1.4 Annual Rainfall (Pt) Variability and Trend

The mean annual rainfall ranged from 1102mm to1777mm with state average of 1402mm (Table 4.1). The standard deviation varied from 165mm to 580mm with the state average of 327mm. The maximum values ranged from 1686mm to 3466mm with the state average of 2154mm while the minimum values ranged from 602mm to 1152mm with state average of 853mm. The distribution of the annual rainfall was right skewed except in Kafanchan and peaked except in Ikara, Zaria, Saminaka, Zonkwa and Kafanchan.

From Table 4.4 the differences in the mean annual rainfall between the time scales, 1961-1990 and 1971-2000, were all positive except in Kauru (-97mm or -7.5%), indicating increases in the annual rainfall above the 1961-1990 mean value. The increases ranged from 25mm (1.8%) in Kachia to 162mm (14.2%) in Kaduna North with the state average of 86mm per decade. Also, from Table 4.4, the differences in the standard deviation were positive except in Kagarko (-50mm or -7.8%), indicating an increase in the variability of the annual rainfall relative to the 1961 – 1990 mean value. The range of increase in the variability of the annual rainfall was from 14mm (5.1%) in Kaduna North to 133mm (50%) in Zonkwa with the state average of 54mm per decade.

The trends per decade were positive except in Kauru (-199mm/decade) which was not statistically significant. The positive trends were significant except in Birnin Gwari, and Kagarko. The range of positive trend was from 25mm/decade in Birnin Gwari to 284mm/decade in Saminaka with the state average of 128mm/decade. The values of the coefficient of variation in Table 4.4 indicate that the variability of the annual rainfall was moderate with the state average coefficient of variation of 0.23 or 23%.

From Figures 4.8 and A1 to A11 (Appendix), general increases were indicated in the annual rainfall from the 1990s in Ikara, Zaria, Kangimi, Kaduna North, Saminaka, Kachia, Zonkwa, and Kafanchan. The wettest year in the state was 1981in Kagarko with an increased in rainfall of 1824mm (111%) relative to 1961-1990 baseline mean value. The high frequency of flood recorded along the banks of River Kaduna (a major River in the Study Area) in the last decade may not be unconnected with the general increase in the annual rainfall ,though urbanization had been showed to have contributed (Alayande and Agunwamba,2010). The highest deficits (declines) of

602mm (40%), 561mm (34%), 554mm (43%), 541mm (47%) , and 456mm (32%) relative to 1961-1990 mean value were recorded in Zonkwa (2000), Kagarko (1988), Kauru (1993), Kaduna North (1981) and Kachia (1995) respectively.

4.2.1.5 Annual Evaporation Variability and Trend

From Table 4.1, the mean of annual evaporation depth ranged from 2352mm to 3065mm with the state average of 2706mm while the standard deviation varied from 169mm to 638mm with the state average of 355mm. The maximum value ranged from 2755mm to 4299mm with the state average of 3398mm while the minimum values ranged from 1084mm to 2759mm with the state average of 1945mm. The distribution of the annual evaporation was right skewed except in Zaria, Kangimi, Kaduna North, Saminaka, Kachia, Zonkwa, and Kafanchan and peaked except in Zaria, Kaduna North, Saminaka and Zonkwa.

From Table 4.4, the differences in the mean between the two time scales, 1961-1990 and 1971-2000 were negative except in Zaria, Kauru, Birnin Gwari, and Kaduna South, indicating decline in the annual evaporation relative to the 1961-1990 baseline mean .The decline ranged from 88mm (3.7%) in Kafanchan to 241mm (7.6%) in Kangimi with the state average decline of 94mm/decade. The differences in the standard deviation between the two time scales were, however, positive except in Birnin Gwari (-33mm or -7.7%), indicating increase in the variability of the annual evaporation relative to 1961-1990 baseline mean value. The range of increase in the variability of the annual evaporation was from 45mm (19%) in Zaria to 331mm (208%) in Zonkwa with the State average of 116mm/decade.

The trends per decade were positive except in Ikara, Kangimi, and Kafanchan (Table 4.4) but statistically significant, only, in Birnin Gwari, Kaduna North, Kaduna South, Saminaka, and Zonkwa. The State average trend was 140mm/decade. The coefficient of variation (CV), which measures the variability of the climate variables, ranged from 0.053 to 0.23 with the state average of 0.13 or 13%, indicating that the variability of the annual evaporation was moderate.

The anomalies were generally negative relative to the 1961-1990 mean value, in Zaria, Birnin Gwari, Kaduna South, Saminaka, and Zonkwa from the 1990s with the highest values of 1726mm (67%) and 1035mm (45%) occurring in Birnin Gwari in 2001 and Kaduna South in 2000 respectively (Figures 4.8 and A1 to A11 (Appendix),). This indicates increases in the annual evaporation over the 1961-1990 mean value. The anomalies were positive in Zaria and Kachia from the 1990s indicating decline in the annual evaporation relative to 1961-1990 mean value. The highest declines were recorded in Birnin Gwari (1489mm or 58%) in 1976, Kafanchan (921mm or 38%) in 1991 and Saminaka (1048mm or 37%) in 2004.

4.3 CLIMATE VARIABILITY IMPACT ON STREAM FLOWS OF STUDY AREA

4.3.1 Results of Climate Variability Impact Estimation

The summary of the results of the estimation of the impacts of Climate Variability on the water resources (streamflows) of Lower Kaduna Catchment are presented in Table4.8 while the trend analyses of hydro-meteorological variables (temperature (T_{mean}), rainfall (R_{total}), Annual discharge (Q_{total}), Annual maximum Discharge (Q_{max}), Annual minimum discharge (Q_{min}) and Annual mean Discharge(Q_{mean})) for the time scales1960-2006, 1961-1990 and 1971-2000 are presented graphically in Figures 4.9 to 4.20.The descriptive statistics are presented in Table 4.7. The results of trend analyses are presented in Figures 4.9 to 4.20.

Table 4.7: Descriptive Statistics of the Hydro-climatic Variables of the Study Area

Hydro-climatic Variables	Statistics								
	Number	Range	Minimum	Maximum	Mean	Standard Deviation	Skewness	Kurtosis	Coefficient of Variation
Annual mean Temperature	47	8.0	20.5	28.5	24.606	1.3829	-0.154	1.781	0.0562
Annual Rainfall	47	1407	926	2333	1385.21	313.810	0.953	0.687	0.2265
Annual Total Discharge	38	71755	8906	80661	55126.95	15497.556	-0.526	1.223	0.2811
Annual Maximum Discharge	38	5512	126	5638	1614.34	1060.243	1.791	4.463	0.6568
Annual Minimum Discharge	38	2.00	0.00	2.00	0.7697	0.57419	0.265	-0.571	0.7460
Mean Monthly Discharge	38	5980	742	6722	4572.00	1325.150	-0.557	1.015	0.2898

Table 4.8 Climate Variability Impact on Stream flows of Study Area

Statistical Parameters	Period	Tmean.	Rtotal	Qtotal	Qmax	Qmin	Qmean
Mean	1961-1990	24.117	1260.6	48380	1205	0.853	3997
	1971-2000	24.617	1298.5	53761	1691	0.694	4452
	Diff.	0.50	37.90	5381	486	-0.159	455
	% Diff.	2.07	3.00	11.12	40.33	-18.64	11.38
Standard Deviation	1961-1990	1.361	189.2	13326	656	0.590	1155
	1971-2000	1.574	275.7	16060	1147	0.577	1377
	Diff.	0.193	86.50	2734	491	-0.013	222
	% Diff.	14.0	45.72	20.52	74.9	-2.20	19.22
Maximum Value	1961-1990	28.5	1597.0	78631	2898	2.00	6552
	1971-2000	28.5	2333.0	78631	5638	2.00	6552
	Diff.	0.00	736.0	0.00	2740	0.00	0.00
	% Diff.	0.00	46.10	0.00	94.60	0.00	0.00
Minimum value	1961-1990	20.50	926.0	8906	126	0.00	742
	1971-2000	20.50	967.0	8906	126	0.00	742
	Diff.	0.00	41.00	0.00	0.00	0.00	0.00
	% Diff.	0.00	4.40	0.00	0.00	0.00	0.00
Coefficient Of variation	1961-1990	5.73	15.01	27.54	54.43	69.21	28.89
	1971-2000	6.39	21.23	29.87	67.83	83.06	30.93
	Diff.	0.66	6.22	2.33	13.40	13.85	2.04
	% Diff.	11.52	41.44	8.46	24.62	20.00	7.06
Skewness	1961-1990	0.33	0.20	-1.03	1.05	0.24	-0.98
	1971-2000	-0.30	2.07	-0.60	1.67	0.39	-0.61
	Diff.	-0.63	1.87	-0.43	0.62	0.15	0.37
	% Diff.	-191.00	935.00	41.80	59.10	62.50	37.80
Kurtosis	1961-1990	3.84	-0.68	3.58	1.05	-0.45	2.73
	1971-2000	1.52	6.17	1.09	3.58	-0.65	0.82
	Diff.	-2.32	6.85	-2.49	2.53	-0.20	-1.91
	% Diff.	-60.40	1007.0	-69.60	241.0	44.40	-70.0
Trend per Decade	1960-2006	0.454	100.0	5280.0	413.0	-0.15	445.0
	1961-1990	0.34	-70.20	-6433	227	-0.45	-568.70
	1971-2000	0.89	111.00	6760	511	-0.30	573.00
	Diff.	0.55	181.2	13193	284	-0.15	1142.0
	% Diff.	161.70	258.00	205.10	125.0	33.30	201.00

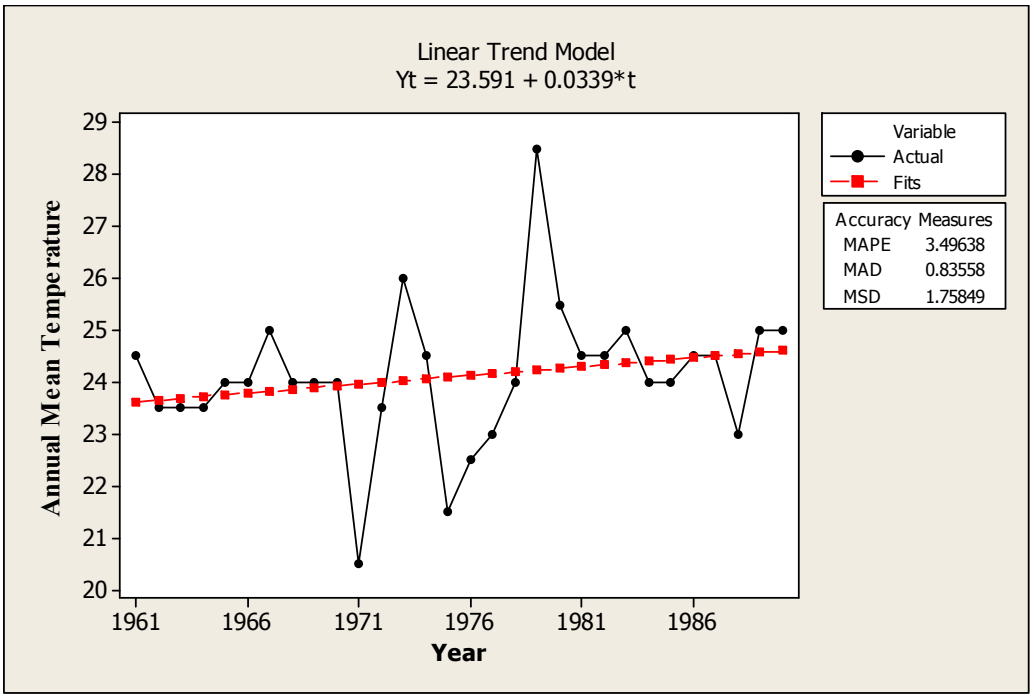


Figure 4.9a: Trend of Annual Mean Temperature for 1961-1990- Study Area

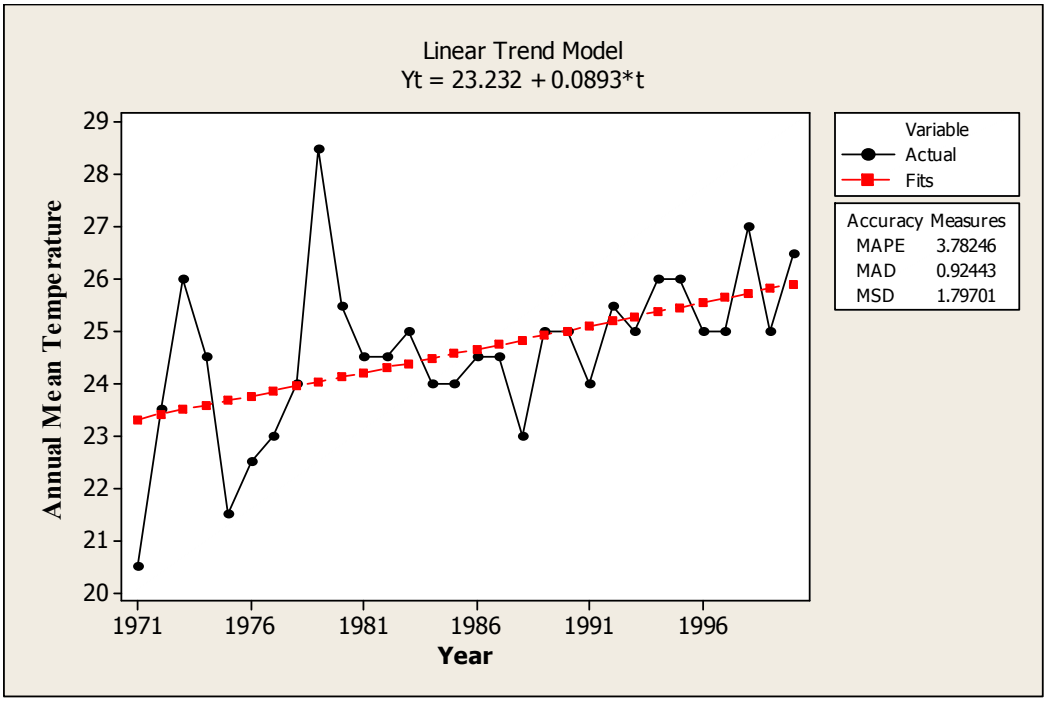


Figure 4.9b: Trend of Annual Mean Temperature for 1971-2000- Study Area

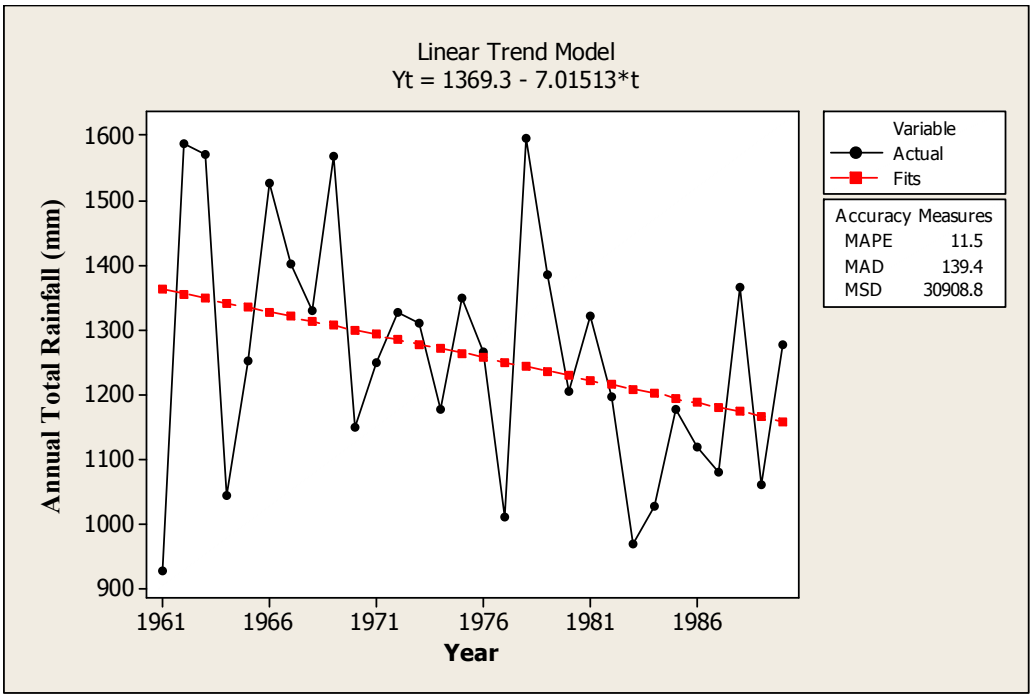


Figure 4.10a :Trend of Annual Total Rainfall for 1961-1990- Study Area

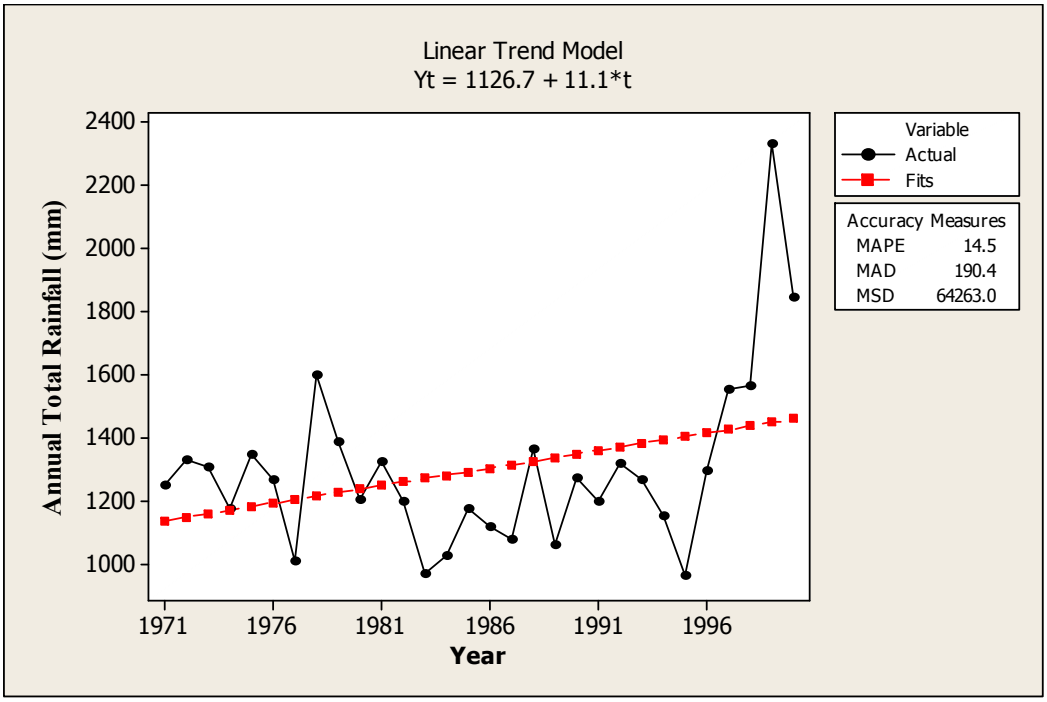


Figure 4.10b :Trend of Annual Total Rainfall for 1971-2000- Study Area

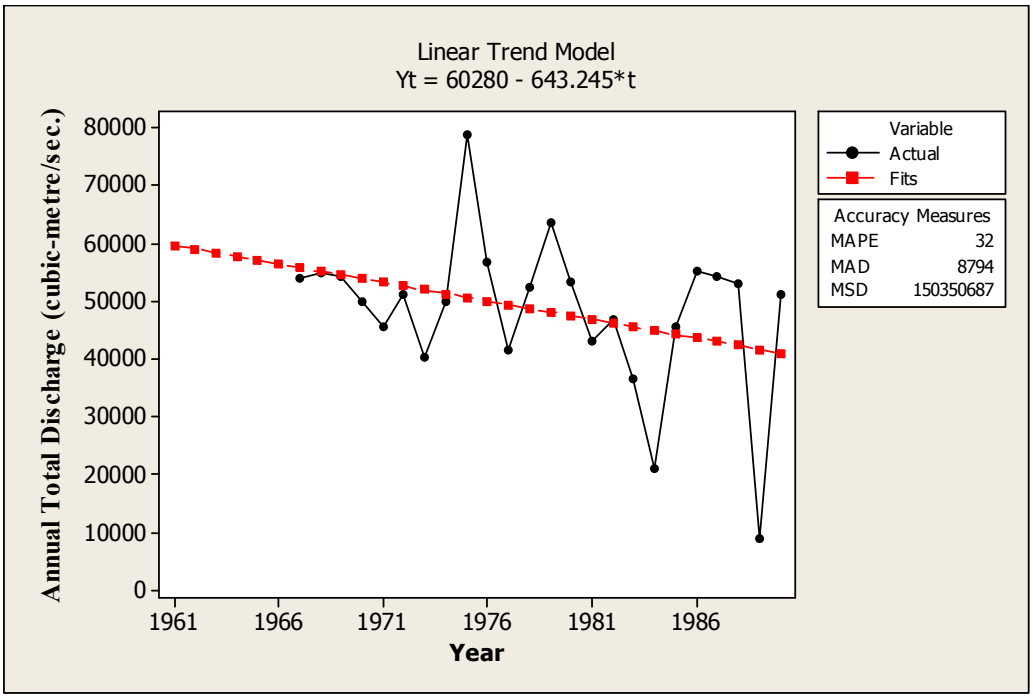


Figure 4.11a :Trend of Annual Total Discharge for 1961-1990- Study Area

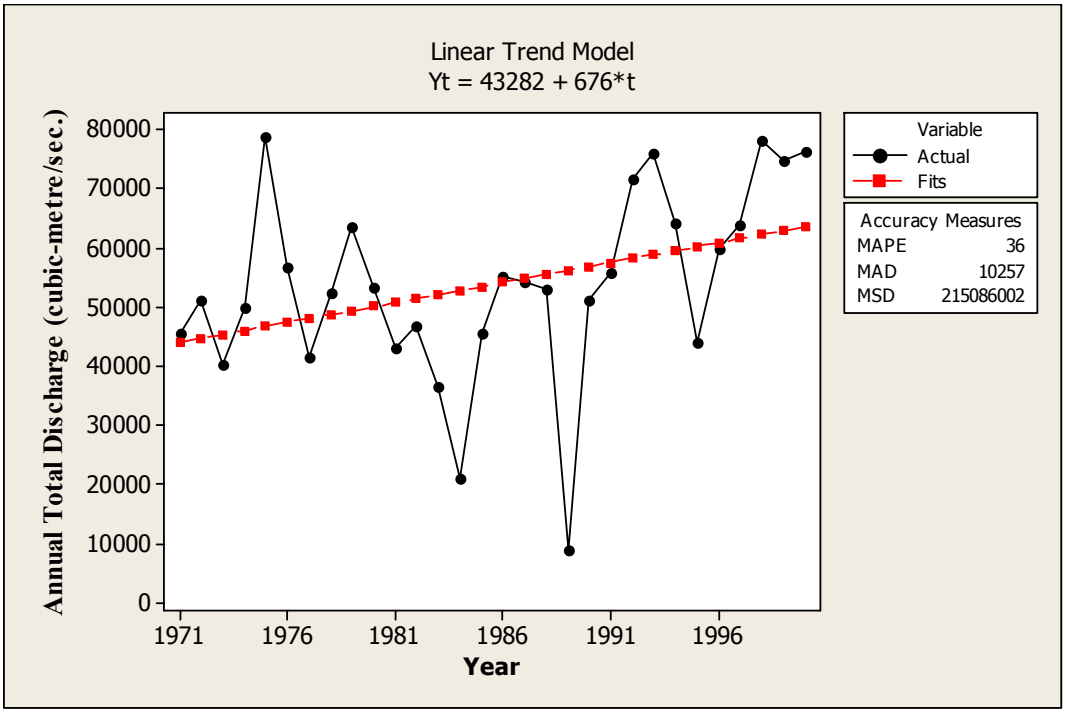


Figure 4.11b: Trend of Annual Total Discharge for 1971-2000- Study Area

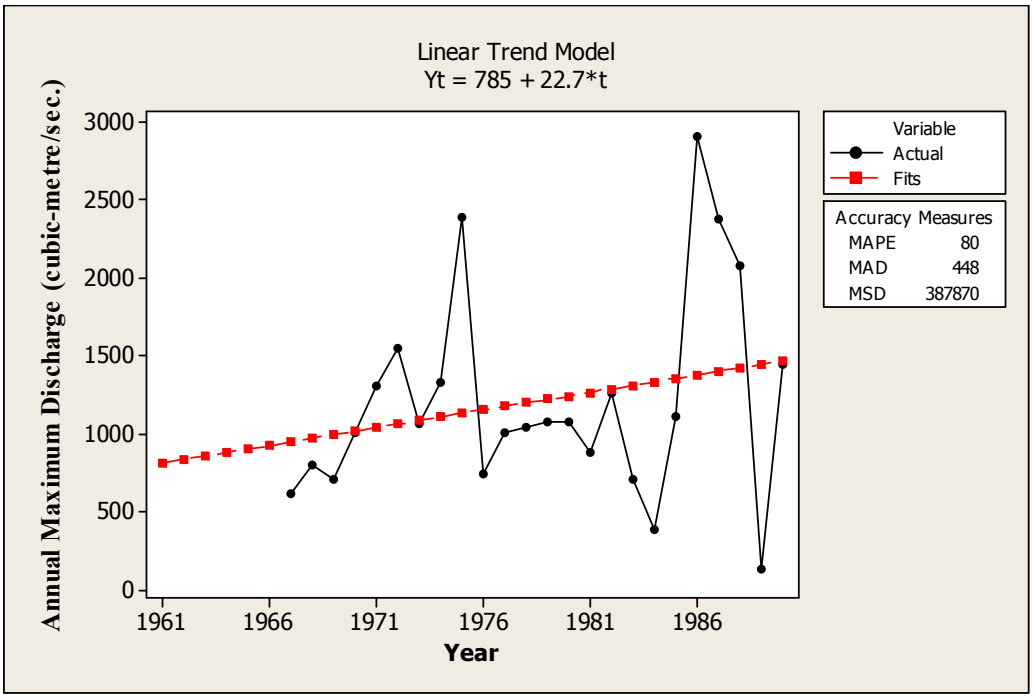


Figure 4.12a :Trend of Annual Maximum Discharge for 1961-1990- Study Area

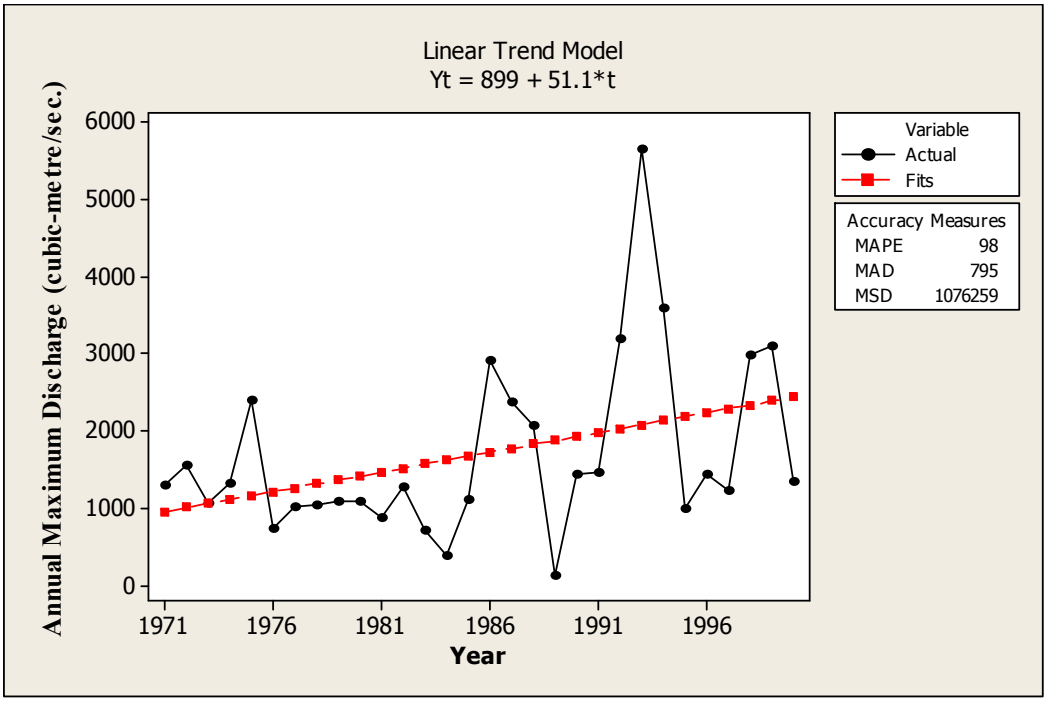


Figure 4.12b :Trend of Annual Maximum Discharge for 1971-2000- Study Area

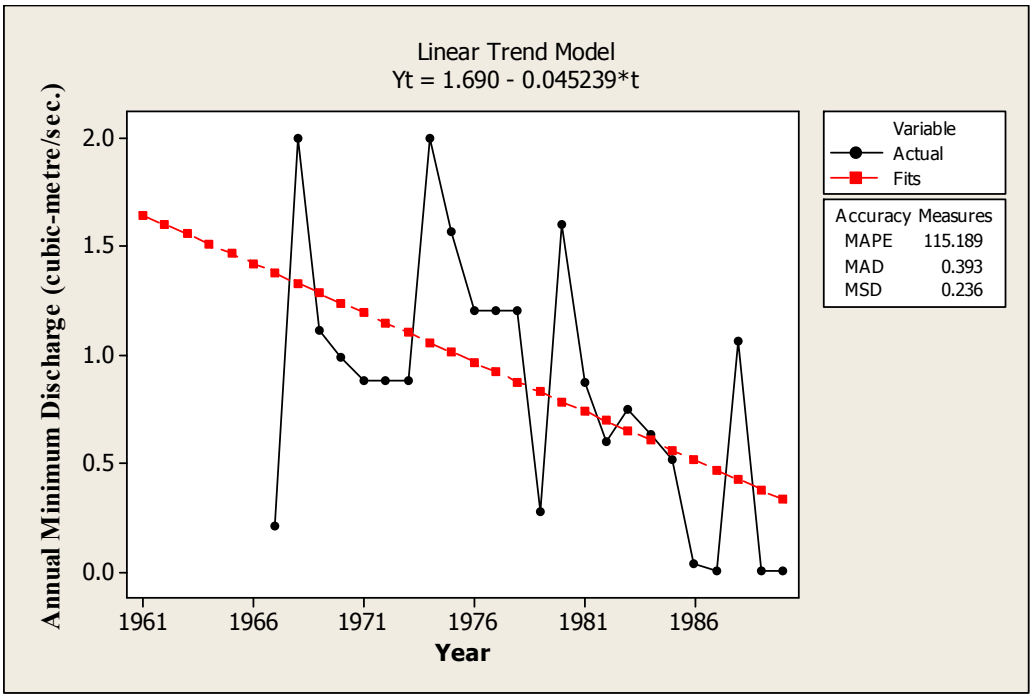


Figure 4.13a: Trend of Annual Minimum Discharge for 1961-1990- Study Area

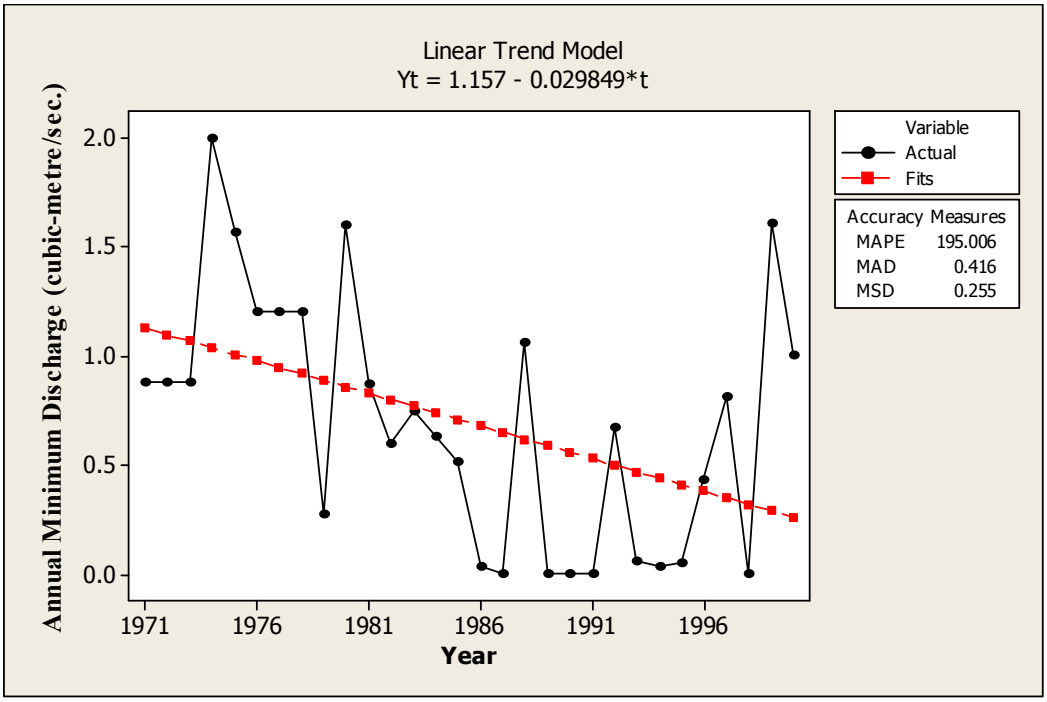


Figure 4.13b :Trend of Annual Minimum Discharge for 1971-2000- Study Area

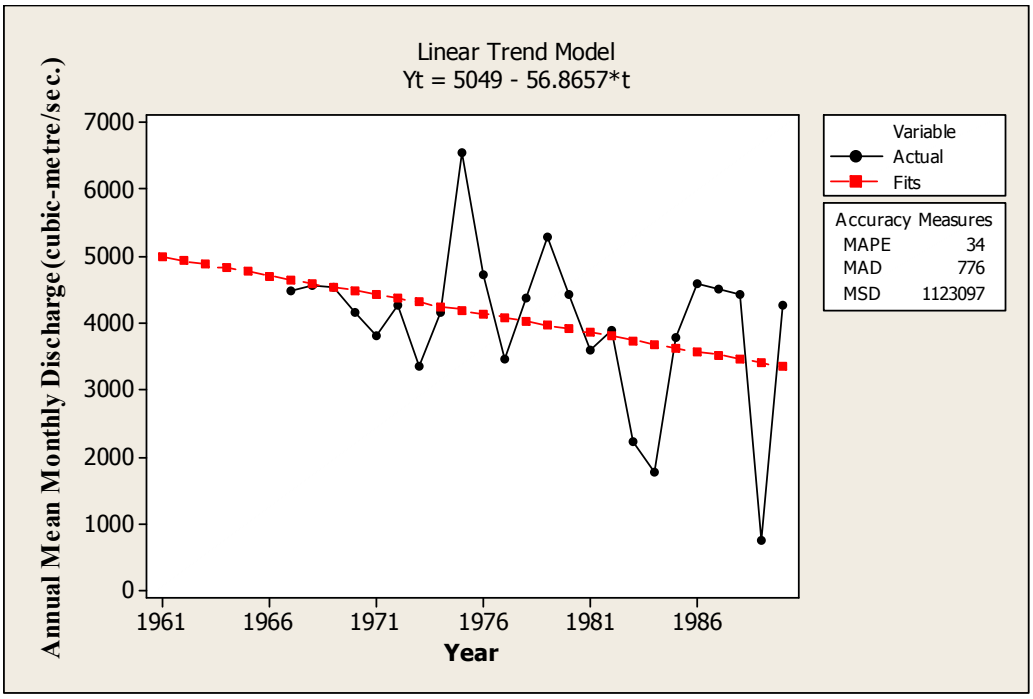


Figure 4.14a: Trend of Annual Mean Monthly Discharge for 1961-1990- Study Area

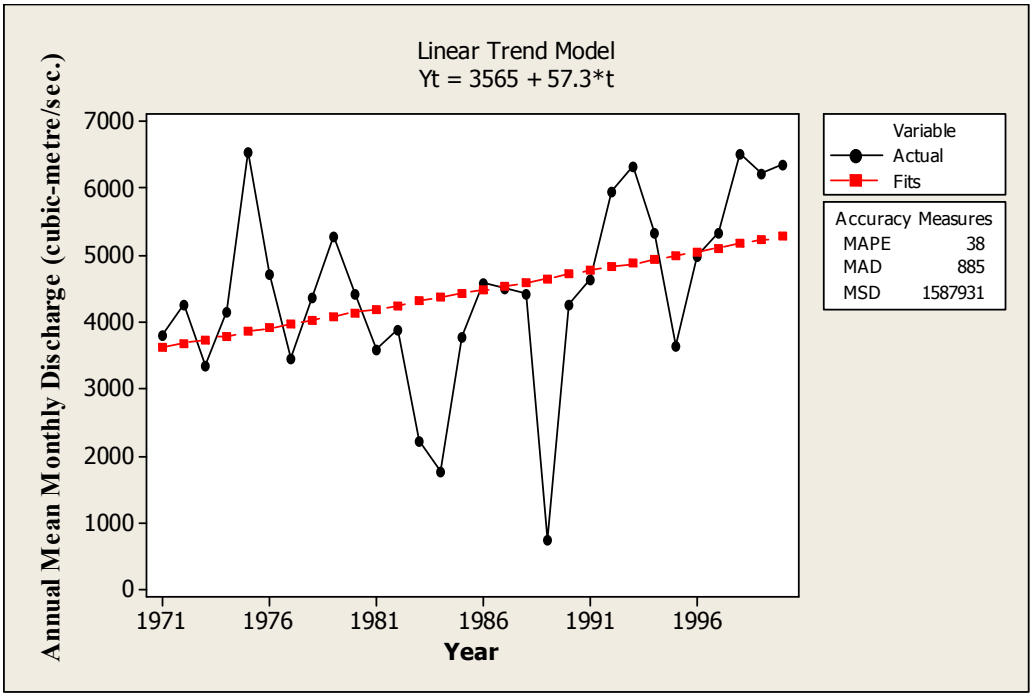


Figure 4.14b:Trend of Annual Mean Monthly Discharge for 1971-2000- Study Area

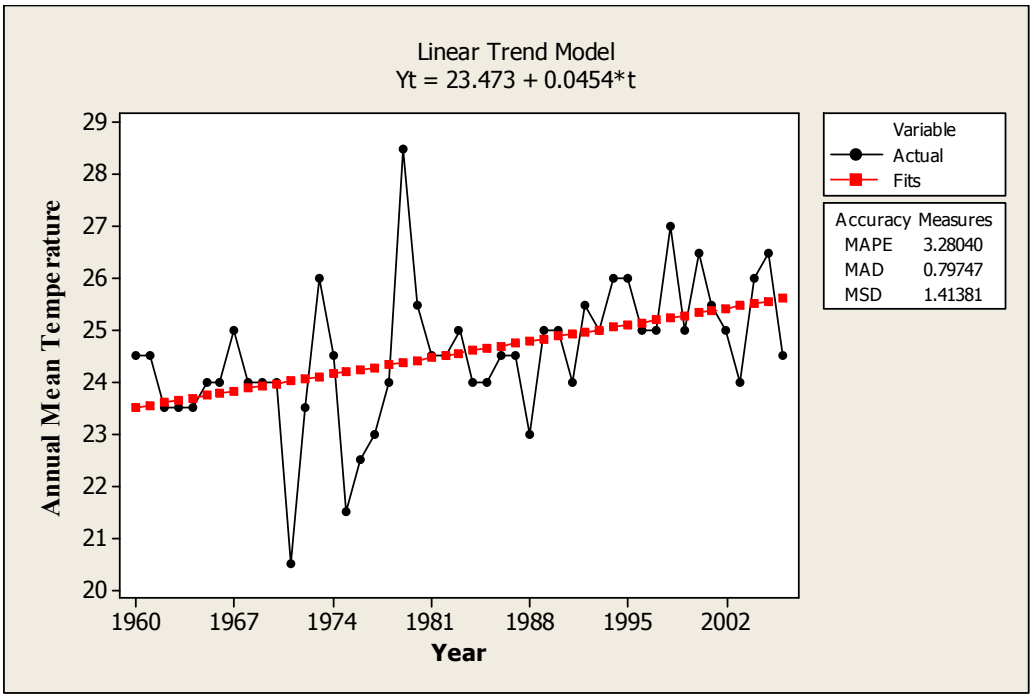


Figure 4.15: Trend of Annual Mean Temperature for 1960-2006- Study Area

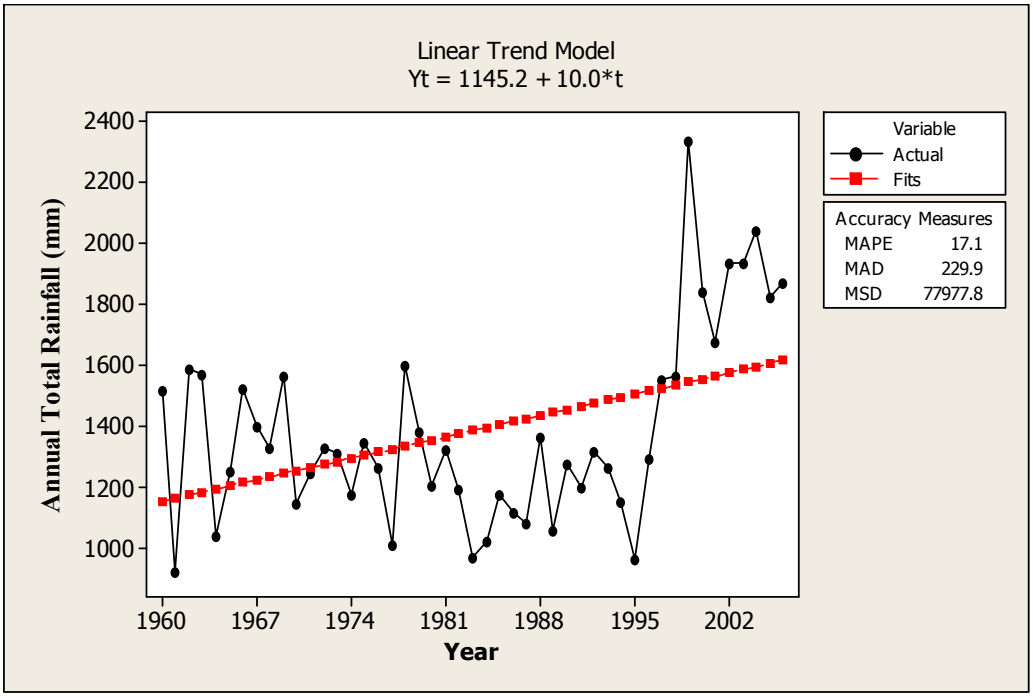


Figure 4.16: Trend of Annual Total Rainfall for 1960-2006- Study Area

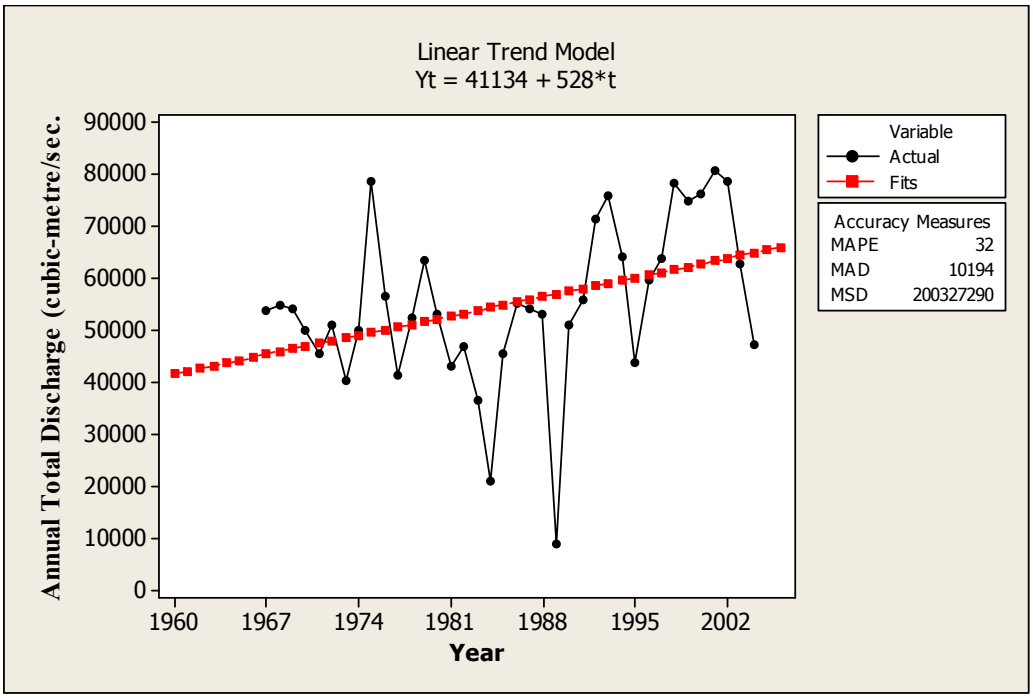


Figure 4.17: Trend of Annual Total Discharge for 1960-2006- Study Area

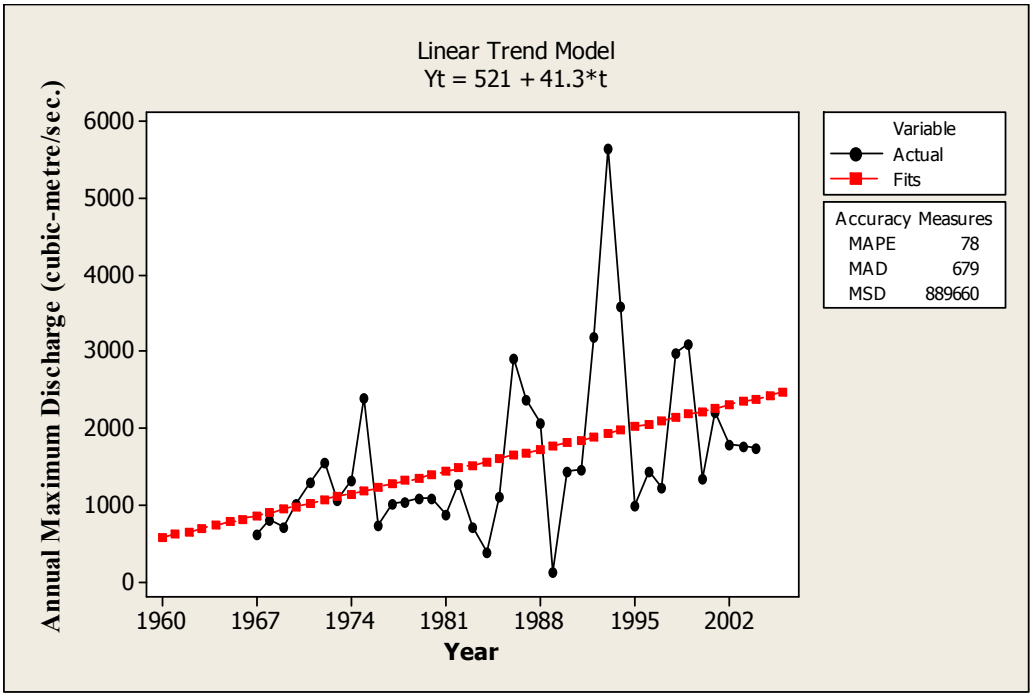


Figure 4.18:Trend of Annual Maximum Discharge for 1960-2006-Study Area

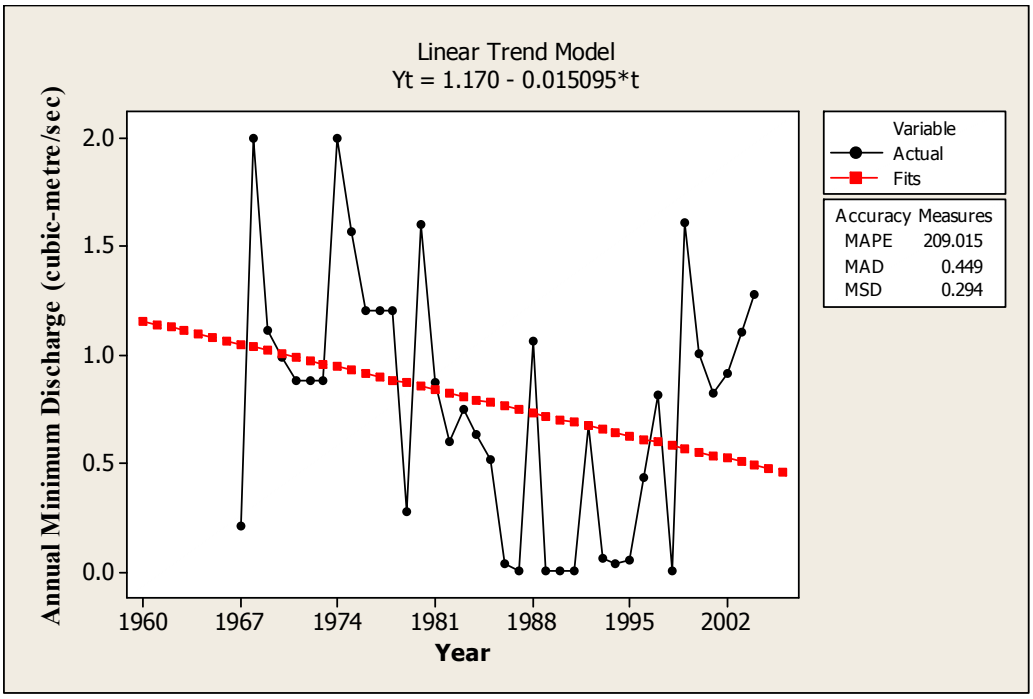


Figure 4.19 :Trend of Annual Minimum Discharge for 1960-2006- Study Area

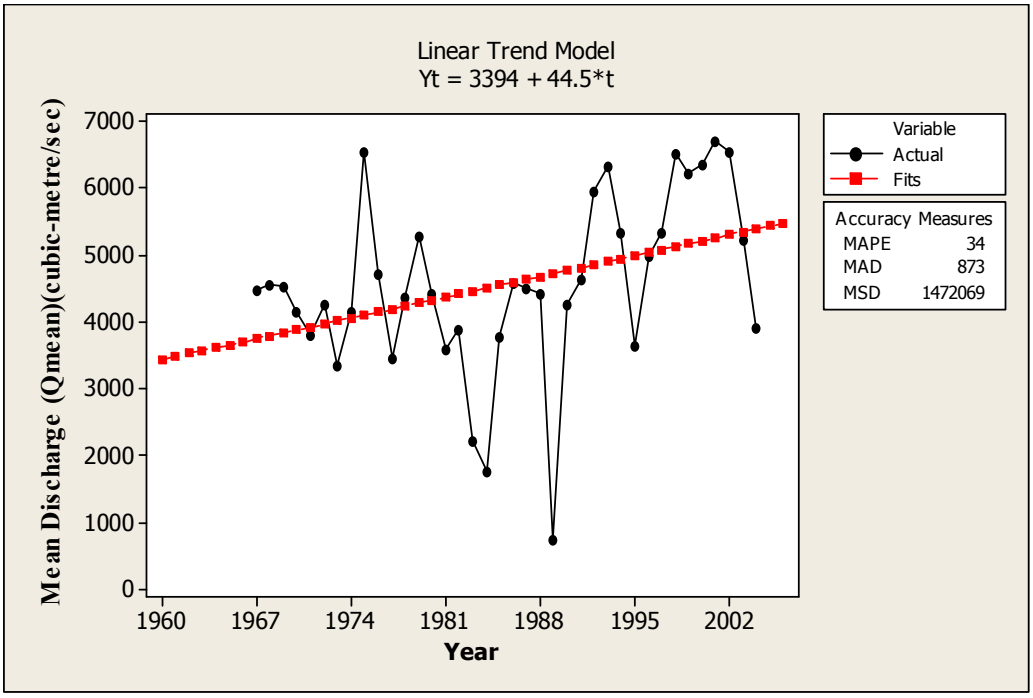


Figure 4.20: Trend of Annual Mean Monthly Discharge for 1960-2006- Study Area

4.3.1.1 Anomaly Analyses of Hydro-climatic Variables

The results of the Anomaly analyses of the Temperature, Rainfall and Discharge data from the Kaduna South station in the study area, based on Equations 3.15, 3.16 and 2.55, are presented in Figures 4.21 to 4.23.

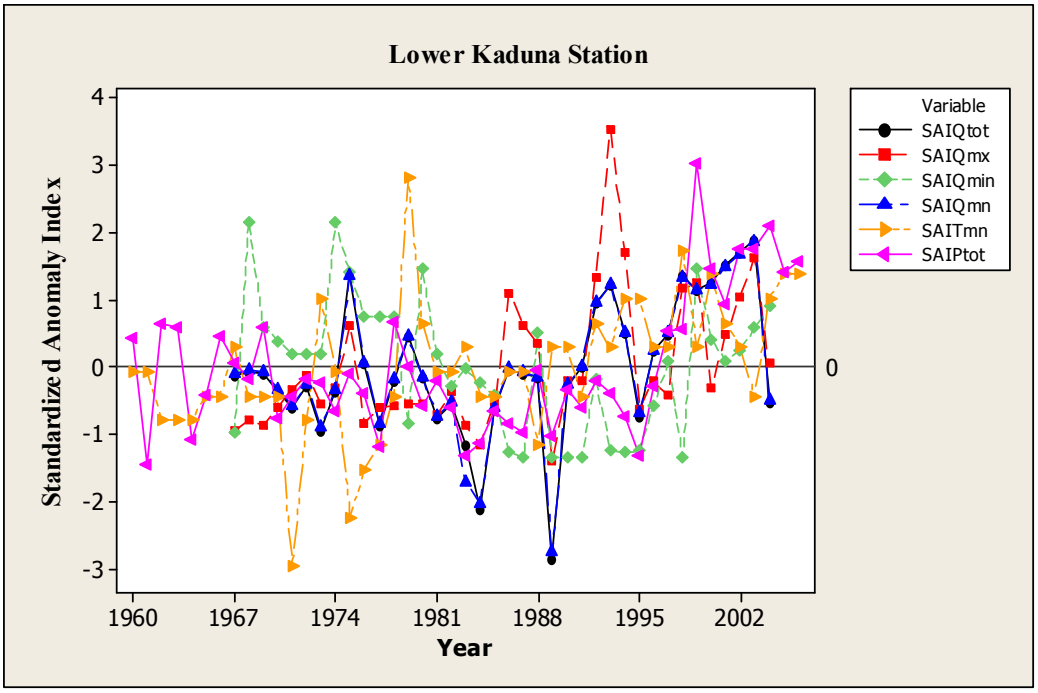


Figure: 4. 21: Standardized Anomaly Index for Temp., Rainfall and Discharges

Legend: SAIQtot = Standardized Anomaly Index of Annual Discharge

SAIQmx = Standardized Anomaly Index of Annual Maximum Discharge

SAIQmin = Standardized Anomaly Index of Annual Minimum Discharge

SAIQmn = Standardized Anomaly Index of Mean Monthly Discharge

SAITmn = Standardized Anomaly Index of Annual Mean Temperature

SAIPtot = Standardized Anomaly Index of Annual Rainfall

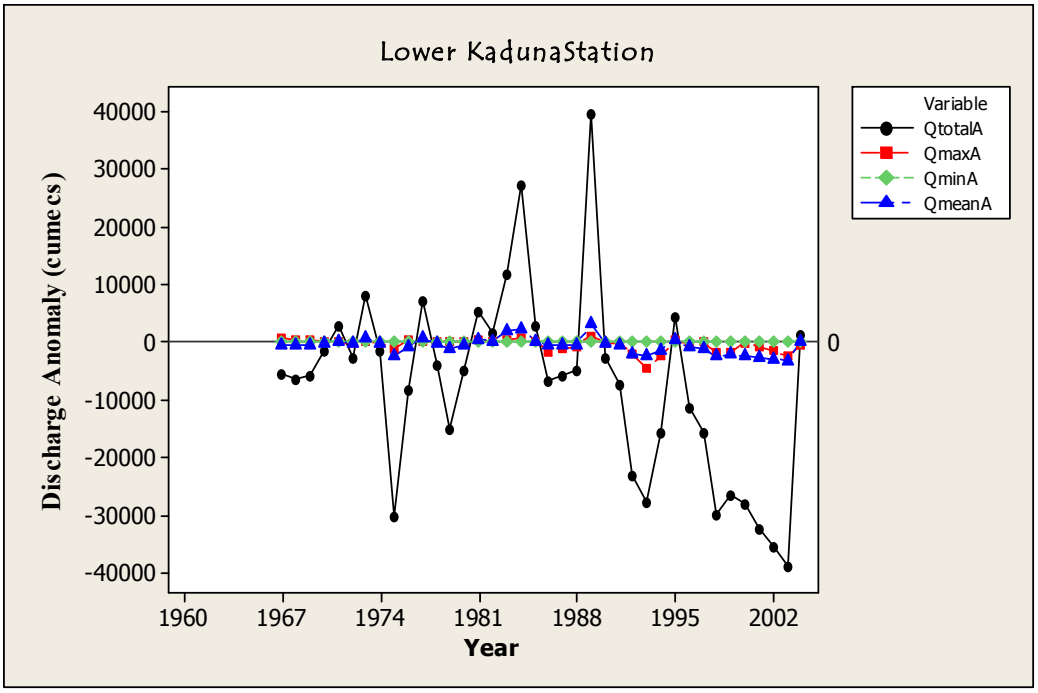


Figure 4. 22: Discharge Anomalies Relative to 1961-1990

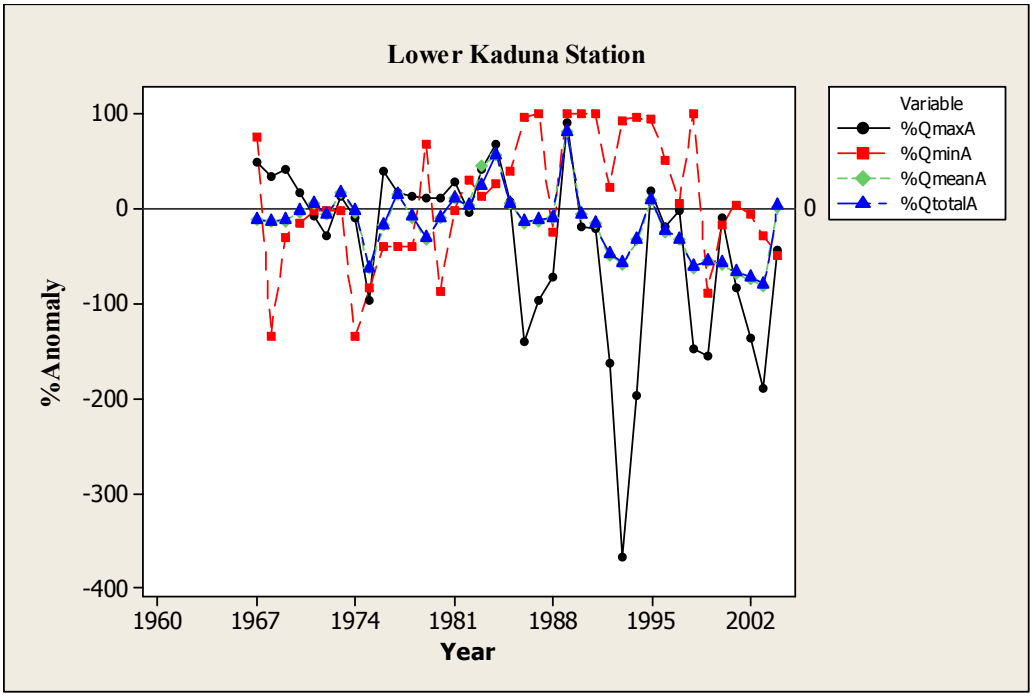


Figure: 4. 23: % Discharge Anomalies Relative to 1961-1990

4.3.1.2 Statistical Trend Tests of Hydro-climatic Variables

The results of parametric (regression model) and non-parametric (Mann-Kendall) statistical trend tests for temperature, annual rainfall and discharges of the Study Area are presented in Table 4.9.

Table 4.9: Statistical Trend Tests for Hydro-climatic Variables

Hydro-meteorological Variables	Regression Statistics		Mann-Kendall's Statistics		
	Regression Model	p-value	Kendall's S	$Z_{\propto}$	p-value
Annual Mean Temp.	Yt=23.473+0.0454t	0.0009	416.000	3.98	0.0001
Annual Rainfall	Yt = 1145.2 + 10.0t	0.0010	216.000	2.04	0.042
Annual Discharge	Yt = 41134 + 528t	0.0070	230.00	∞	0.002
Annual Maximum. Discharge	Yt = 521 + 41.3t	0.0010	249.000	3.24	0.001
Annual Minimum Discharge	Yt = 1.170 – 0.015095t	0.0751	-150.000	1.98	0.051
Mean Discharge	Yt = 3394 + 44.5t	0.0079	230.000	∞	0.002

Legend

t = time;

p -value less than 0.01, means highly significant trend.

4.3.1.3 Correlation Coefficient Tests of Hydro-climatic Variables

The results of Parametric (Pearson) and non-Parametric (Kendall tau) correlation coefficient tests are presented in Tables 4.10 and 4.11 respectively.

Table 4.10 Parametric Correlations Matrix (Equations 3.20 and 3.21)

Correlations

		Tmean	Rtotal	Qtotal	Qmax	Qmin	Qmean
Tmean	Pearson Correlation	1	.251	.187	.138	-.346*	.178
	Sig. (2-tailed)		.089	.262	.408	.034	.286
	Sum of Squares and Cross-products	87.968	5005.436	153783.3	7794.289	-10.549	12513.000
	Covariance	1.912	108.814	4156.304	210.656	-.285	338.189
	N	47	47	38	38	38	38
Rtotal	Pearson Correlation	.251	1	.559**	.206	.354*	.567**
	Sig. (2-tailed)	.089		.000	.216	.029	.000
	Sum of Squares and Cross-products	5005.436	4529916	1E+008	2526264	2358.632	8703645
	Covariance	108.814	98476.432	2714893	68277.404	63.747	235233.6
	N	47	47	38	38	38	38
Qtotal	Pearson Correlation	.187	.559**	1	.640**	.099	.995**
	Sig. (2-tailed)	.262	.000		.000	.554	.000
	Sum of Squares and Cross-products	153783.3	1E+008	9E+009	4E+008	32585.069	8E+008
	Covariance	4156.304	2714893	2E+008	1E+007	880.678	2E+007
	N	38	38	38	38	38	38
Qmax	Pearson Correlation	.138	.206	.640**	1	-.229	.639**
	Sig. (2-tailed)	.408	.216	.000		.166	.000
	Sum of Squares and Cross-products	7794.289	2526264	4E+008	4E+007	-5161.467	3E+007
	Covariance	210.656	68277.404	1E+007	1124115	-139.499	897157.4
	N	38	38	38	38	38	38
Qmin	Pearson Correlation	-.346*	.354*	.099	-.229	1	.097
	Sig. (2-tailed)	.034	.029	.554	.166		.562
	Sum of Squares and Cross-products	-10.549	2358.632	32585.069	-5161.467	12.198	2730.800
	Covariance	-.285	63.747	880.678	-139.499	.330	73.805
	N	38	38	38	38	38	38
Qmean	Pearson Correlation	.178	.567**	.995**	.639**	.097	1
	Sig. (2-tailed)	.286	.000	.000	.000	.562	
	Sum of Squares and Cross-products	12513.000	8703645	8E+008	3E+007	2730.800	6E+007
	Covariance	338.189	235233.6	2E+007	897157.4	73.805	1756022
	N	38	38	38	38	38	38

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 4.11 Nonparametric Correlations Matrix (Equations 3.18 and 3.19)

Correlations

			Tmean	Rtotal	Qtotal	Qmax	Qmin	Qmean
Kendall's tau_b	Tmean	Correlation Coefficient	1.000	.133	.168	.132	-.249*	.168
		Sig. (2-tailed)	.	.210	.157	.267	.038	.157
		N	47	47	38	38	38	38
	Rtotal	Correlation Coefficient	.133	1.000	.416**	.204	.277*	.416**
		Sig. (2-tailed)	.210	.	.000	.072	.016	.000
		N	47	47	38	38	38	38
	Qtotal	Correlation Coefficient	.168	.416**	1.000	.487**	.030	1.000**
		Sig. (2-tailed)	.157	.000	.	.000	.791	.000
		N	38	38	38	38	38	38
	Qmax	Correlation Coefficient	.132	.204	.487**	1.000	-.069	.487**
		Sig. (2-tailed)	.267	.072	.000	.	.545	.000
		N	38	38	38	38	38	38
	Qmin	Correlation Coefficient	-.249*	.277*	.030	-.069	1.000	.030
		Sig. (2-tailed)	.038	.016	.791	.545	.	.791
		N	38	38	38	38	38	38
	Qmean	Correlation Coefficient	.168	.416**	1.000**	.487**	.030	1.000
		Sig. (2-tailed)	.157	.000	.000	.000	.791	.
		N	38	38	38	38	38	38

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

4.3.2 Discussion of the Results of Climate Variability Impact on Stream Flows of Study Area

From the descriptive statistics presented in Table 4.7, the low variability (5.62%) of the annual mean temperature (T_{mean}) impacted high variability (66%) on the annual maximum discharge (Q_{max}) and annual minimum discharge (Q_{min}) (75%). However, the variability of the annual rainfall (Rtotal) and the annual discharge (Qtotal) were moderate, 23% and 28% respectively.

From Table 4.8, an increase of 0.5℃ (2.07%) in the average annual mean temperature relative to 1961-1990, impacted an increase of 40% on the average annual maximum discharge (Q_{max}),11% increase on average annual discharge and average mean monthly discharge and 3% on the average annual rainfall but a decline of 19% on the average annual minimum discharge. The 14% increase in the standard deviation of annual mean temperature (T_{mean}), also caused an increase of 46% and 75% in annual discharge (Q_{total}) and annual maximum discharge (Q_{max}) respectively indicating an increase in the variability of the rainfall and maximum discharge.

Although the maximum value of Tmean remained constant for the two time scales considered, the maximum values of the rainfall and maximum discharge increased by 46% and 95% respectively. The minimum values of all the variables, however, remained constant except for a marginal increase (4.4%) in the annual rainfall.

On the bases of the values of the coefficient of variation (CV) (Table 4.8), the variability of the annual rainfall and annual maximum discharge increased by 41% and

25% respectively due to 11.5% increase in annual mean temperature. Climate variability, in particular, the variability of the annual mean temperature, also, impacted positively on the annual rainfall and stream discharges. While the Tmean continued to be skewed to the left, the rainfall and discharges tended to be skewed to the right. The annual rainfall shifted to the right by as much as 935% relative to the 1961-1990 mean value, the annual discharge 42%, annual maximum discharge, 59% and the annual minimum discharge 63%. The distribution of the annual rainfall, also, changed from flat to peak (1007% shift relative to 1961-1990 baselines) due to 60% decline in the peakness of the annual mean temperature. The annual discharge, however, declined in peakness by 70% but the annual maximum discharge increased in peakness by 241% indicating that the rainfall and maximum discharge are becoming more concentrated, hence the high frequency of flood events in recent years. The minimum and mean discharges, also decline in peakness by 44% and 70% respectively.

The results of the trend analyses (Table 4.8 and Figures 4.9 – 4.20) indicated an increasing trend in the annual rainfall, annual discharges and annual mean temperature. The increase in annual rainfall relative to 1961-1990 period was 258% (181mm) per decade, annual discharge, 205% (13193 m^3/day) maximum discharge 125% (284 m^3/day)and mean monthly discharge 201% (1142 m^3/day) due to 161% (0.55℃) change in the annual mean temperature between 1961-1990 and 1971-2000 time scales.

Generally, the variability of the climate, in particular, the variability of the annual mean temperature indicated more impacts on the annual maximum discharge than the annual rainfall and total annual discharge except in the trend characterization where the impact was more on annual rainfall (258%). Also, the trend analyses indicated increasing trends in the discharges (Q_{total}, Q_{max}, and Q_{mean}) from the 1970s due to the increasing variability of the climatic elements, in particular, the annual mean temperature and annual rainfall. The long-term (1960-2006) trend analysis indicated that the mean temperature rise of 0.454℃ per decade (2%) relative to the average value for the period, increased the annual rainfall by 100mm (26%)/decade, annual discharge by 5280 m^3/day (10%)/decade, annual maximum discharge by 413 m^3/day (26%)/decade, and mean monthly discharge by 445 m^3/day (10%)/decade but decreased the annual minimum discharge by 0.15 m^3/day (20%)/decade relative to their long-term average values.

From the parametric and nonparametric correlation tests on annual mean temperature, annual rainfall and the annual series of discharges from the Study Area catchment presented in Tables 4.10 and 4.11, the annual mean temperature and the annual minimum discharge were significantly correlated, indicating that the mean temperature had negative impact (decreasing trend, though not significant, Table 4.9) on the annual minimum discharge of river Kaduna. The annual rainfall correlated, positively with the annual discharge (Q_{total}), annual minimum discharge (Q_{min}) and mean discharge (Q_{mean}), indicating that increase in the annual rainfall would lead to increases in Q_{total}, Q_{min}, and Q_{mean} which implies positive significant impact of Climate variability on the discharges of River Kaduna at Lower Kaduna River Catchment.

4.3.2.1 Climate Variability and Impacts on Discharges of River Kaduna

The average annual maximum, minimum, and mean temperatures for the catchment were 38.45°C, 10.75°C, and 24.65°C respectively. These were observed to have increased per decade, by 0.30°C, 0.70°C and 0.50°C respectively. The standard deviations (which measure variability) of the annual maximum, minimum, and mean temperatures were computed to be 1.12°C , 2.60°C, and 1.28°C respectively. These were, also, shown to have increased per decade, by 0.15°C (14.6%), 0.23°C (8.4%), and 0.20°C (14%) respectively (Tables 4.1 and 4.4). Also, relative to the 1961-1990 mean values, the annual maximum temperature increased, on the average per annum, by 0.07°C, the annual minimum temperature by 0.91°C and the annual mean temperature by 0.50°C which indicate that the nights have become hotter than the days. The highest increase in the annual maximum temperature of 2.60°C (6.8%) was recorded in 1973, 1998, and 2000, while the highest increases in annual minimum and mean temperatures of 9.20°C and 4.90°C respectively, were recorded in 1979 (Figure 4.8).

The long-term (1960 -2006) analyses of temperature trends indicated increasing trends which are statistically significant except for the annual mean temperature. The increasing trends per decade, for the annual maximum, minimum, and mean temperatures were, respectively, 0.12°C, 0.88°C and 0.48°C(Table 4.4), indicating warming, especially, at nights.

The average annual rainfall and evaporation for the catchment area were 1385mm and 2453mm respectively. The rainfall and evaporation indicated increasing trends of 100mm and 99mm per decade, which was not significant in the case of annual evaporation. Relative to the 1961 – 1990 mean values, the annual rainfall and evaporation indicated average annual increase of 125mm and 131mm respectively. The highest increase in annual rainfall of 1072mm (85%) was recorded in 1999, while that of evaporation of 1035mm (45%) was recorded in 2000. From the results of the analyses, it can be observed that the general increases in the temperatures influenced the increases in the annual rainfall and evaporation.

The mean annual total, maximum, minimum and mean discharges were 55,127m^3/day, 1614 m^3/day, 0.80 m^3/day and 4572 m^3/day respectively, with standard deviations that were, respectively, 15,498 m^3/day, 1060 m^3/day, 0.60 m^3/day, and 1325 m^3/day. The trend analyses of the discharge time series for the period, 1960 – 2006, showed that the annual total discharge, the annual maximum discharge and mean discharge had increased significantly (with p-values of 0.007, 0.001 and 0.008 respectively) during the past 47 years, whereas, the annual minimum discharge during the same period indicated a decline which is not statistically significant (p-value = 0.075). Increasing temperatures influenced more evaporation and consequently increased rainfall and discharges. However, because of high temperatures, the discharge tended to decline during dry season (November to December and January to April every year). This has implications for water resources development. From the anomaly analyses of the Kaduna River discharges and rainfall time series in the study area(Figures 4.21, 4.22

and 4.23), the increased annual rainfall relative to the 1961-1990 mean values of 301mm in 1998 ,1072mm in 1999, 582mm in 2000, 413mm in 2001, 674mm in 2002 and 675mm in 2003 coincided with the high annual discharges of 29847 m^3/day in1998, 26480 m^3/day in 1999, 27970 m^3/day in 2000, 32281 m^3/day in 2001, 35517 m^3/day in 2002, and 38753 c m^3/day in 2003 respectively, which generated excessive surface runoff in River Kaduna system in recent years. These periods of excessive rainfalls and discharges, also, coincided with the periods of increases in the annual minimum temperatures as indicated in Figure 4.8.

The analyses of the distribution of the historic data for the period 1960 – 2006 showed that the annual rainfall, annual maximum discharge, and annual minimum discharge were right skewed , whereas, the annual mean temperature, annual total discharge and mean discharge were left skewed. Also, the annual mean temperature, rainfall, total discharge, maximum discharge, and mean monthly discharge indicated peaked distribution , whereas, the annual minimum discharge showed flat distribution Table 4.7). These results suggest that the annual rainfall and maximum discharge have become unevenly distributed and more concentrated, occurring over shorter number of rainy days in a year. This is in agreement with Nigerian Meteorological Agency (NIMET) observation of late onset and early cessation of rainfall since 1911, leading to shorten length of rainy season and shift in the occurrence of August break (Anuforom, 2010). The implication of this is that the tendency for flood events is increased. The declining minimum discharge increases water supply demand for domestic, industrial and agricultural uses especially, during dry season.

4.3.2.2 Implications of the Impacts of Climate Variability on Streamflows for Water Resources Development

River Kaduna at Kaduna is the main source of fresh water supply to Kaduna town and its numerous industries. The abstraction for piped water distribution in Kaduna is carried out at two Treatment Plants which are located at the Northern and Southern parts of the town. The Kaduna South Waterworks (KSW), which is older, was commissioned in 1949 with a capacity of 30, m^3/day but was abandoned in the early 1980s because of the deteriorating quality of water at its intake due to industrial effluent pollution. The Kaduna North Waterworks (KNW), which has been providing water for the domestic demands in Kaduna town, had a capacity of 200,000 m^3/day as at 1998.

The water requirement of Kaduna was estimated by the Water Division of the Ministry of Works and Survey at 227,273 m^3/day with a projected population of 700,000. It was, then, considered unlikely that the discharge in River Kaduna at Kaduna would ever fall below 45,455 m^3/day and with the provision of additional flow of 181,818 m^3/day expected from Kangimi Reservoir, the raw water demand of Kaduna town would be ensured for the unforeseeable future (Bamgboye, 2004).

From the results of the present study, the mean annual minimum discharge in River Kaduna at Kaduna is less than 1.0 m^3/day (Table 4.7) as against the 45,455 m^3/day projected in the last century. This suggests serious deficit in the water supply demand for domestic requirement alone, especially, during dry season. Based on the 1970 demand of 45,455 m^3/day by a population of 200,000, the demand by the 2011 estimated population of 1,582,102 would be about 360,000 m^3/day, which translates to a deficit of about 160,000 m^3/day. Also, based on the 2005 abstraction rate of 1,580 m^3 per month (KSWB, 2005) the deficit and surplus in the demand is presented in Figure 4.25 below. The figure indicated deficit from November to December and from January to May every year. Generally, water stress is usually experienced during these periods. These periods, also, coincided with the periods of high increases in the temperatures and annual evaporations and little or no rainfalls (dry season) as indicated in Figures 4.26 and 4.27 below.

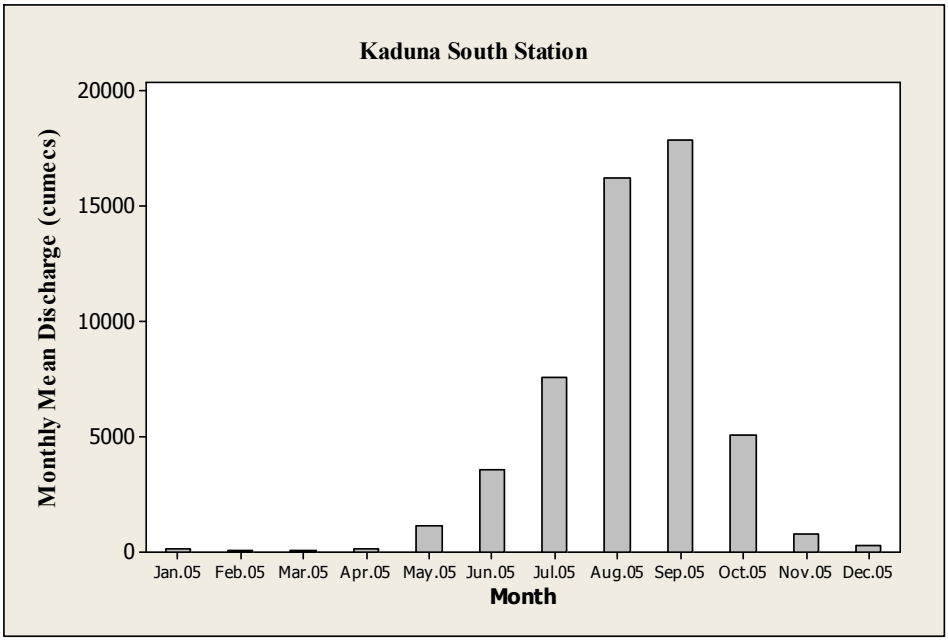


Figure 4.24: Monthly Mean Discharge of River Kaduna at Kaduna South Station

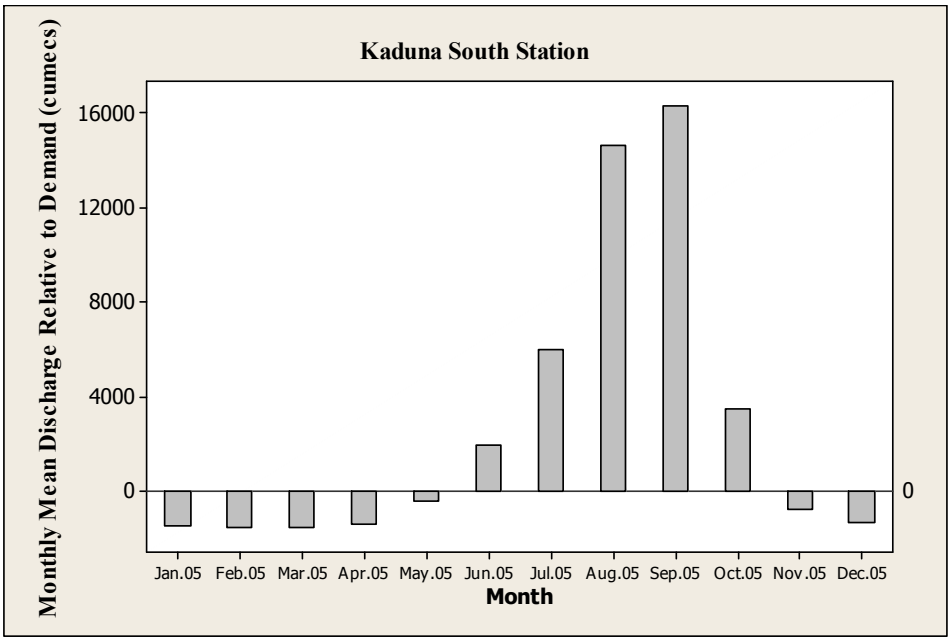


Figure 4.25: Monthly Mean Discharge Anomaly Relative to Mean Abstraction of Kaduna River at Kaduna South Station

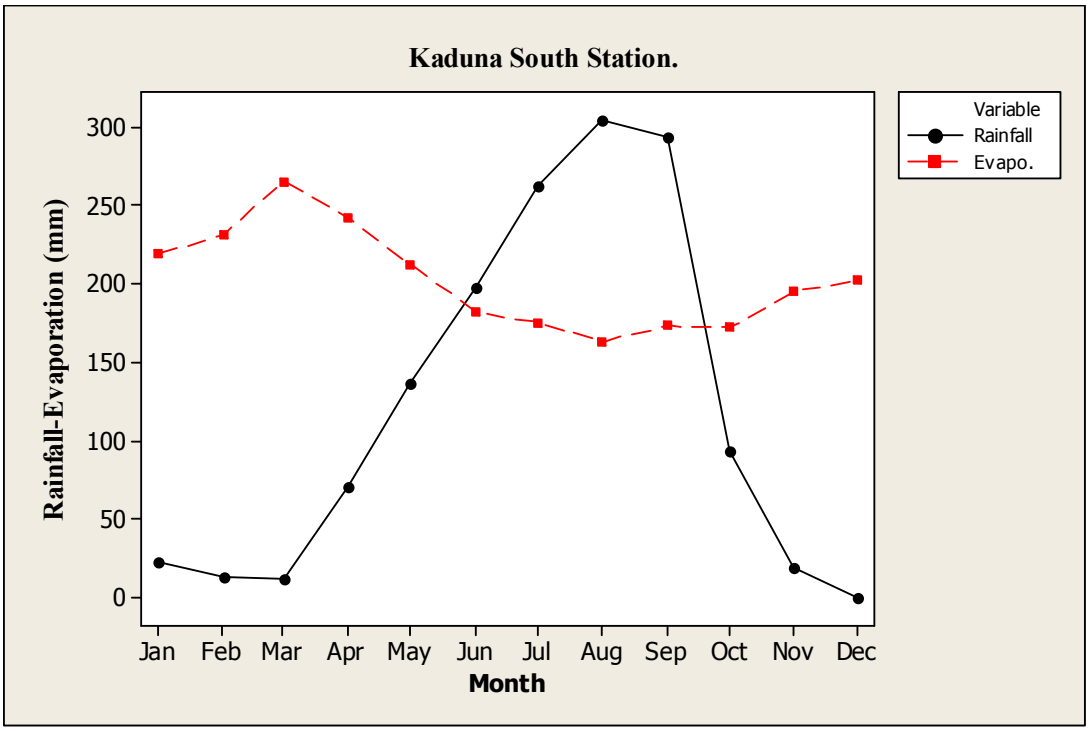


Figure 4.26: Variations of Mean Monthly Rainfall and Evaporation

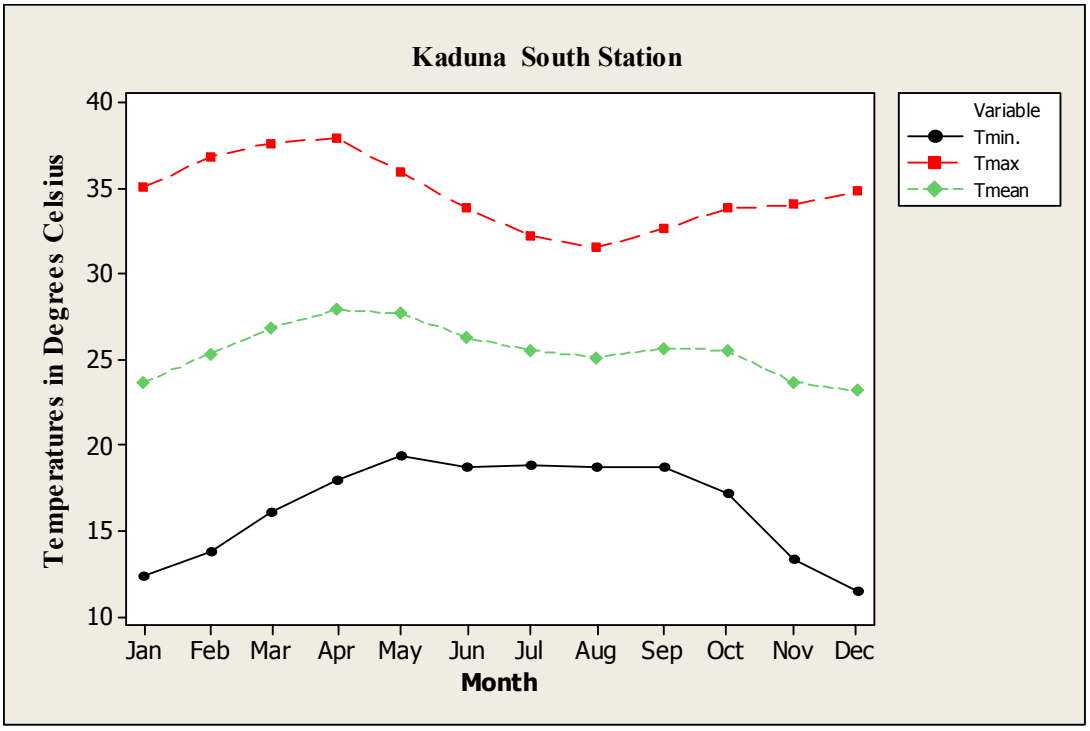


Figure 4.27: Variations of Mean Monthly Temperatures (Maximum, Minimum and Mean Temperatures)

Apart from being a source of water supply, River Kaduna at Kaduna, also, serves as a sink for industrial effluent and domestic wastes. Downstream of the river has consistently and extensively been used for irrigation and livestock watering, especially during dry season. With declining minimum discharge and increasing temperatures, there would be declining quantity and quality of the water in the river available for irrigation and livestock watering and increasing hazards to health as a result of industrial effluent and domestic wastes discharged into the river which would, progressively reduce the river water quality and increase pathogenic load.

CHAPTER FIVE
SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 SUMMARY OF RESULTS

Climate Variability is the collective variability of the climate variables, in this case, the temperatures, annual rainfall and the annual evaporation. The results summary is, therefore presented according to the climate states as follows:

5.1.1Annual Maximum Temperature (T_{max})

The Kaduna State average annual maximum temperature was 38.54℃ with a standard deviation of 2.23℃. The state maximum value was 44.92℃ and minimum for the period of study was 35.25℃ . The distribution of the annual maximum temperature was generally right skewed and peaked. There was a state increase in the mean value of the annual maximum temperature of 0.08℃ (warming) over the 1961-1990 mean value with 0.5℃ increase in the standard deviation relative to the current climate (1961-1990), indicating increase in the variability of Tmax. However, there was a general decline in the trend at the state level of -0.3℃ per decade (cooling) which is not statistically significant with a low coefficient of variation of 0.06 (6%). The highest increase in the day time temperature was 15.3℃ recorded in 1993. This is higher than 0.78℃ world maximum temperature increase recorded in 1860 and 1.1℃ recorded in Nigeria (Odjugo, 2010). The increase generally started from 1992 and ranged from 7.88℃ - 15.3℃ relative to 1961-1990 mean value.

5.1.2 Annual Minimum Temperature (T_{min})

The range of the mean annual minimum temperature is from 8.3℃ - 14.2℃ with a state average of 11.1℃ and a state average standard deviation of 1.89℃. The maximum values of Tmin ranged from 10℃ - 20℃ with a zonal average of 15.1℃ and a state minimum value of 6.75℃. The distribution of Tmin is generally right skewed and peaked. The average state increase in the mean annual minimum temperature was 0.26℃ over the 1961-1990 mean value while the state average increase in the standard deviation relative to 1961-1990 mean value was 0.28℃, indicating increase in the climate variability within the state.

The trend per decade ranged from -0.68℃ to 2.92℃ which are statistically significant with a state average of 0.68℃ (higher than 0.6℃ estimate by IPCC (2007) for Africa in the 21st century). The coefficient of variation ranged from 0.08 – 0.36 with a state average of 0.20, indicating moderate increase in the climate variability.

Generally, the increases in the annual minimum temperature (Tmin) were from the 1990s. The warmest yeas in terms of night time temperatures were 1998 (Zaria) with an increase of 8.2℃ (120%), 2004 and 2005 (Kangimi) with an increase of 8.0℃ (67%) over the 1961 -1990 mean values. The coolest year was 1993 (Kafanchan) with Tmin decline of 9.1℃ (82%) below the 1961 – 1990 mean values.

5.1.3 Annual Mean Temperature (T_{mn})

The average annual mean temperature ranged from 23.71℃ to 25.94℃ with the Kaduna state average of 24.82℃ and state standard deviation of 1.34℃. The state maximum

Tmn is 28.42°C while the state minimum Tmn is 22.3°C. The overall change in the mean between the two time scales 1961 – 1990 and 1971 – 2000 ranged from -0.27°C (-1.1%) to 0.91°C (3.9%) with the state average of 0.17°C indicating warming relative to 1961 – 1990 period while the change in standard deviation ranged from -0.22°C (15%) to 1.21°C (192%) with the state average increase of 0.25°C (35.2%), indicating increase in the climate variability over the 1961 – 1990 period.

Both negative and positive trends were indicated in the annual mean temperature and were statistically significant in three of the stations with the state average of 0.20°C per decade and state coefficient of variation of 0.054 (5.4%) indicating low climate variability.

Generally, the increases in the anomalies relative to 1961-1990 were consistent from the 1990s and ranged from 0.08°C (0.34%) to 7.3°C (28.4%) while the decline ranged from 0.1°C (.4%) to 5.1°C (21%). The coolest year was 1993 (Kafanchan) with 5.1°C (21%) decline in the annual mean temperature relative to 1961 – 1990 mean value.

5.1.4 Annual Rainfall

The mean annual rainfall ranges from 1102mm to 1777mm with the state average of 1402mm and state standard deviation of 327mm. The state maximum annual rainfall was 2154mm with a minimum of 853mm. The distribution of the annual rainfall is generally right skewed and peaked. There was a general increase in the mean value relative to the 1961 – 1990 mean value with the state average of 86mm per decade and a state average increase in standard deviation of 54mm per decade indicating high (63%) increase in the variability of the annual rainfall within the state relative to 1961 – 1990 mean value.

The trends per decade, which are generally positive, and mostly statistically significant, had a state average of 128mm per decade. The state coefficient of variation was 0.23 (23%) indicating moderate variability of the climate. The general increases in the anomalies relative to the 1961 – 1990 mean value were indicated from the 1990s in almost all the stations. The wettest year was 1981 in Kagarko with an increase of 1824mm (111%) per decade over the 1961 – 1990 mean value.

5.1.5 Annual Evaporation

The mean annual evaporation ranged from 2352mm to 3065mm with the state average of 2706mm and standard deviation of 355mm. The state maximum and minimum values of evaporation were 3398mm and 1945mm respectively. The distribution of the annual evaporation is right skewed and peaked in most of the stations.

There was a general decline in the mean values of the annual evaporation relative to the 1961 – 1990 mean value in most of the stations with the state average decline of 94mm per decade. However, the change in the standard deviation increased relative to 1961 – 1990 mean value with the state average of 116mm per decade, indicating a very high

(123%) variability of the annual evaporation. Trends are positive in most of the stations with the state average of 140mm per decade. The state coefficient of variation is 0.13 (13%) indicating low variability of the climate. There was a general increases in the anomalies from the 1990s with the highest increase of 1726mm (67%) in 2001 relative to the 1961 – 1990 mean values.

5.1.6 Impacts of Climate variability on Water Resources of Lower Kaduna River Catchment

An increase of 0.5℃ (2.07%) in the average annual mean temperature (Tmn) impacted an increase of 40% in the average annual maximum discharge with 75% increase in the standard deviation, 11% increase in the annual discharge with 46% increase in the standard deviation, and 3% increase in the average annual rainfall but a decline of 19% in the average annual minimum discharge relative to 1961-1990 mean values. The distribution of the annual rainfall and annual maximum discharge increased in peakness by 1007% and 241% respectively, indicating that the rainfall and the annual maximum discharge are becoming more concentrated, thereby, increasing the risk of flood events. They are, also, more skewed to the right. There was, however, a decline in the peakness of the annual minimum and annual mean monthly discharges by 44% and 70% respectively. The effect of these patterns of rainfall distribution is the late onset of rainfall and early cessation of rainfall as observed by NIMET (2010) since 1911. Also, the increasing rainfall from the 1990s, especially from 1998 to 2003 had generated increasing discharges in River Kaduna (Figures 4.21 – 4.23) which resulted in the flood events in the river system in 2003.

5.2 CONCLUSIONS

Climate variability and its impact on the water resources (stream flows) of Lower Kaduna River Catchment based on discharges in River Kaduna at Kaduna South Station, and temperatures, rainfall and evaporation data from twelve (12) meteorological stations across Kaduna State for the past 47 years (1960 – 2006) were investigated. Simple approach, which considered climate variability as the difference between the means and standard deviations of the climatic variables of two equal-length time scale (1961-1990 and 1971-2000) were used with Coefficient of Variation, Anomaly and Time series analyses to assess the climate variability while comparative and correlation analyses were used to evaluate the impacts of climate variability on streamflows of the study area. From the results of the analyses, the following conclusions can be drawn:

5.2.1 Climate Variability

1. .At the regional level, the variability in the mean values of the annual maximum, minimum, and mean temperatures were 0.08℃, 0.26℃,and 0.17℃ per decade

respectively, while the variations in their standard deviations were 0.50℃, 0.28℃, and 0.25℃ per decade respectively, which are consistent with global trends.

2. The long-term (1960-2006) trends, at the regional level ,of the annual maximum, minimum, and mean temperatures were 0.30℃, 0.68℃ , and 0.20℃ per decade respectively, which are also, consistent with global trend; warmer nights (IPCC, 2001).
3. The variability of the annual maximm, minimum, and mean temperatures at the regional level relative to the 1961-1990 mean values were +15.30℃ (40%)/ -8.42℃ (22%) , +8.20℃ (120%) / -9.10℃ (82%) , and +7.30℃ (28.4%) / -5.10℃ (21%) respectively. These are higher than 1.4℃ - 5.8℃ estimated by IPCC (2001) over the period 1990-2100 for all range of emission scenarios and 1.1℃ observed in Nigeria by Odjugo (2010) in 2009 probably due to the constant and continous burning of hydrocarbon (methane) at Kaduna Refinery and Petro-chemical company.
4. The highest positive variability in the annual rainfall within the region was 1824mm (111%) (flood) in 2004 while the highest negative variability was 602mm (40%) (Draught) in 1993. The variability of the mean and standard deviation of the annual rainfall were 86mm and 54mm per decade respectively while the trend per decade was 128mm within the region.
5. The variability of the annual evaporation within the region was +1726mm (67%) and -1489mm (58%) with a trend of 140mm per decade while the variability of the maen and standard deviation were – 94mm and + 116mm per decade.
6. Within the Lower Kaduna River Catchment Area ,the average annual maximum, minimum, and mean temperatures were 38.45℃, 10.75℃, and 24.65℃

respectively. These were observed to have increased per decade, by 0.30℃, (0.78%), 0.70℃ (7.1%) and 0.50℃ (2%) respectively. The standard deviations (which measure variability) of the annual maximum, minimum, and mean temperatures were computed to be 1.12℃, 2.60℃, and 1.28℃ respectively. These were, also, shown to have increased per decade, by 0.15℃ (14.6%), 0.23℃ (8.4%), and 0.20℃ (14%) respectively. Also, relative to the 1961-1990 mean values, the average increase per annum in the annual minimum temperature (0.91℃) is higher than that of the annual maximum (0.07℃) and annual mean (0.50℃) temperatures, which indicate that the nights have become hotter than the days and it is consistent with the global trends (IPCC,2001).

7. The observed variability of the annual maximum, minimum, and mean temperatures of the Lower Kaduna River Catchment were + 2.60℃ (6.8%) / -3.40℃ (8.9%) ,+9.20℃ (93.2%) / -7.80℃ (80%), and +4.90℃ (18.2%) /- 3.60℃ (1.5%) respectively. The trends were 0.12℃, 0.88℃, and 0.48℃ per decade respectively and are statistically significant at 5% level of significance. They are also consistent with the global trend. The highest positive increase in the annual maximum temperature of 2.60℃was recorded in 1973, 1998, and 2000, while the highest positive increases in annual minimum and mean temperatures of 9.20℃ and 4.90℃ respectively, were recorded in 1979.
8. The minimum temperature increase (0.91℃) is more than maximum temperature increase (0.07℃) within the study area,creating a narow range in daily temperature with moderate variability.
9. Most of the warming in the study area occurred in the past 20years (from the 1990s) which consistent with global trend.

10. The average annual rainfall and evaporation for the Lower Kaduna River Catchment area were 1385mm and 2453mm respectively. The rainfall and evaporation indicated increasing trends of 100mm and 99mm per decade respectively, which was not significant in the annual evaporation. Relative to the 1961 – 1990 mean values, the annual rainfall and evaporation indicated average annual increase of 125mm and 131mm respectively. The variability of annual rainfall of 1072mm (85%) (flood) and -335mm (27%) (draught) were recorded in 1999and 1961 respectively, while that of evaporation of 1035mm (45%) and -421mm (18.3%) were recorded in 2000 and 1975 respectively. .

5.2.2 Impact of Climate Variability on Stream flows of the Study Area

1. The variability of the statistical parameters of the climatic variables generally increased as the variability of the statistical parameters of the water resources variables (stream flows) (Table 4.9) indicating positive impact.
2. From the trend analyses, the trends of the climatic variables increased significantly as the trends of the water resources variables except for the annual minimum stream flow (Table 4.9) , which also, indicate positive impact. This is in accordance with IPCC (2007) observations that significant trends in streamflow/runoff have demonstrated statistically significant links with trends in rainfal or temperature.The increases in the trends were consistent from the 1970s which is in line with global trend (Chen et al,2007 as cited by Durdu ,2010). The declining trend exhited by the minimum discharge was due to lower rainfall and warmer temperatures during the dry season. The decline in the annual minimum discharge was 0.15cumecs (20%) per decade.
3. The increased annual rainfall anomalies (flooding) between 1998 and 2003 corresponded, positively, with the increased anomalies of the annual stream

flows of Kaduna River at Lower Kaduna River catchment within the same period (Figure 4.22), which resulted in the flood events in the river system in 2003,though, most climate variability scenarios predicted a decline in rainfall in the range of 0.5 to 40% in West Africa (Niasse et al, 2004). With higher temperatures,the water holding capacity of the atmosphere and evaporation into the atmosphere increase and this favours increased climate variability with more intensed rainfall and floods (Durdu, 2010).

4. From the parametric and non-parametric correlation analyses, the climatic variables and the water resources (stream flows) variables are positively and significantly correlated at 5% and 10% levels of significance (Tables 10and 11), indicating that climate variability has positive influence on the stream flows of Lower Kaduna River Catchment.
5. The observed climate variability accounts for changes in the annual stream flow of river Kaduna at Lower Kaduna River Catchment of up to 13193 m^3/day (205%) per decade and changes in the annual maximum discharge of up to 284 m^3/day (125%) which were consistent from the 1970s and in accordance with the global trend (IPCC, 2007).
6. The implications of these results for water resources development are that the increasing demand for domestic and industrial water, irrigation water and water for livestock watering may become increasing difficult to be satisfied using direct streamflows alone especially, during the dry season periods of November to December and January to May every year (Figure 4.26).This is in accordance with the study by Alcamo et al (Durdu, 2010) which indicated that climate variability increases water stress and risk of flooding.

5.3 RECOMMENDATION S

The recommended adaptive responses to climate variability are

1. Implementation of water conservation measures;These include creation of wetlands and shelter belts.
2. Reduction of the current variability by means of increased storage capacity by constructing buffer dams and reservoirs in order to store excess runoff duing the periods of high flows in June to October which can reduce flood effects and can be used during the dry months of November to December and January to May.
3. Enhancement in the measurement, monitoring, forecasting, and knowledge of the hydrologic system. :
4. Crop diversification should be increased with improved soil management practice and improved access to agricultural equipment and fertilizer and agro-chemicals because of the decreasing length of rainy days.
5. Land use pattern has a significant impacts or effects on the water resources of any region. The variability of the water resources of the Lower Kaduna catchment, in particular, the variability of the annual rainfall and the annual discharges (Qtotal, Qmax, Qmin, and Qmean) may not be due entirely to the climate variability. It is therefore, recommended that the effects of the land use pattern, particularly, deforestation and urbanization on the water resources be further investigated.
6. Water managers should begin a systematic re-examination of engineering designs, operating rules, contingency plans, and water allocation policies under a wider range of climate conditions and extremes than have been used traditionally. For

example, the standard engineering practice of designing for the worst case in the historical observational record may no longer be adequate.

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APPENDICES

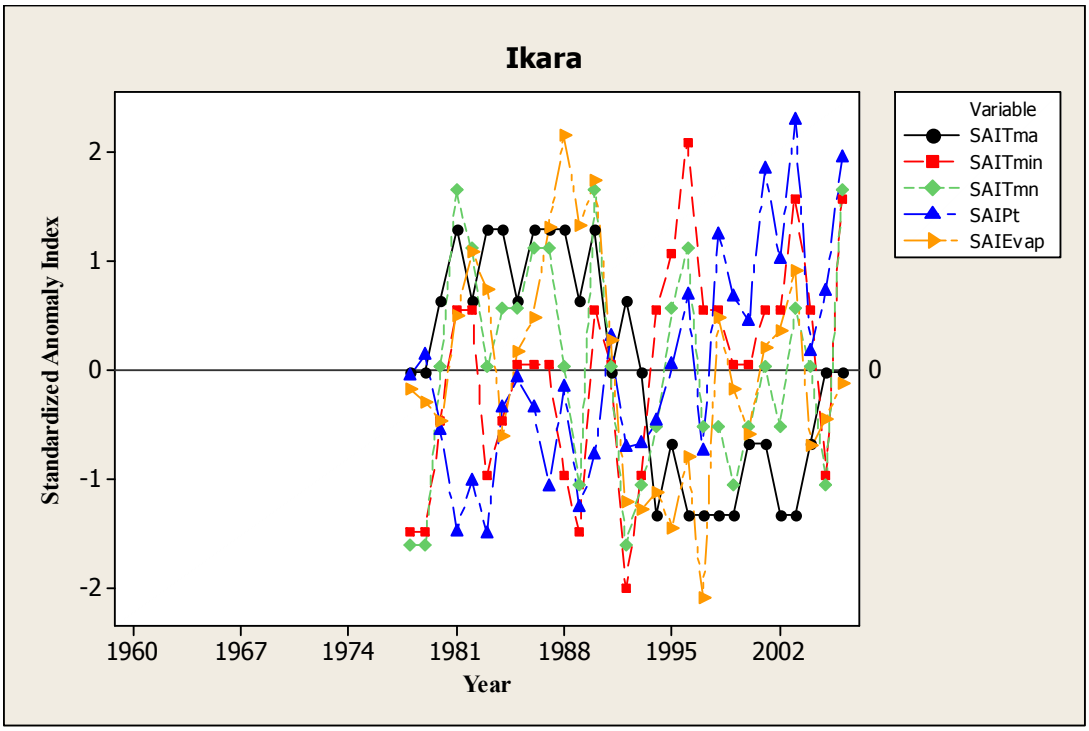
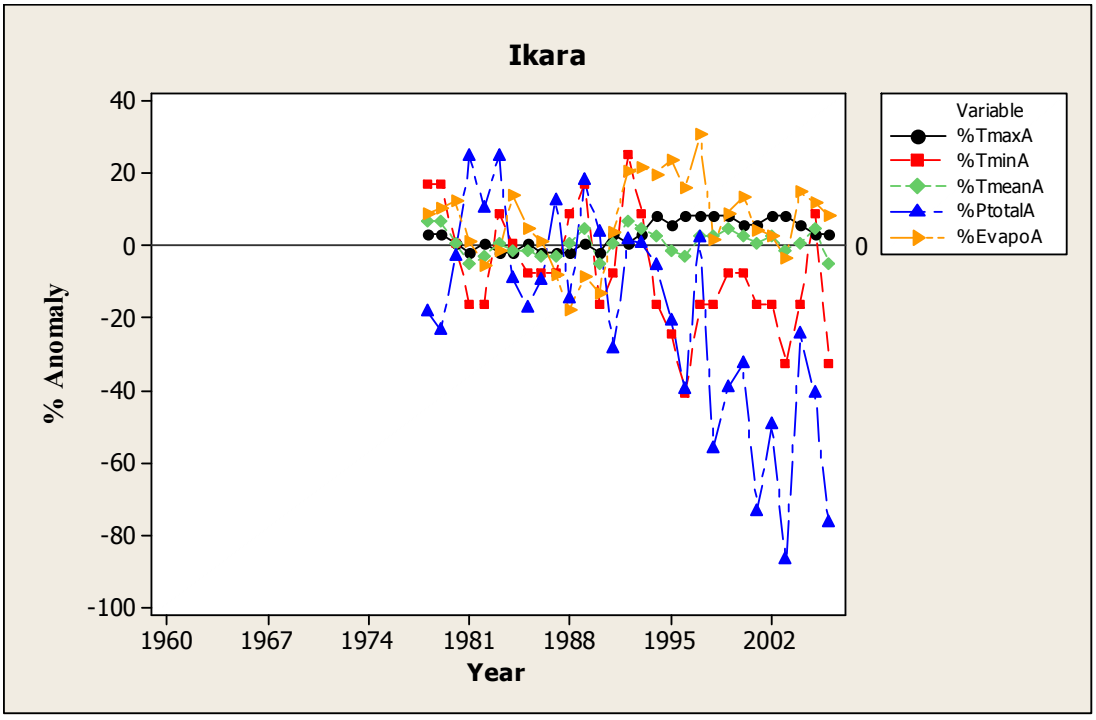


Figure A.1a :Standardized Anomaly Index for Temperatures, Rainfall and Evaporation



FigureA1b: %Anomalies of Temperatures, Rainfall & Evaporation relative to 1961-1990

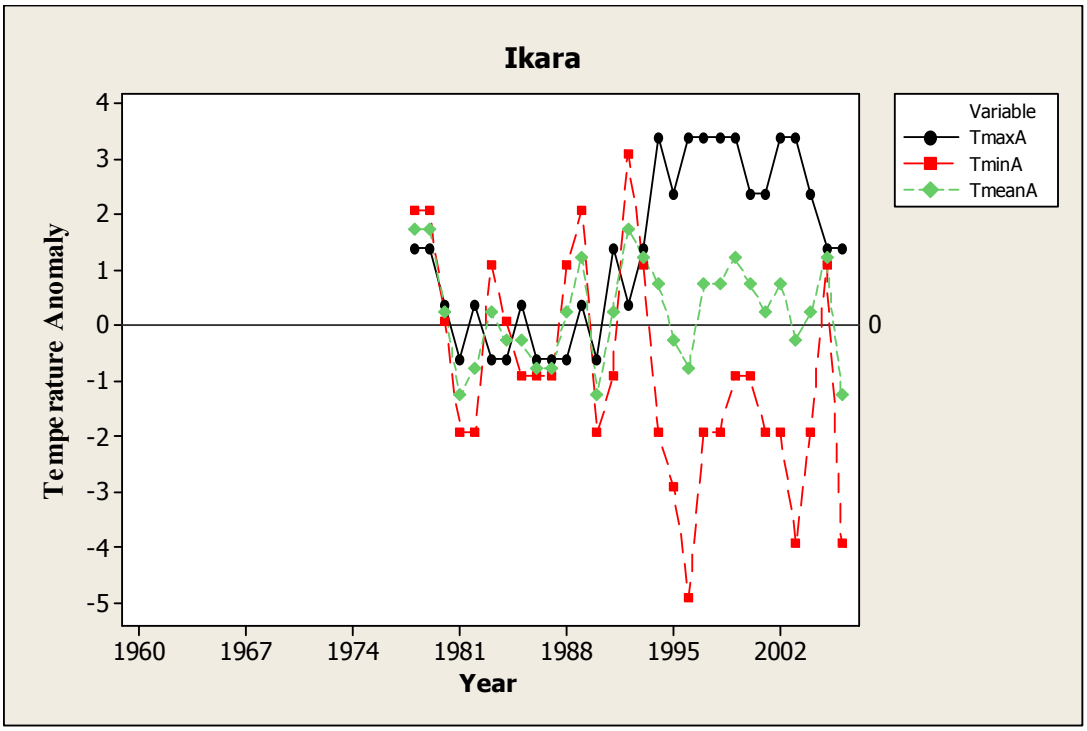


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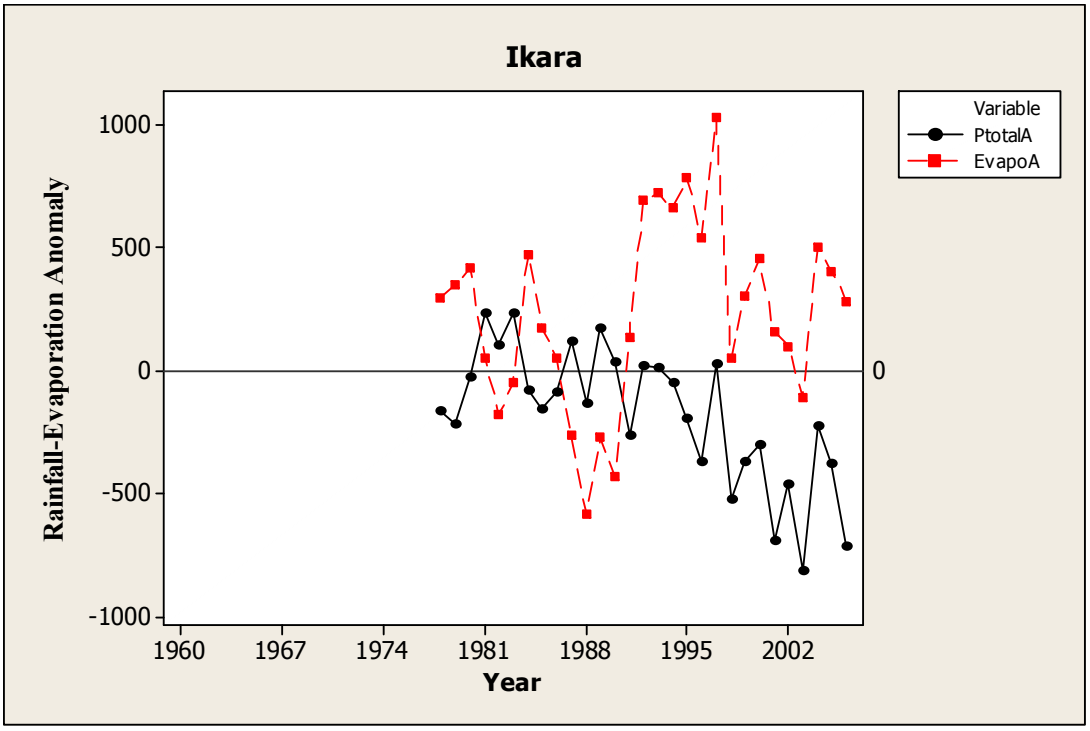
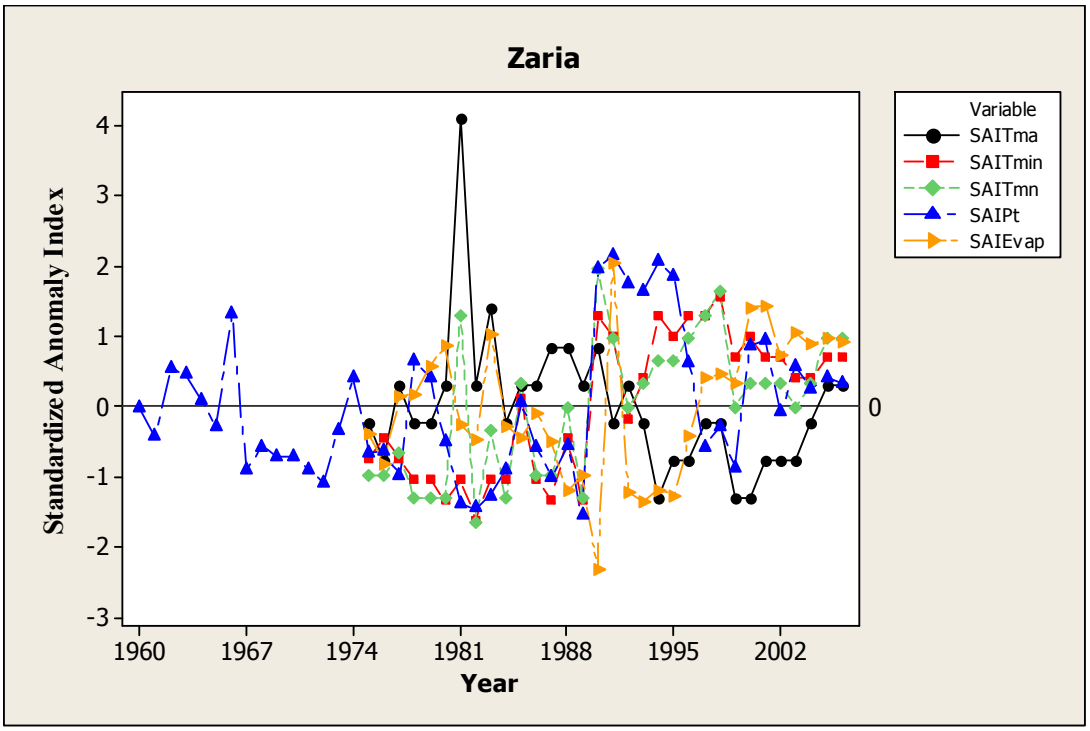
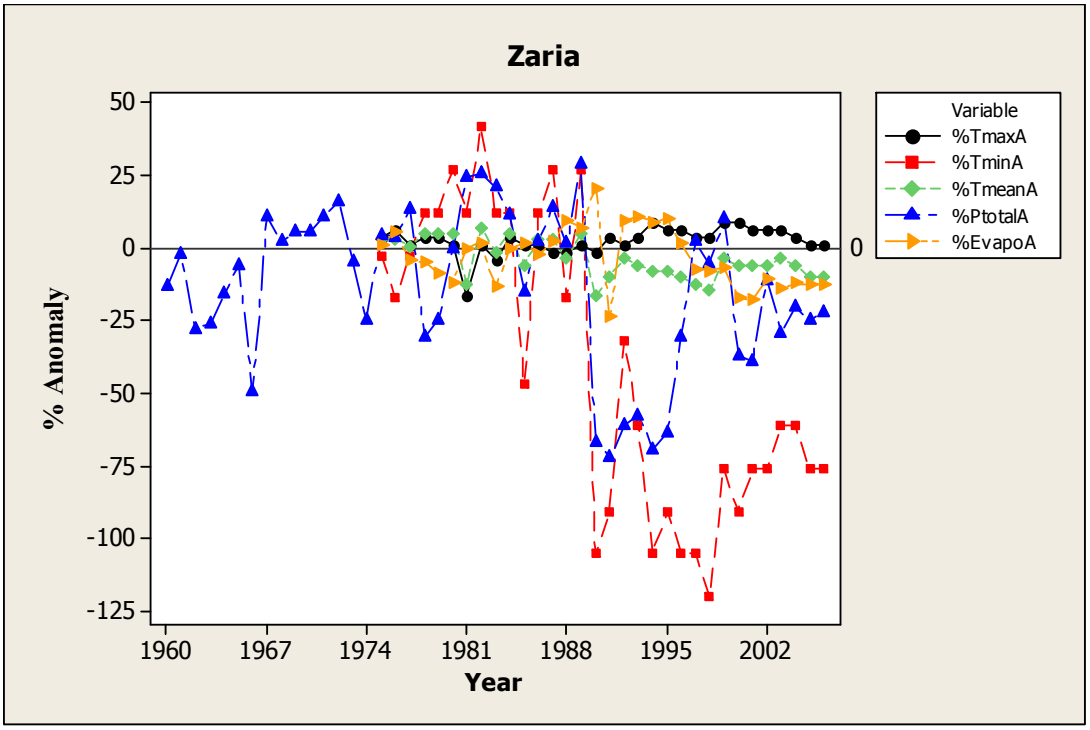


Figure A1d :Rainfall and Evaporation Anomalies relative to 1961-1990



FigureA.2a: Standardized Anomaly Index for Temperatures, Rainfall and Evaporation



FigureA.2b: %Anomalies of Temperatures, Rainfall & Evaporation relative to 1961-1990

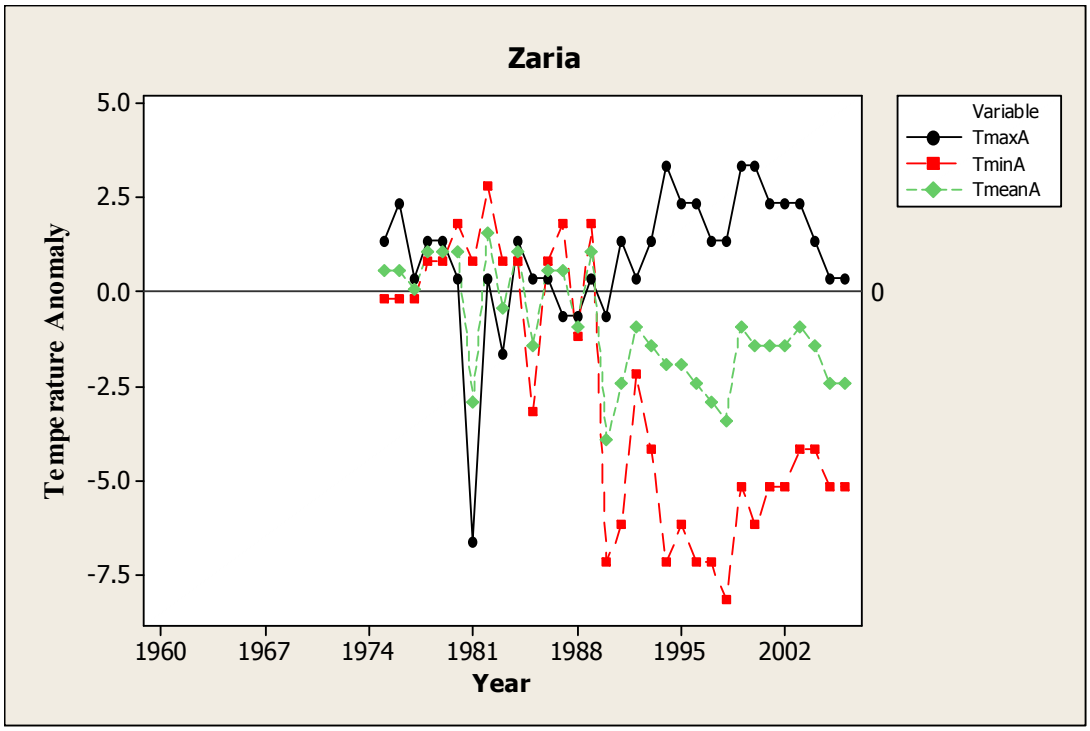


Figure A.2c: Temperature Anomalies relative to 1961-1990

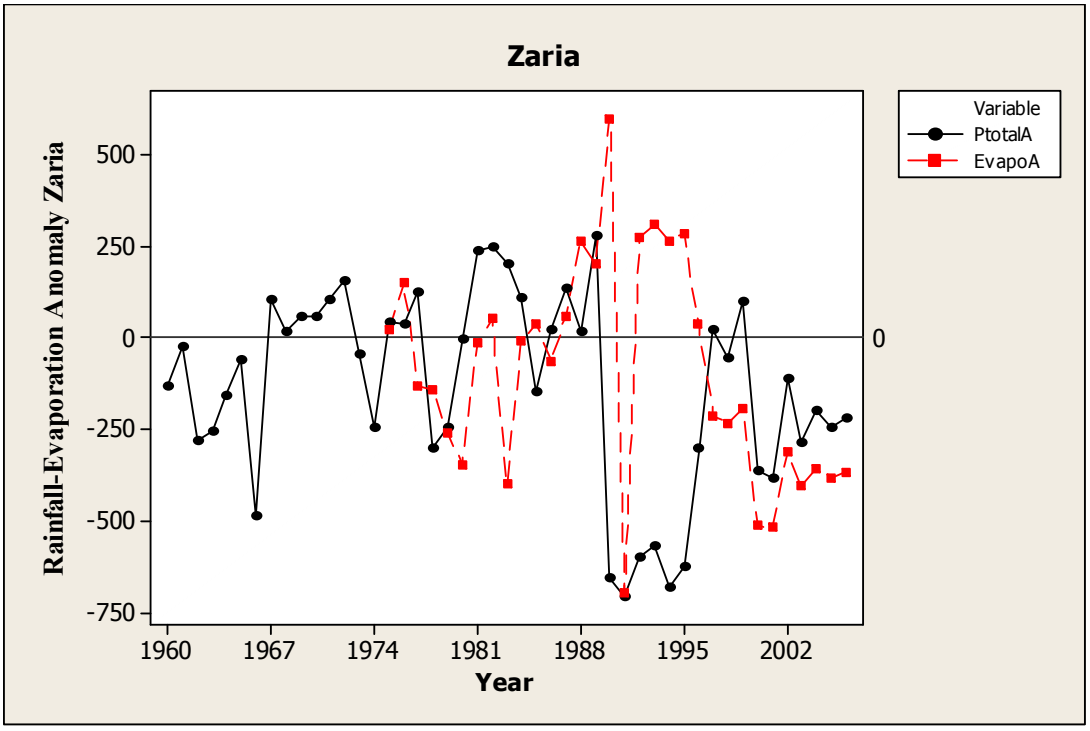


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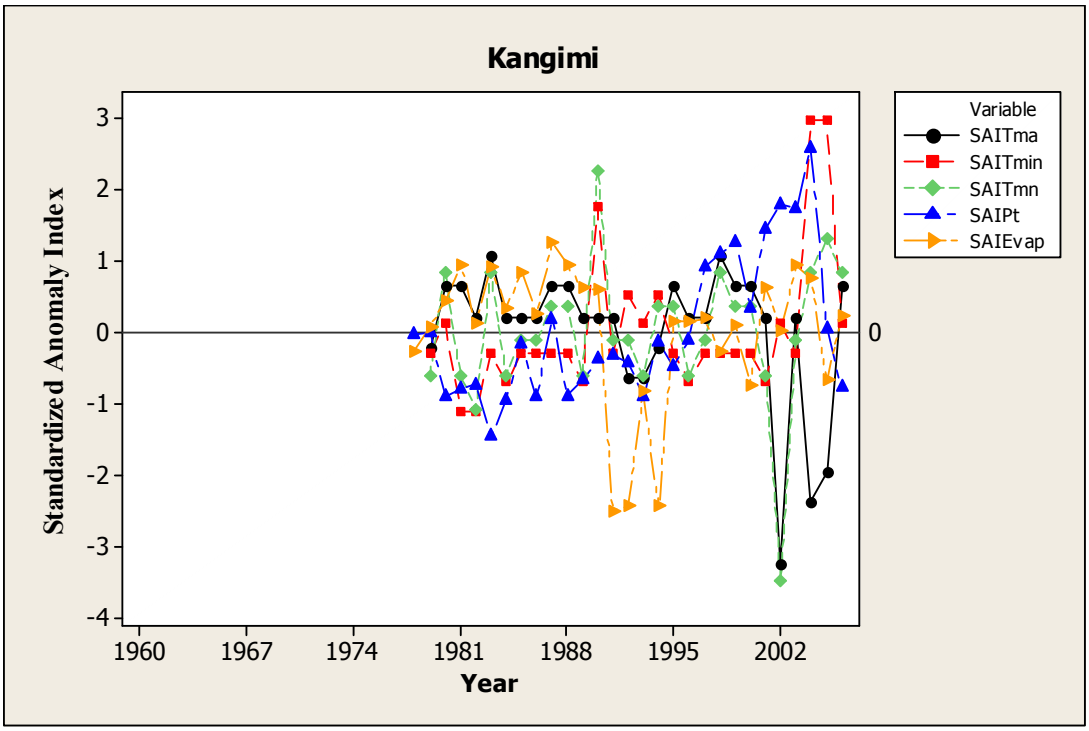
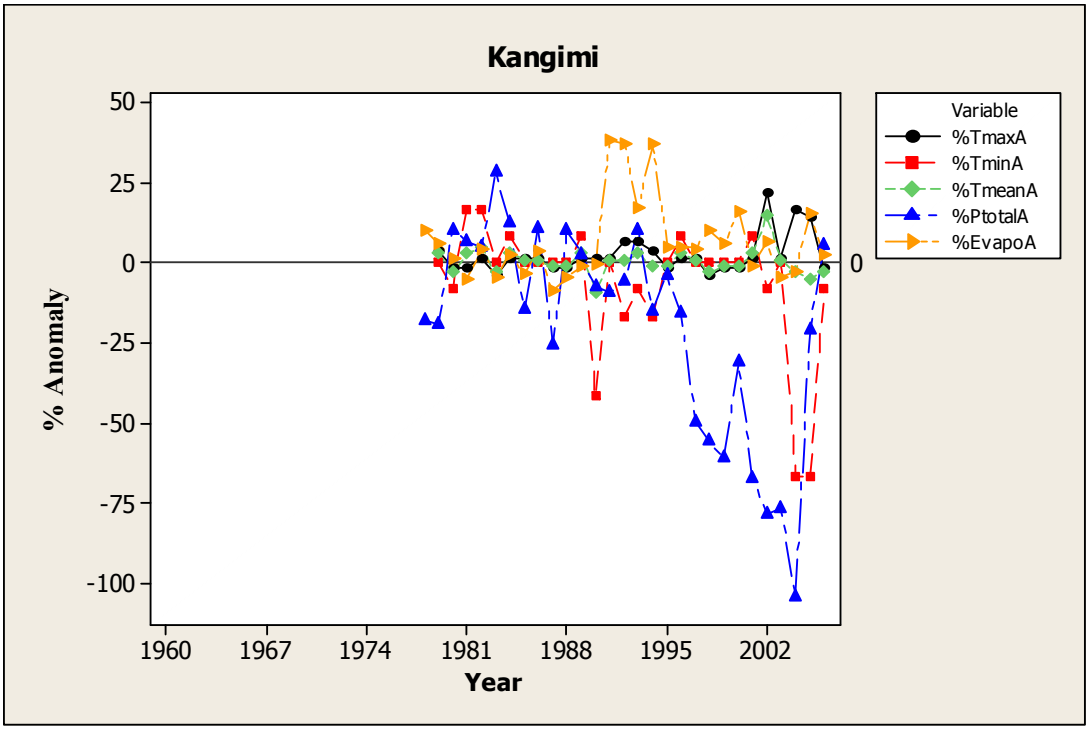


Figure A.3a :Standardized Anomaly Index for Temperatures, Rainfall and Evaporation



FigureA.3b: %Anomalies of Temperatures, Rainfall & Evaporation relative to 1961-1990

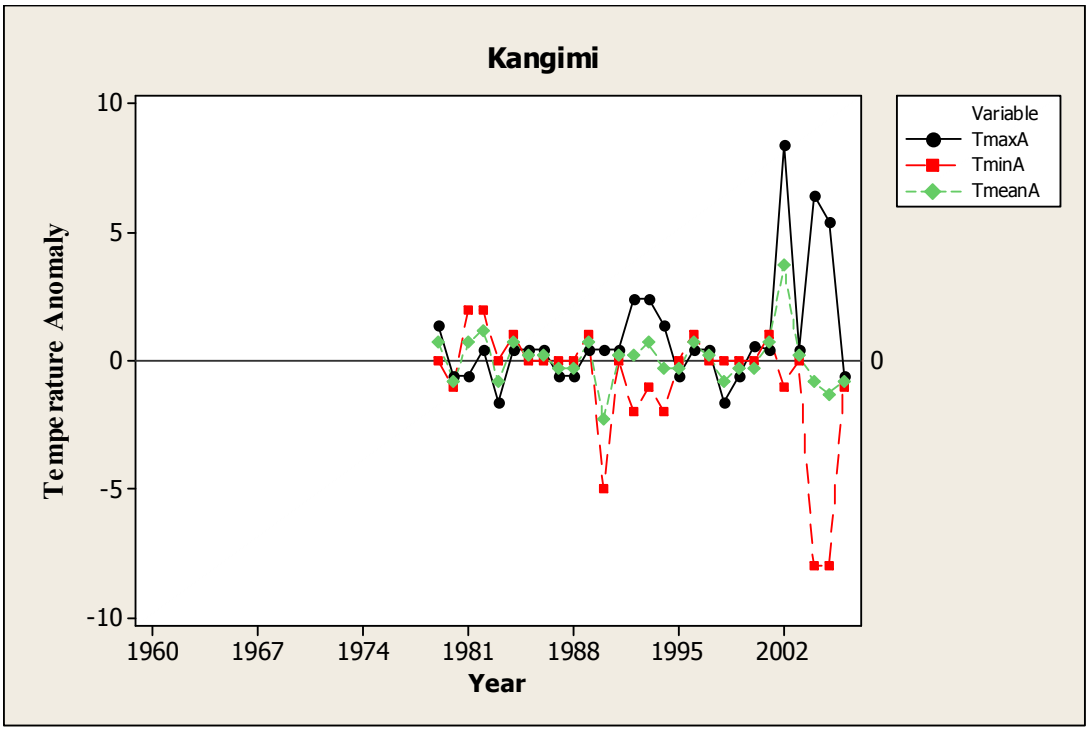


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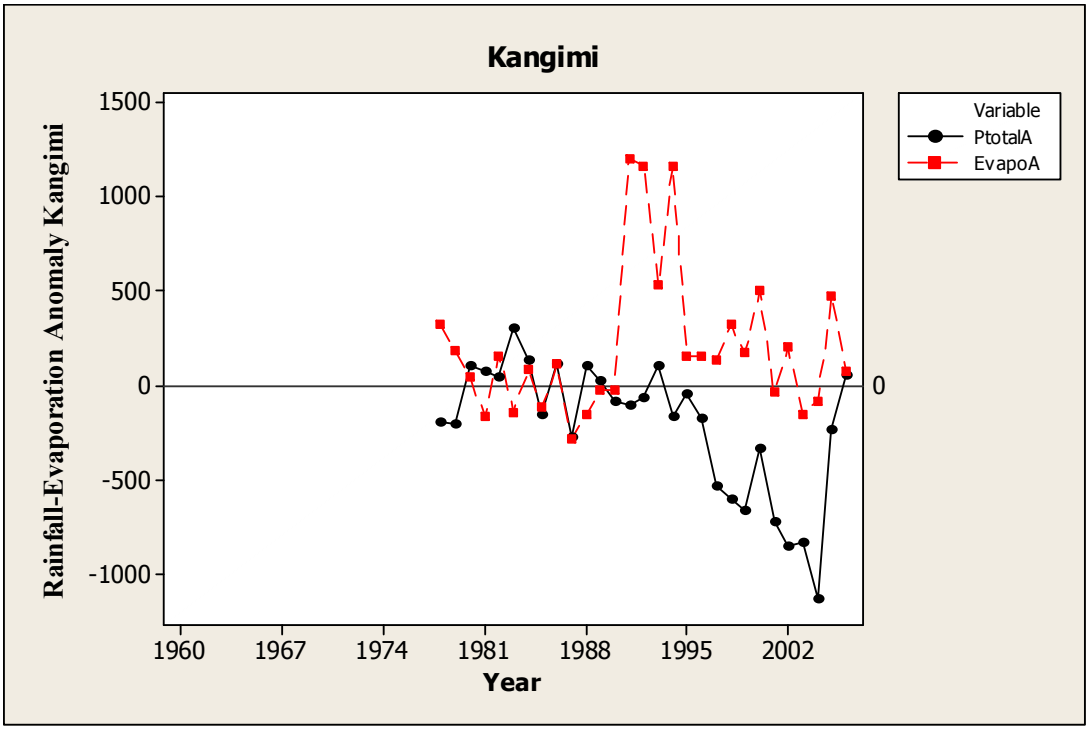


Figure A.3d: Rainfall and Evaporation Anomalies relative to 1961-1990

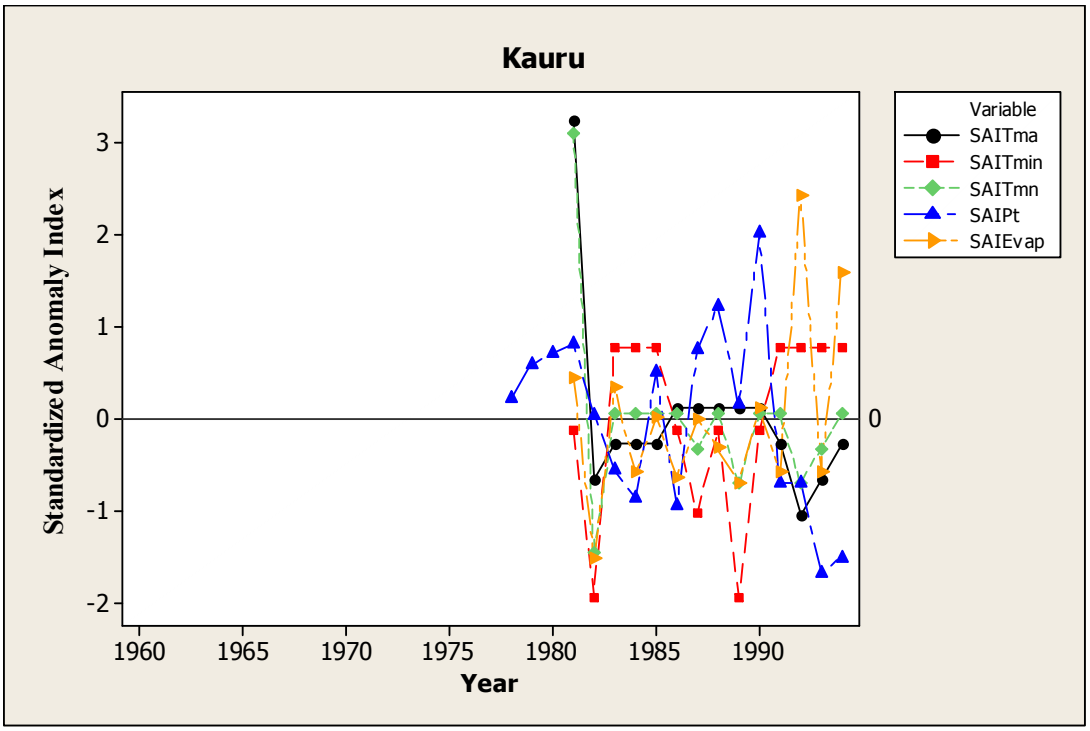
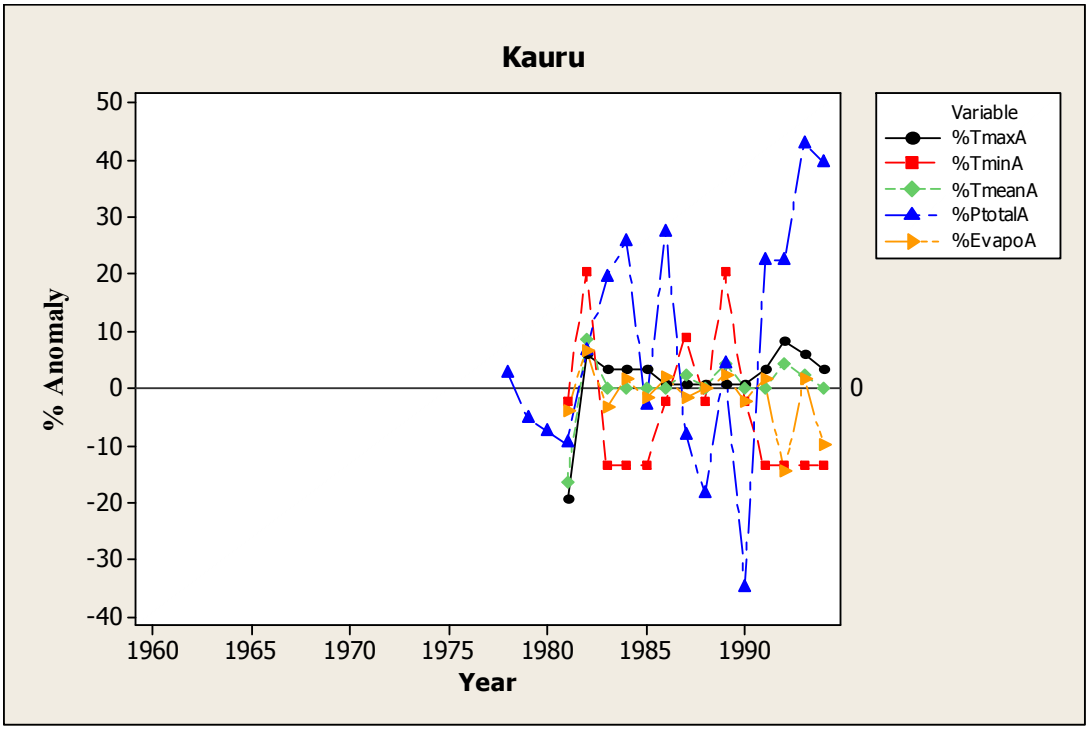


Figure A.4a: Standardized Anomaly Index for Temperatures, Rainfall and Evaporation



FigureA.4b: %Anomalies of Temperatures, Rainfall & Evaporation relative to 1961-1990

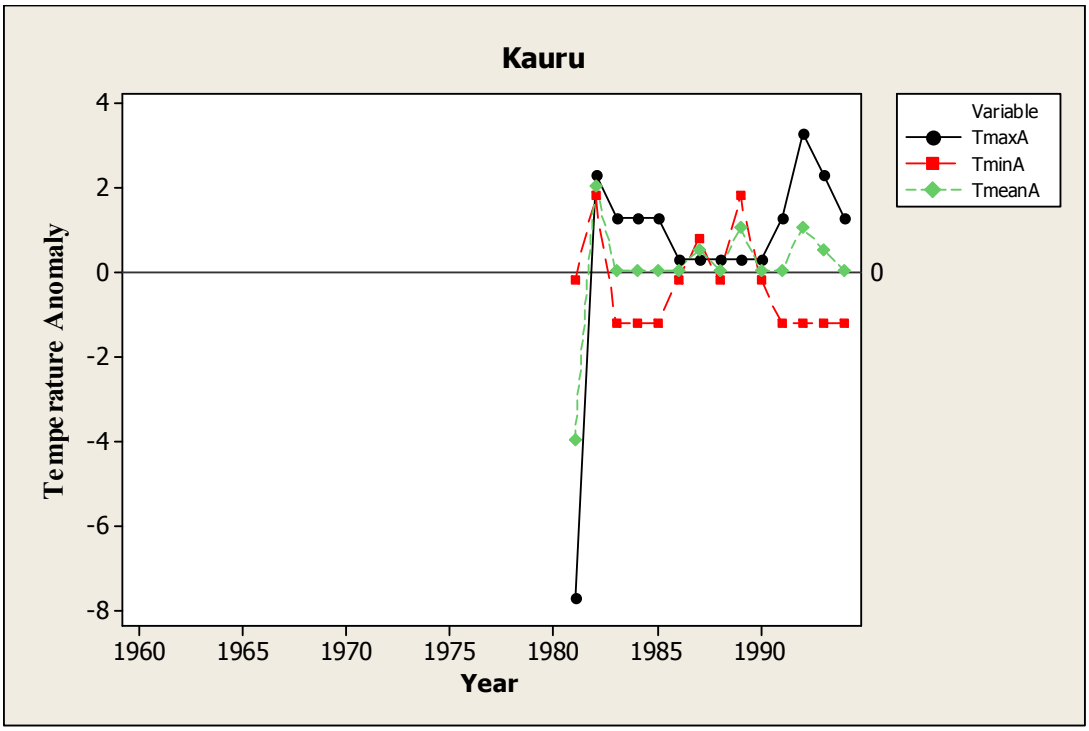


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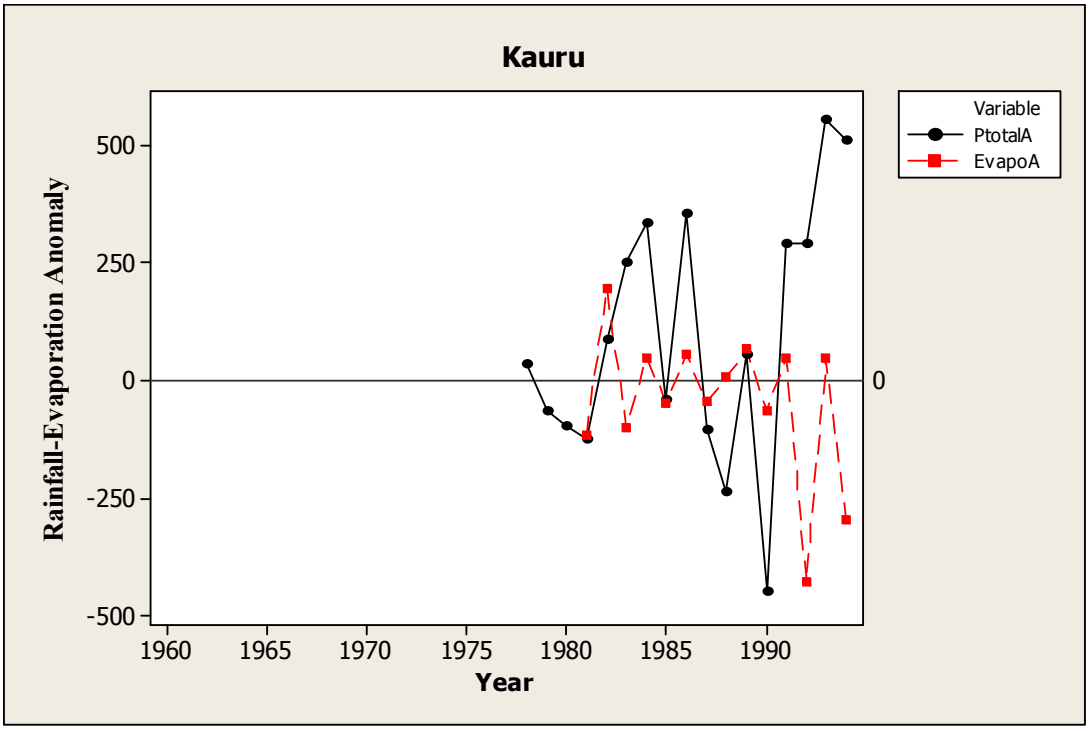


Figure A4d: Rainfall and Evaporation Anomalies relative to 1961-1990

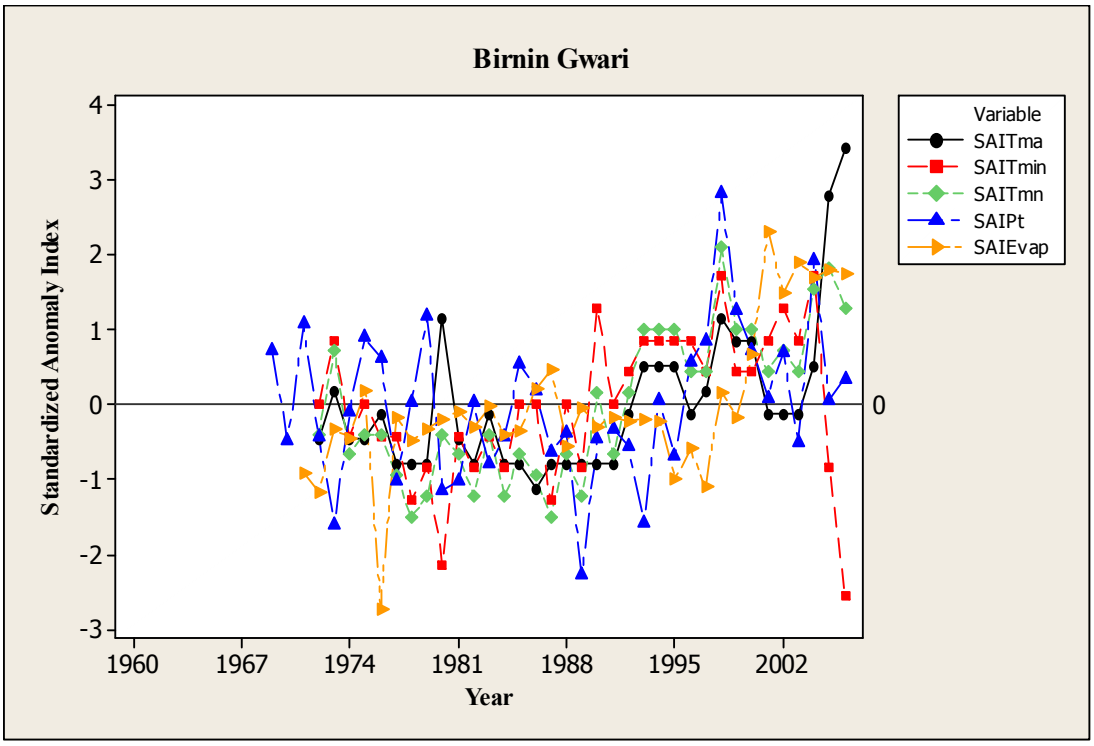
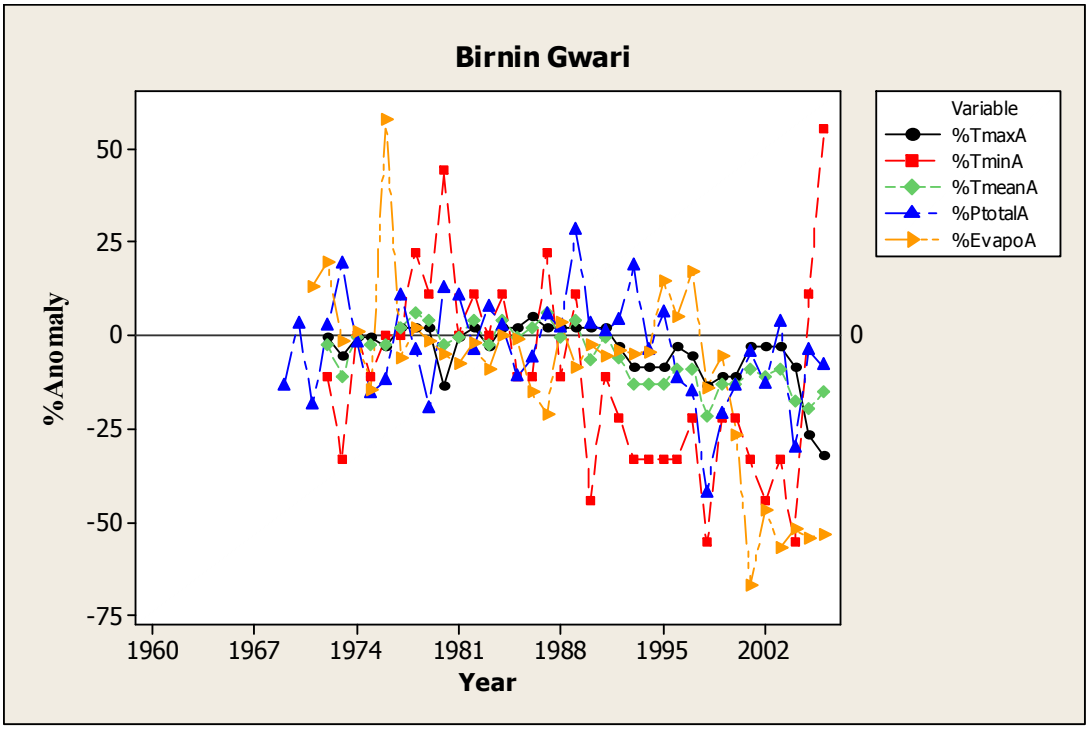


Figure A.5a :Standardized Anomaly Index for Temperatures, Rainfall and Evaporation



FigureA.5b: %Anomalies of Temperatures, Rainfall & Evaporation relative to 1961-1990

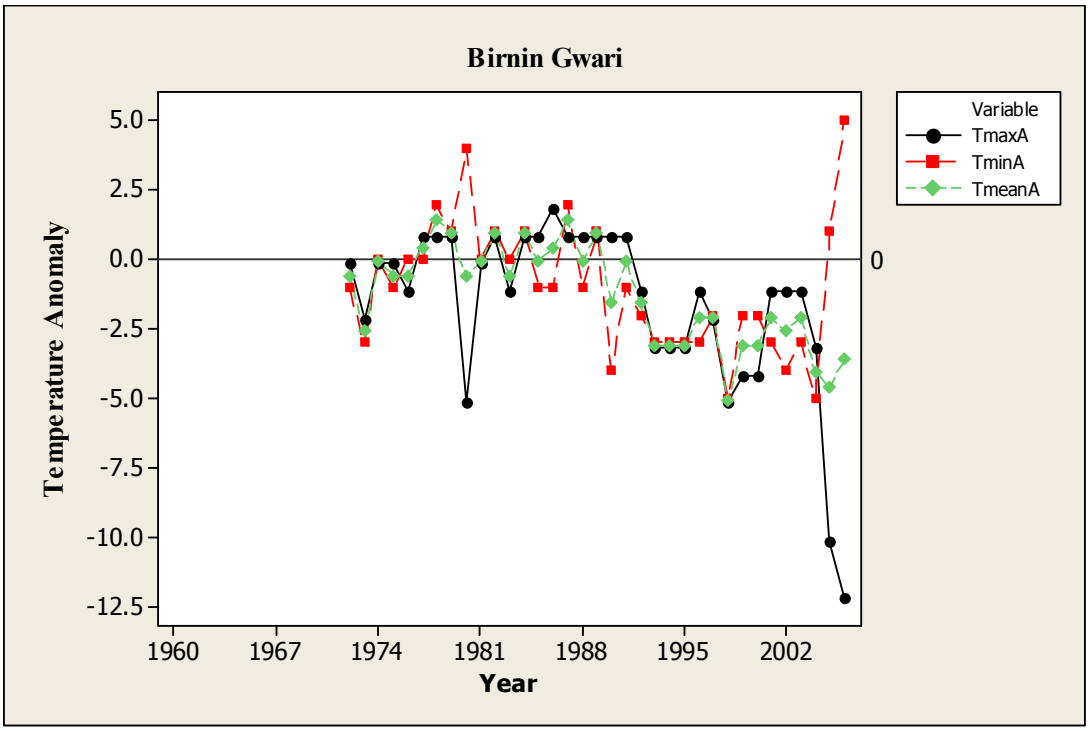


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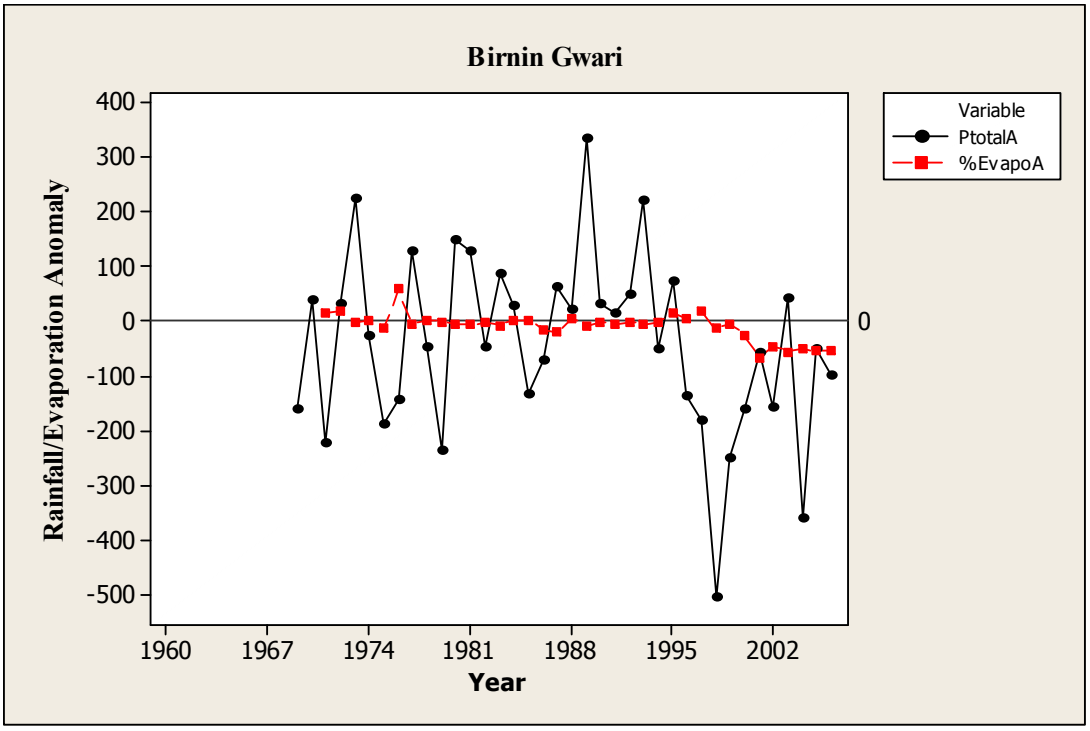


Figure A.5d: Rainfall and Evaporation Anomalies relative to 1961-1990

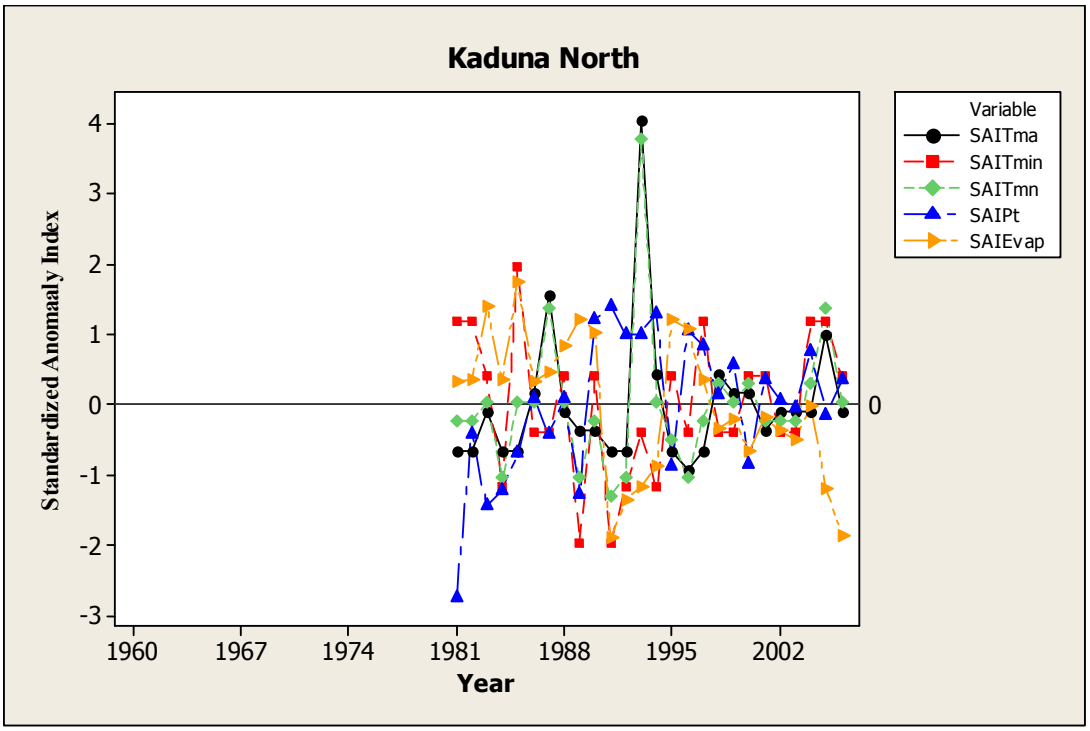


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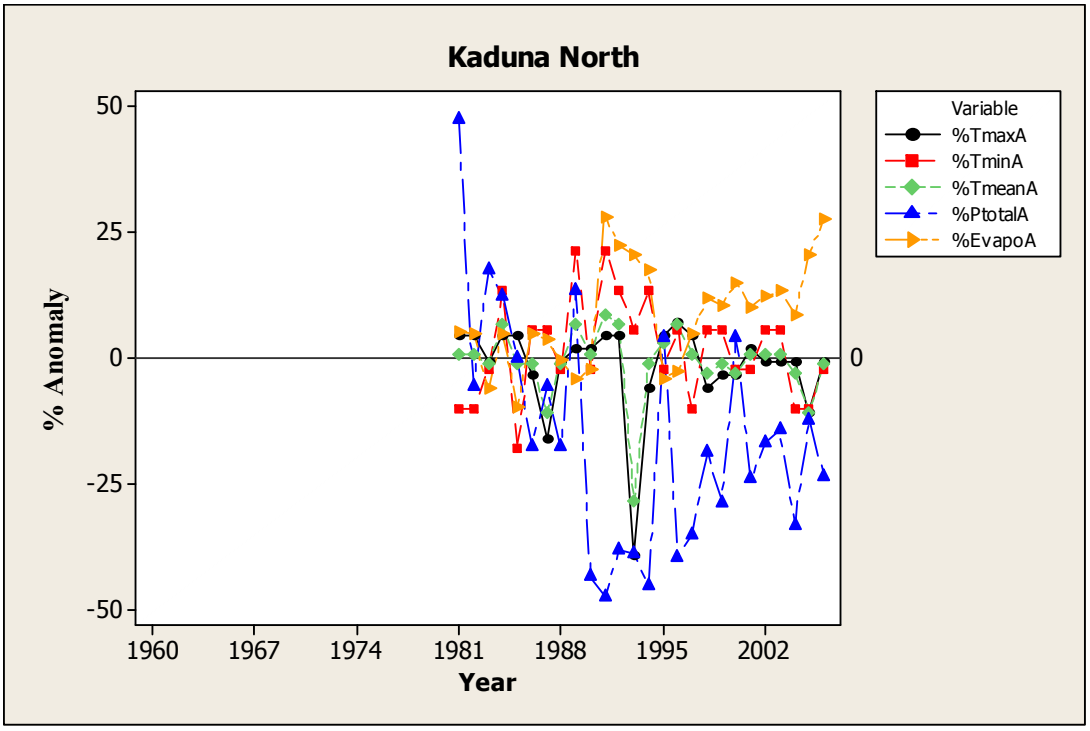


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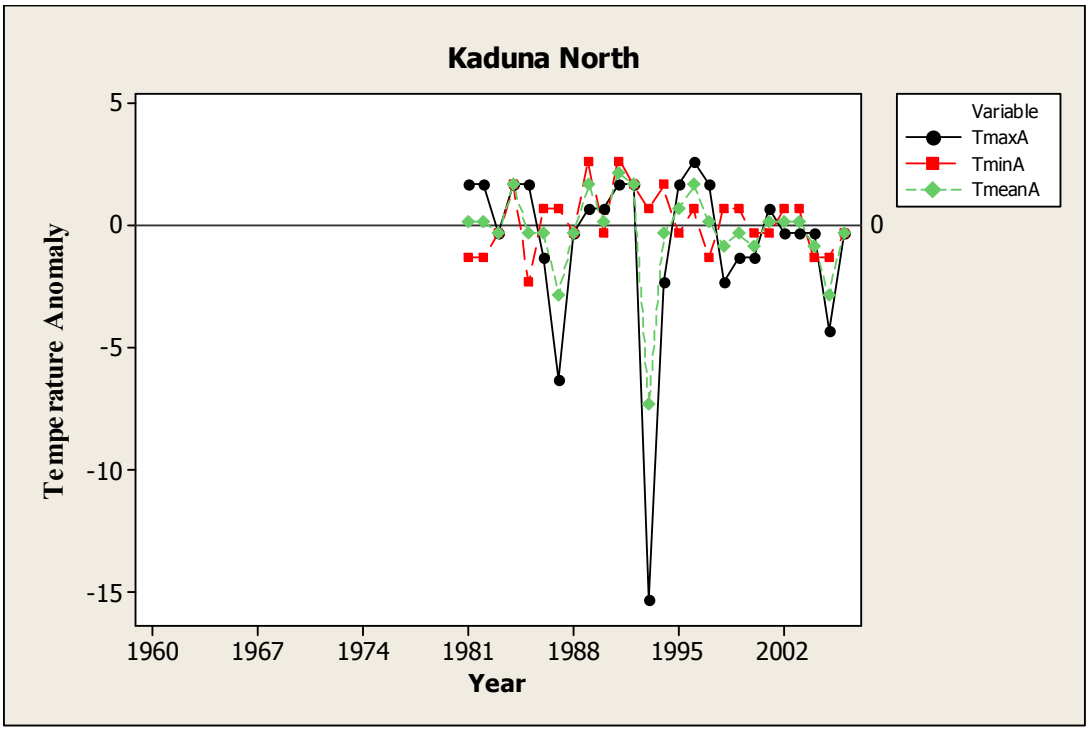


Figure A.6c: Temperature Anomalies relative to 1961-1990

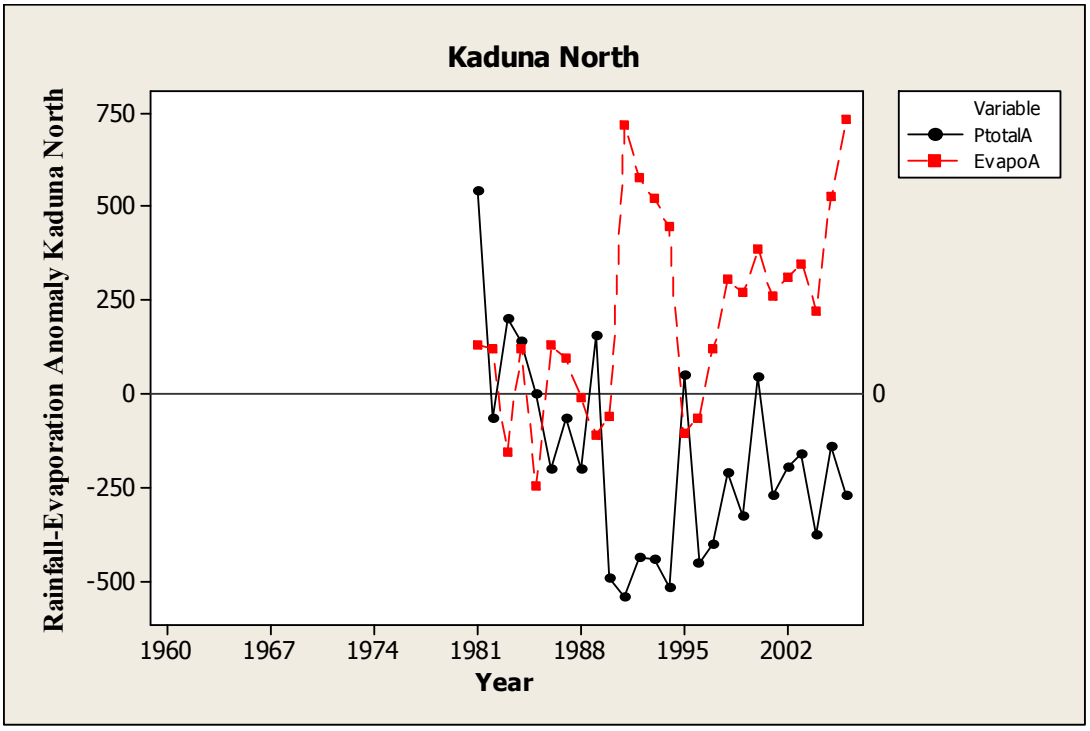


Figure A.6d: Rainfall and Evaporation Anomalies relative to 1961-1990

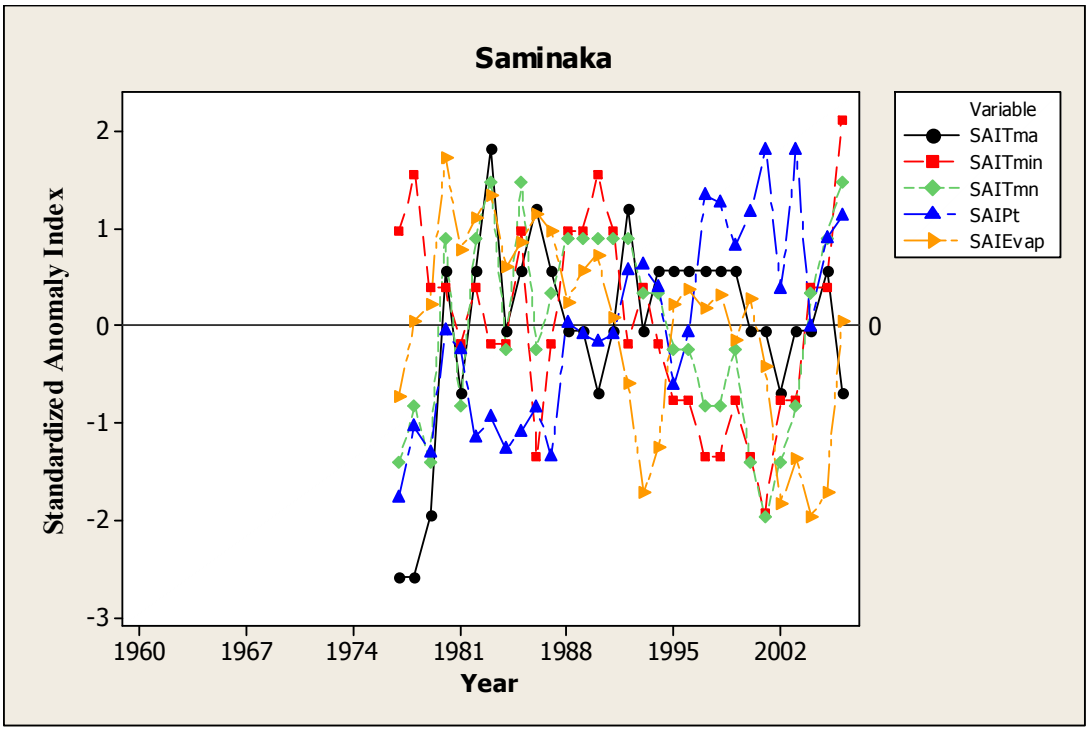


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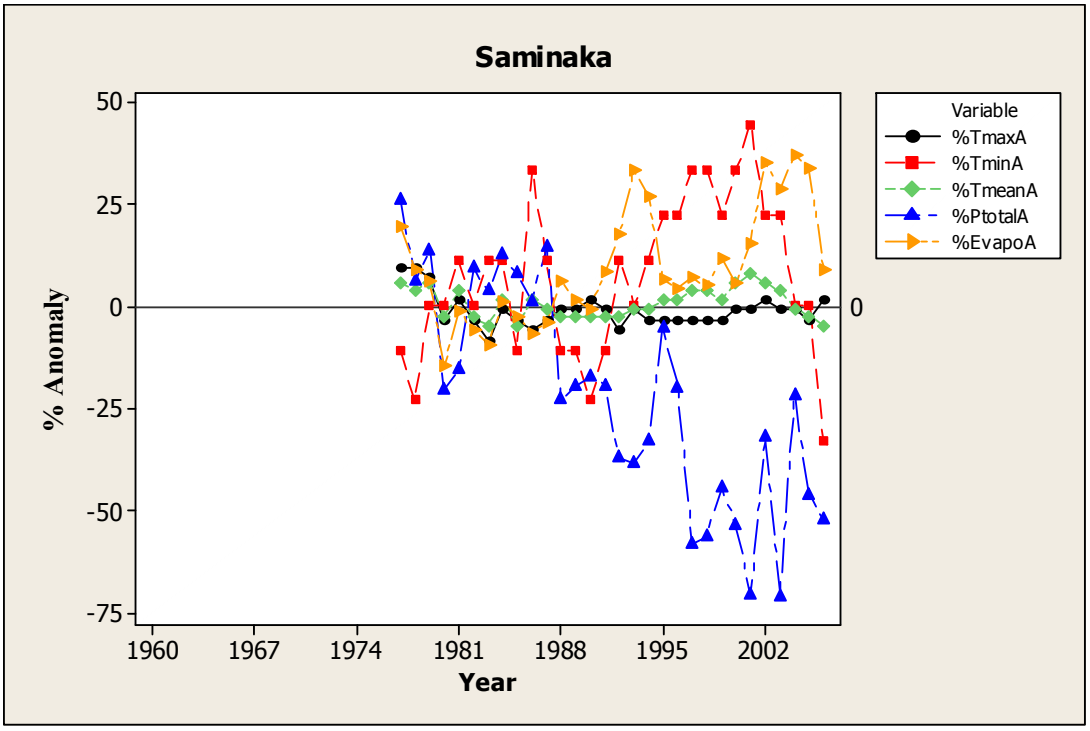


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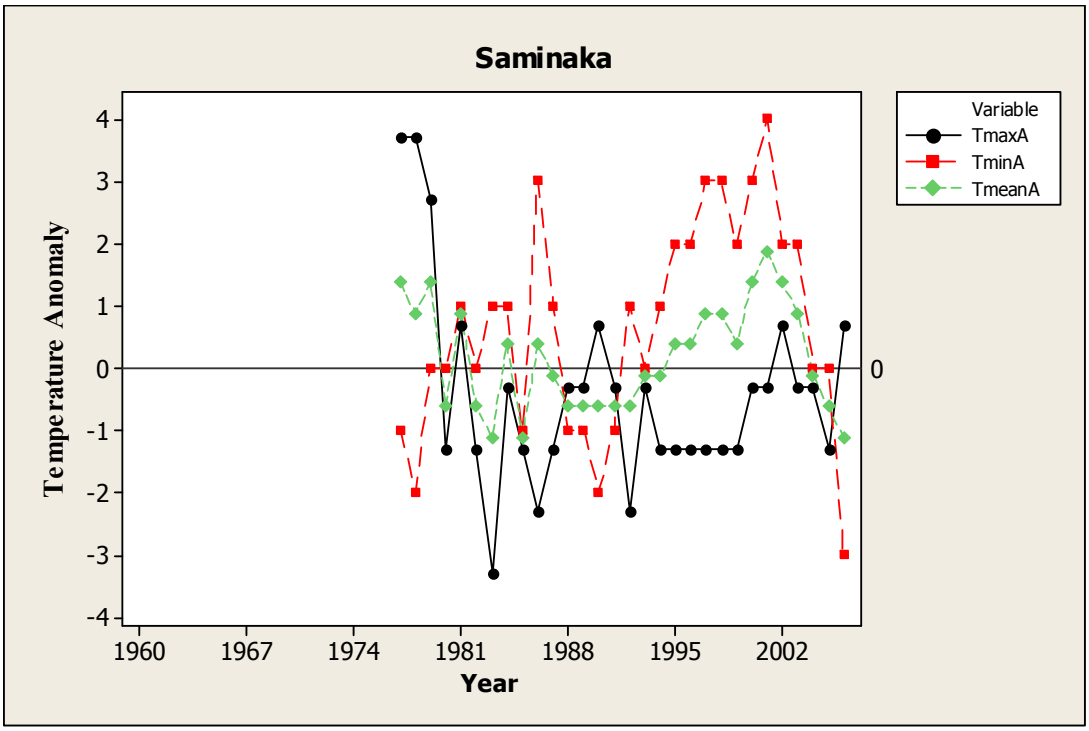


Figure A7c: Temperature Anomalies relative to 1961-1990

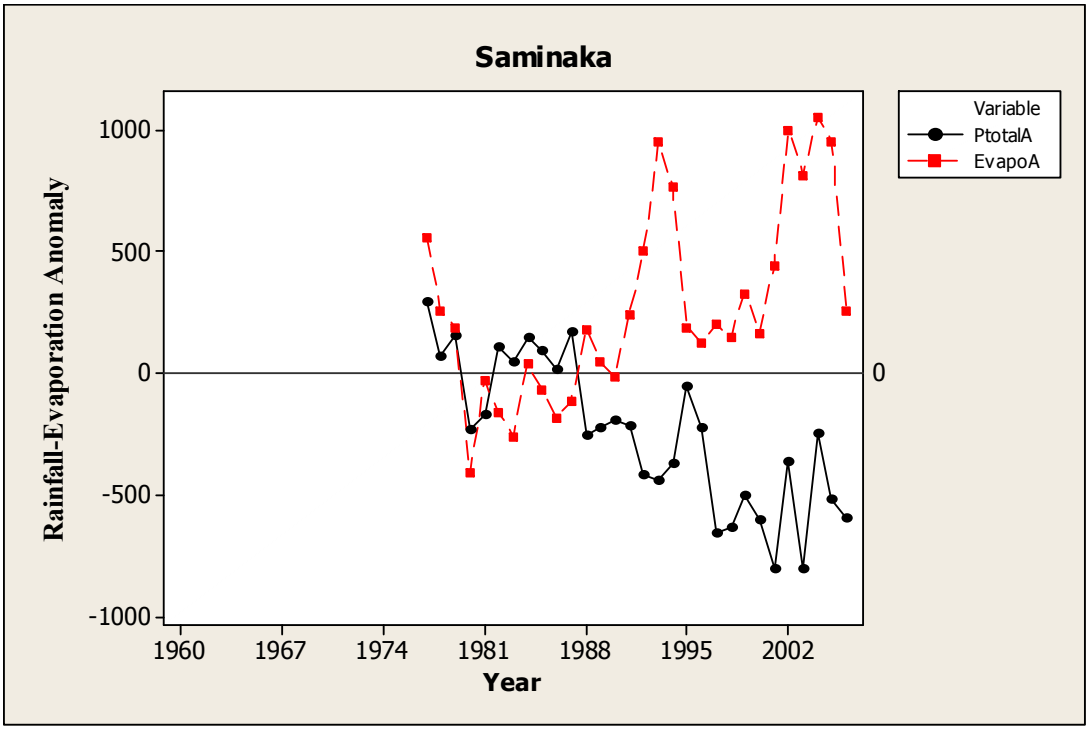


Figure A7d: Rainfall and Evaporation Anomalies relative to 1961-1990

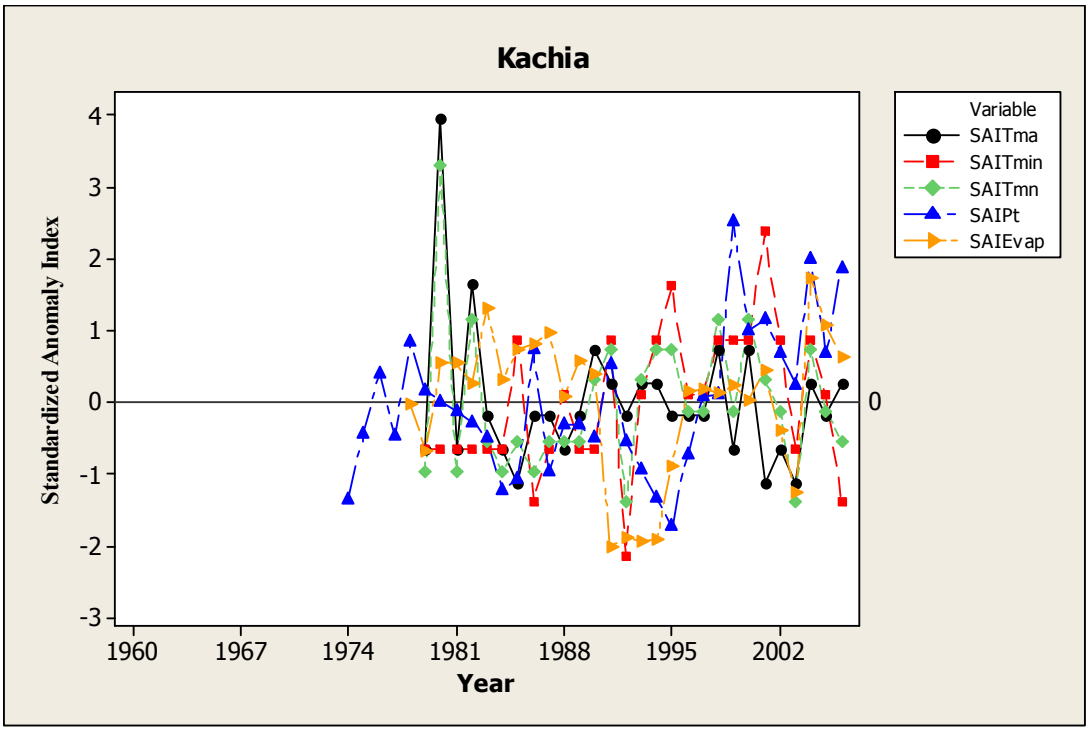


Figure A8a: Standardized Anomaly Index for Temperatures, Rainfall and Evaporation

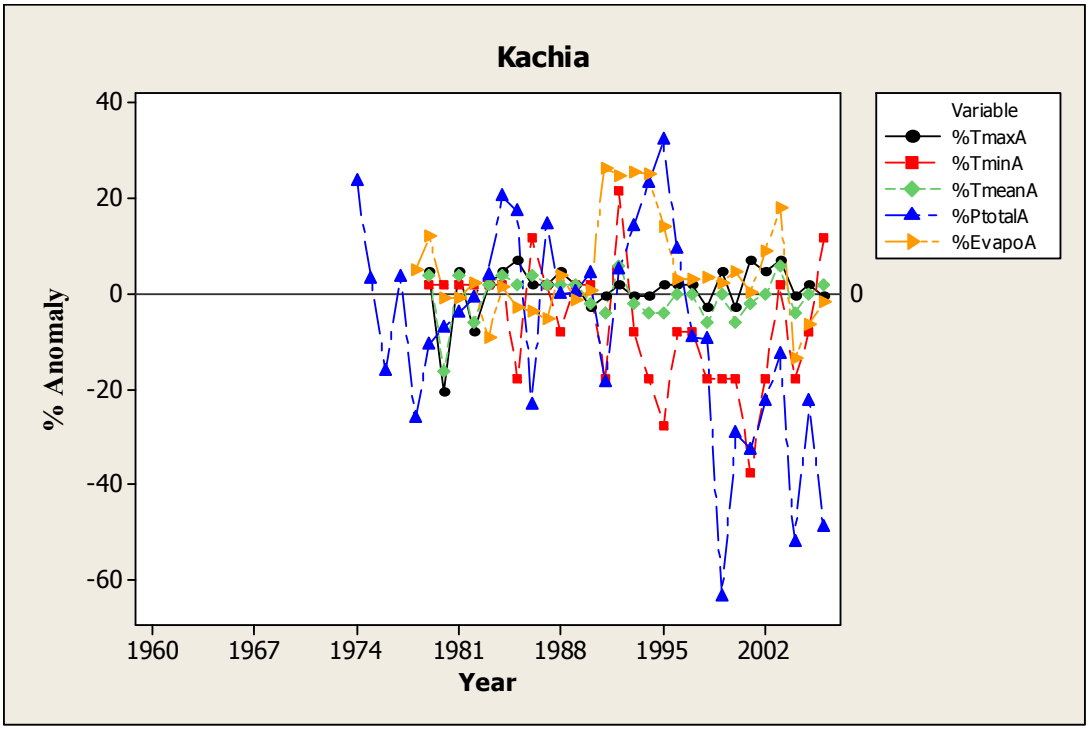


Figure A8b: %Anomalies of Temperatures, Rainfall & Evaporation relative to 1961-1990

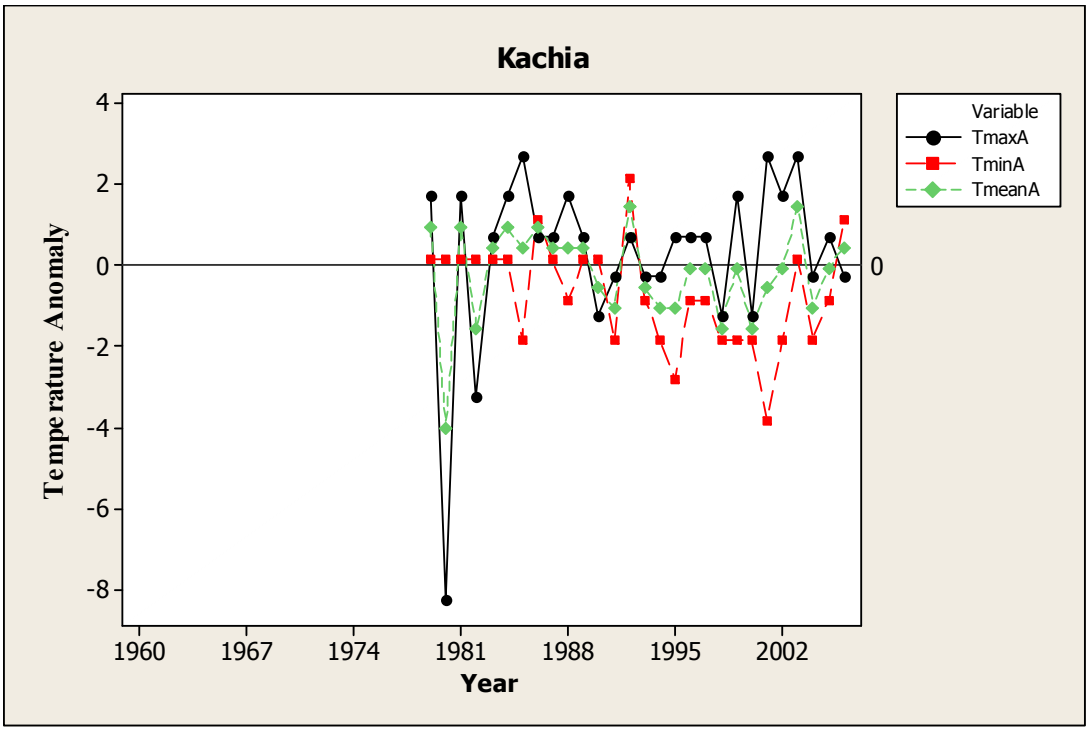


Figure A8c: Temperature Anomalies relative to 1961-1990

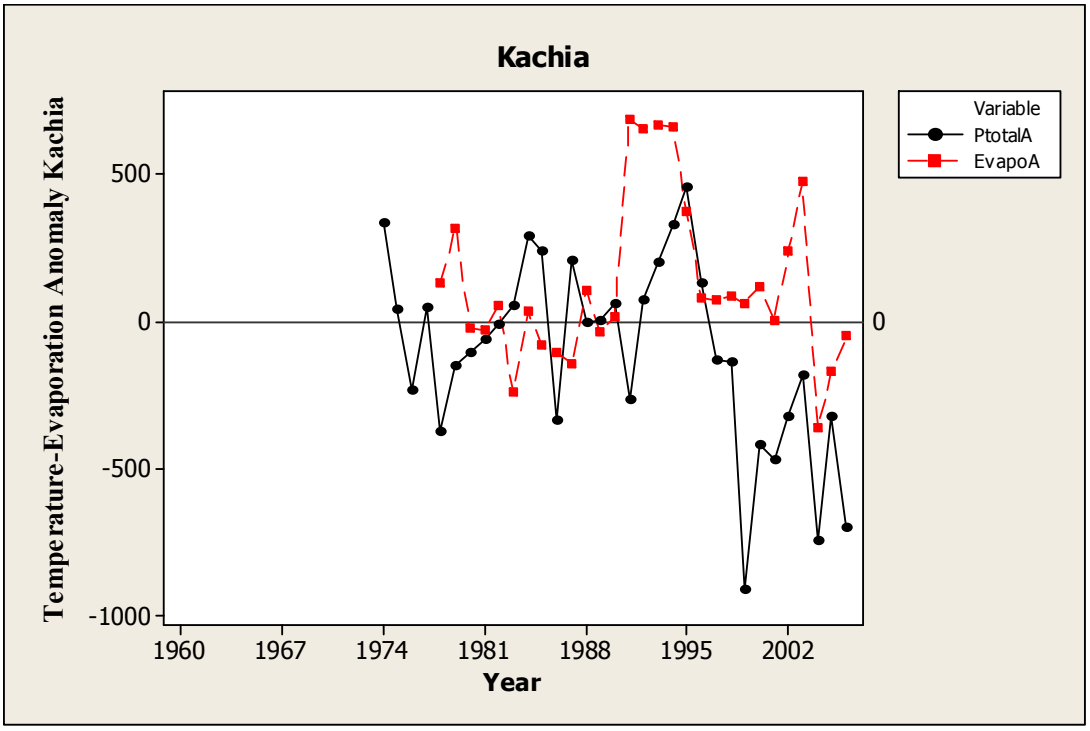


Figure A8d: Rainfall and Evaporation Anomalies relative to 1961-1990

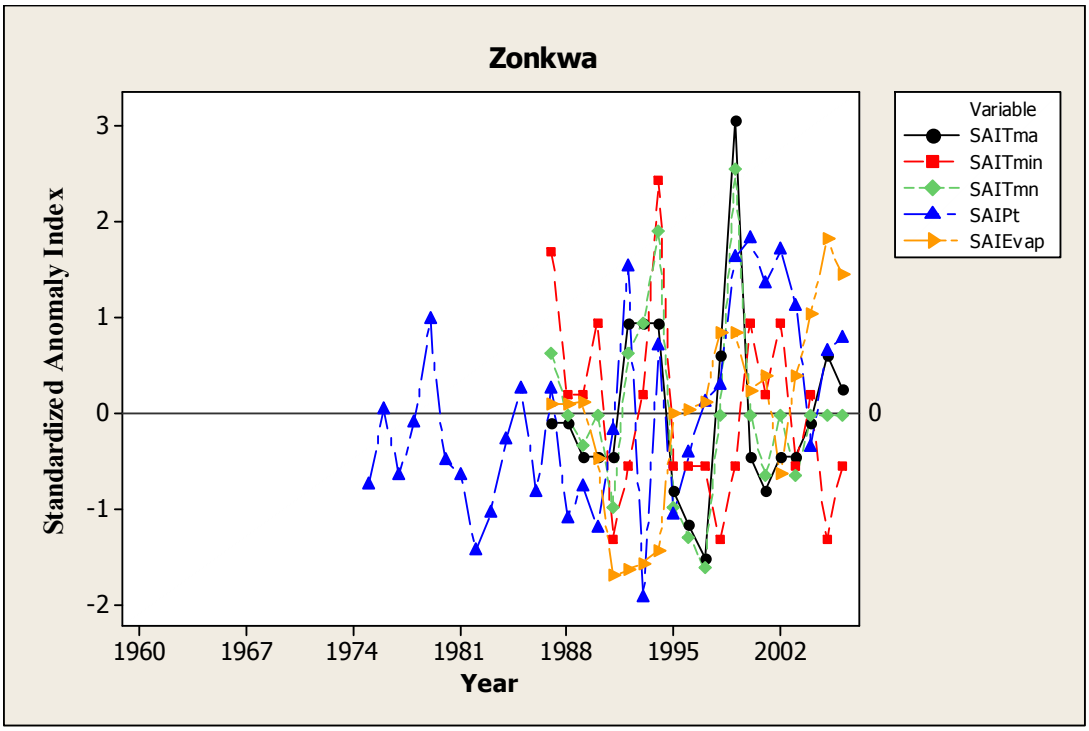


Figure A9a: Standardized Anomaly Index for Temperatures, Rainfall and Evaporation

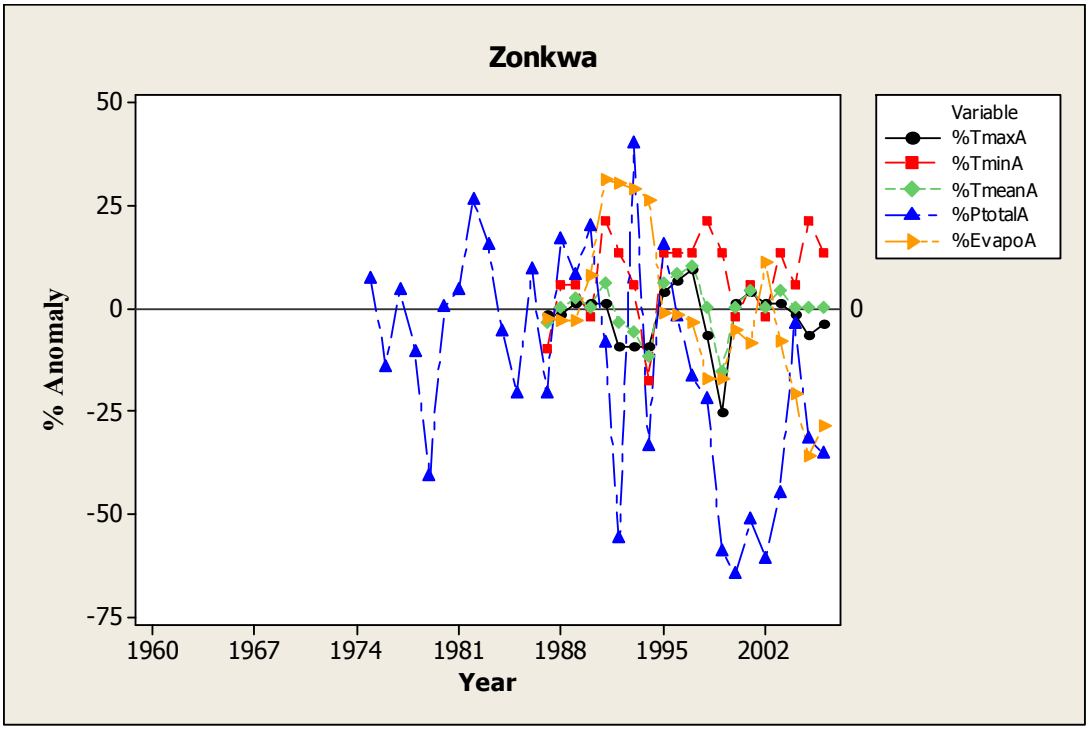


Figure A9b: %Anomalies of Temperatures, Rainfall & Evaporation relative to 1961-1990

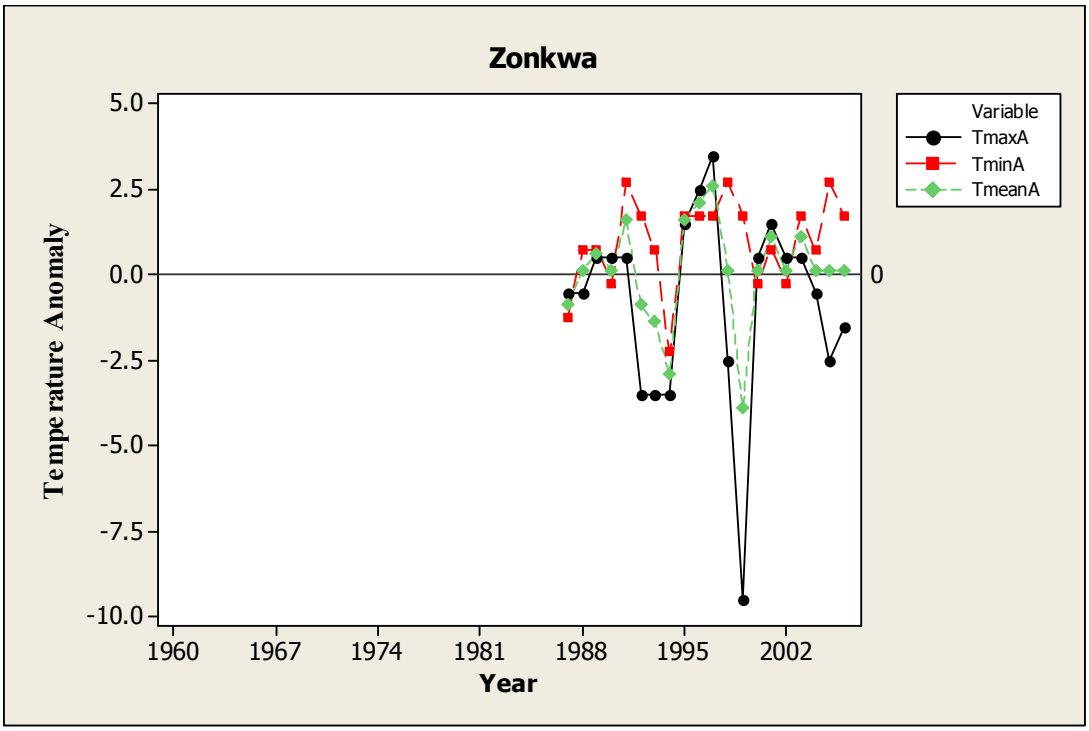


Figure A9c: Temperature Anomalies relative to 1961-1990

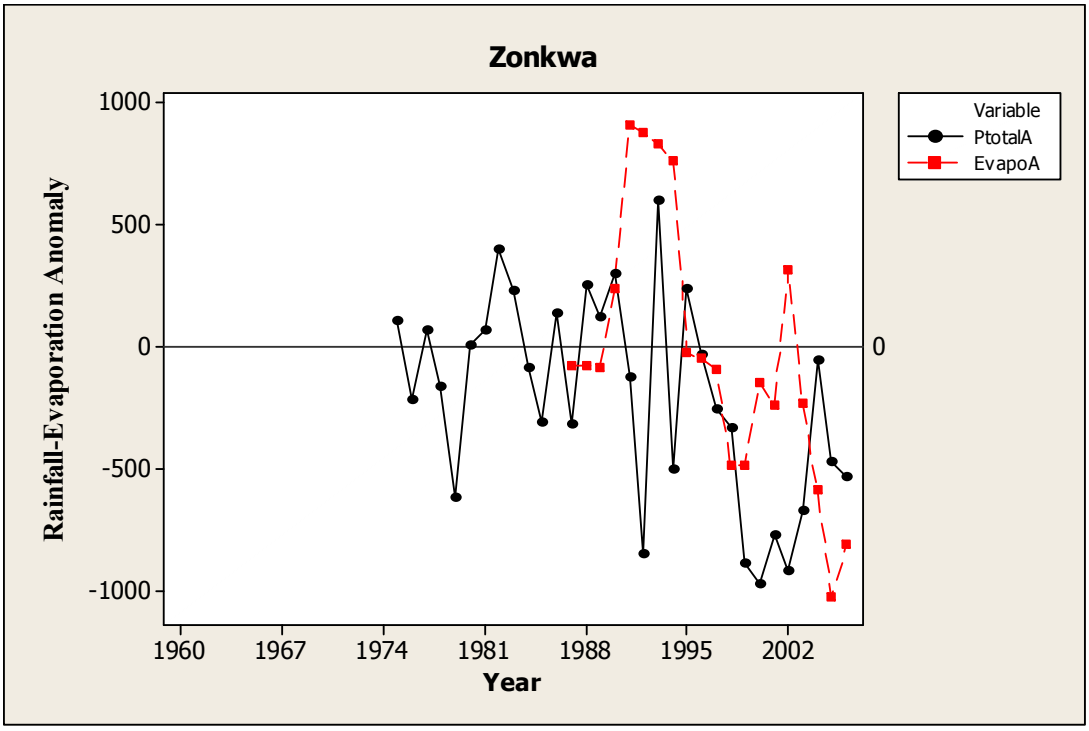


Figure A9d: Rainfall and Evaporation Anomalies relative to 1961-1990

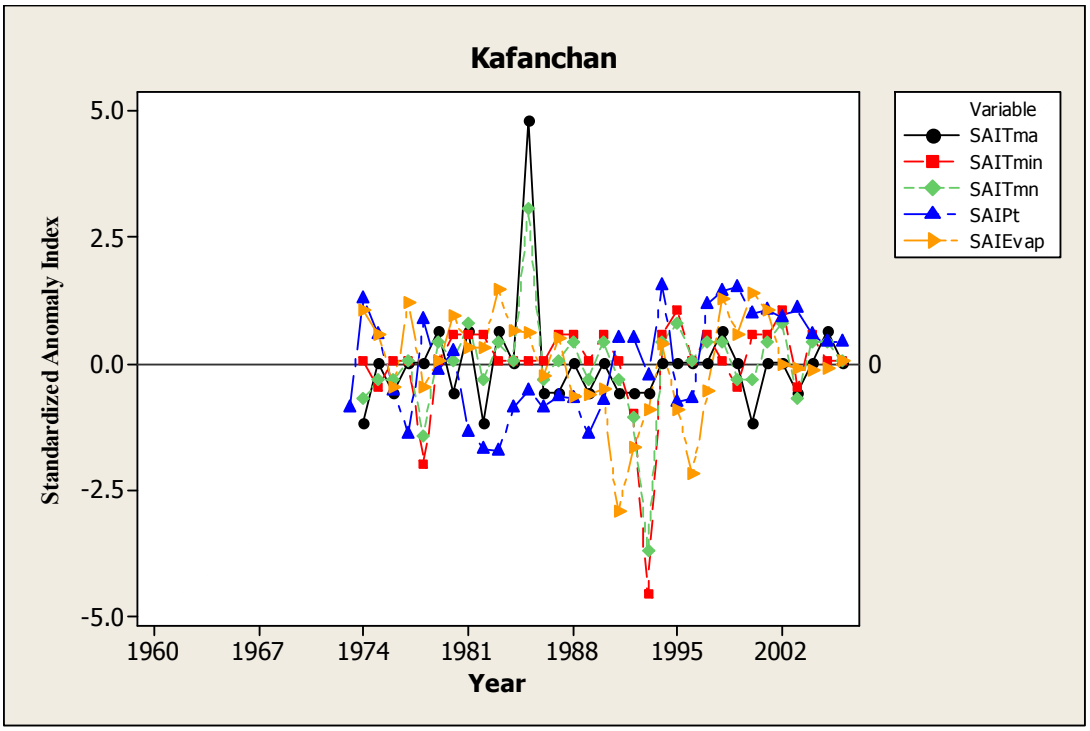


Figure A10a: Standardized Anomaly Index for Temperatures, Rainfall and Evaporation

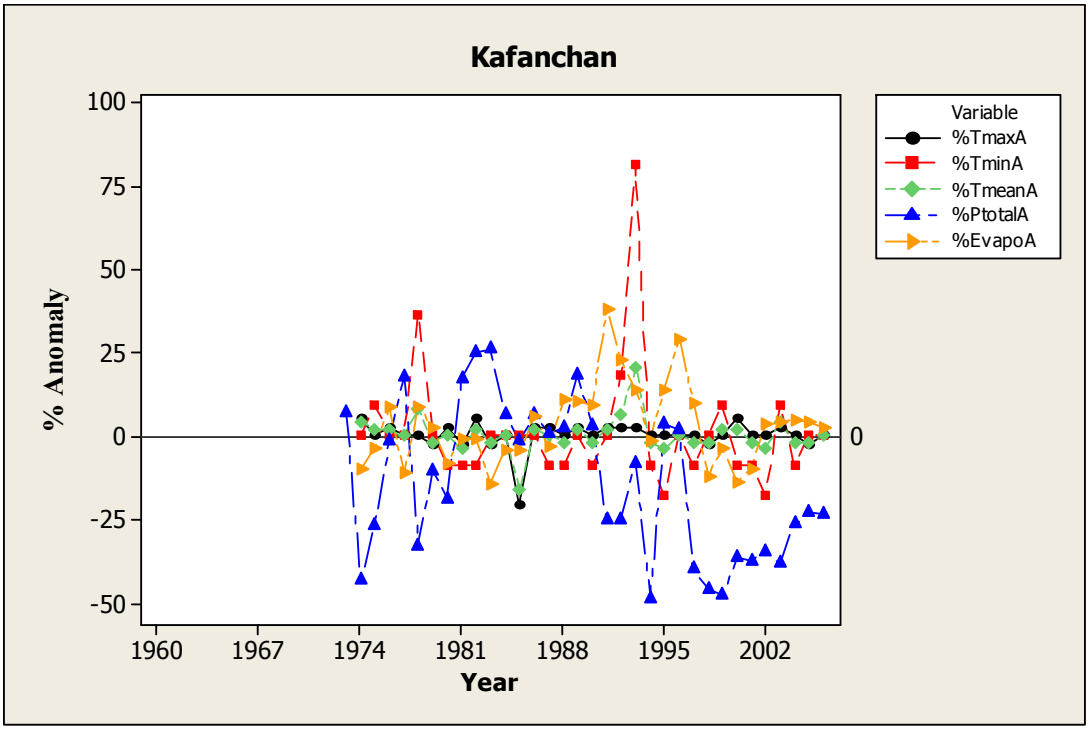


Figure A10b: %Anomalies of Temperatures, Rainfall & Evaporation relative to 1961-1990

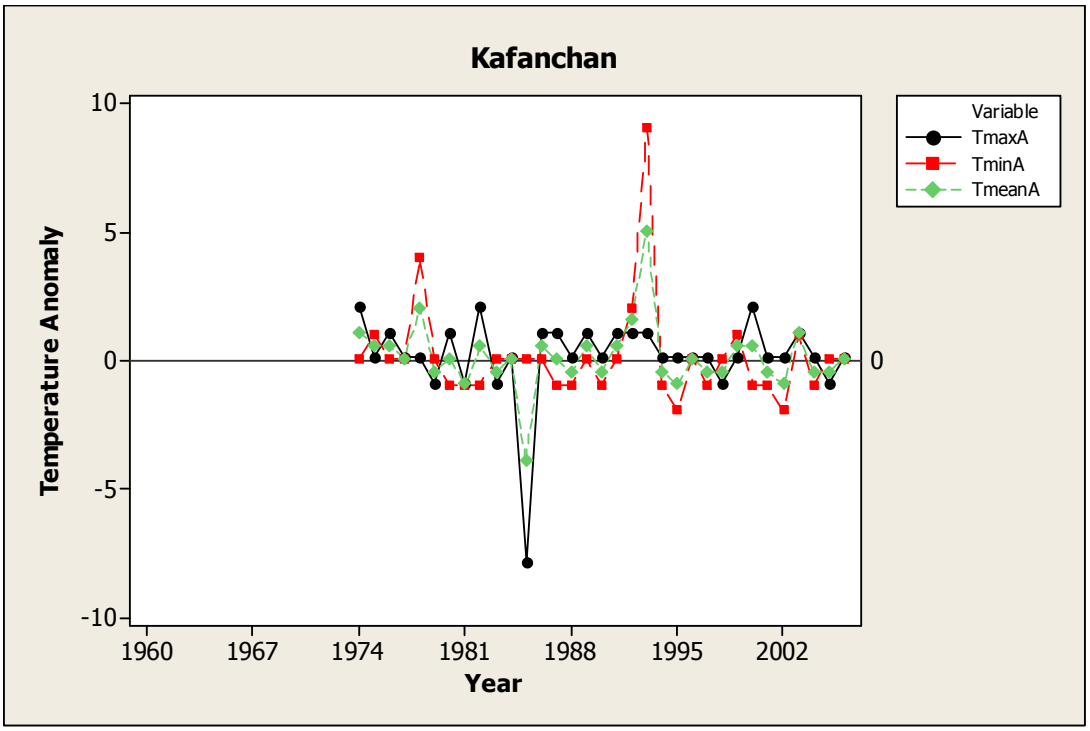


Figure A10c :Temperature Anomalies relative to 1961-1990

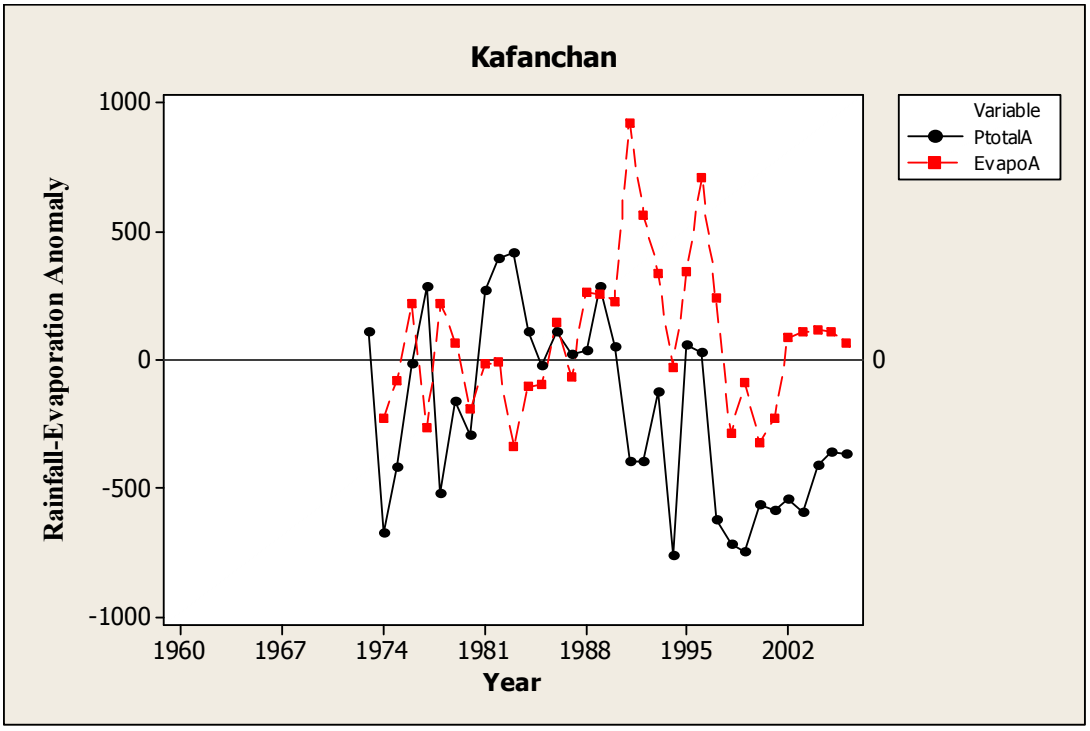


Figure A10d :Rainfall and Evaporation Anomalies relative to 1961-1990

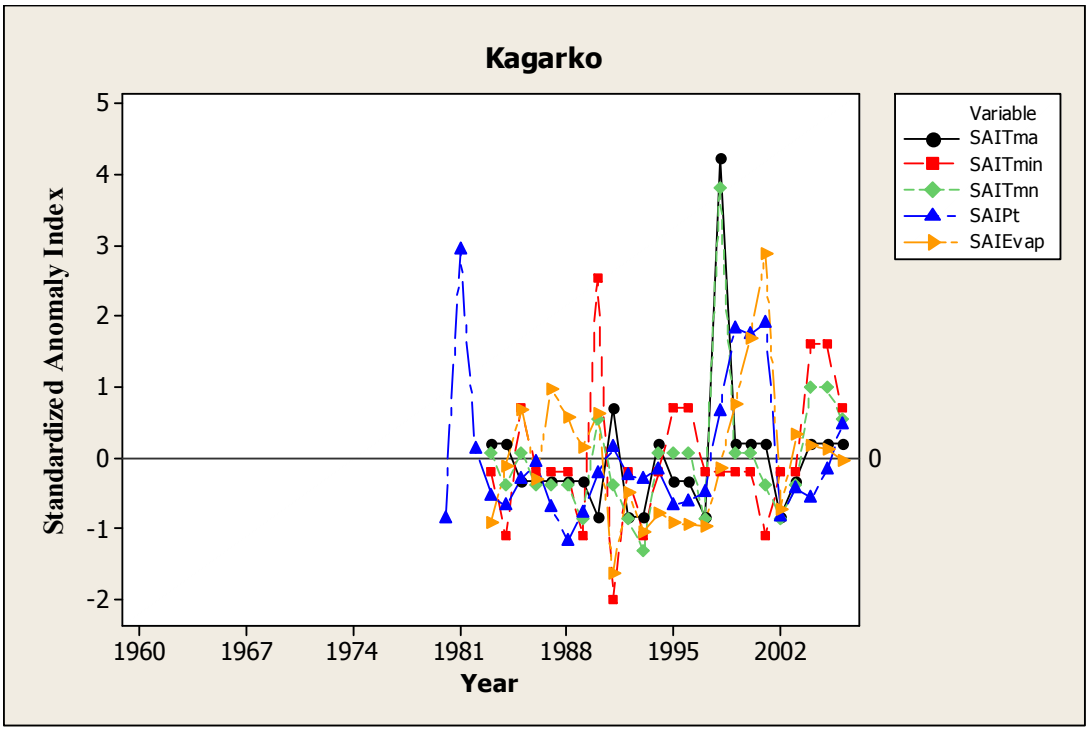


Figure A11a :Standardized Anomaly Index for Temperatures, Rainfall and Evaporation

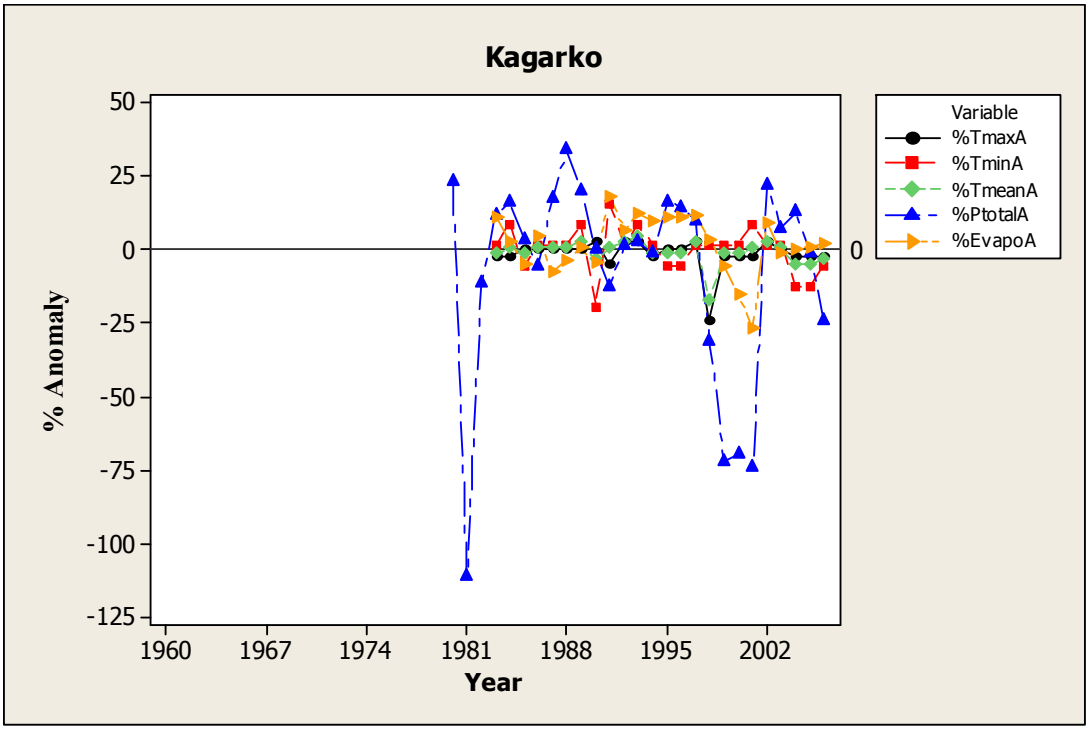


Figure A11b: %Anomalies of Temperatures, Rainfall & Evaporation relative to 1961-1990

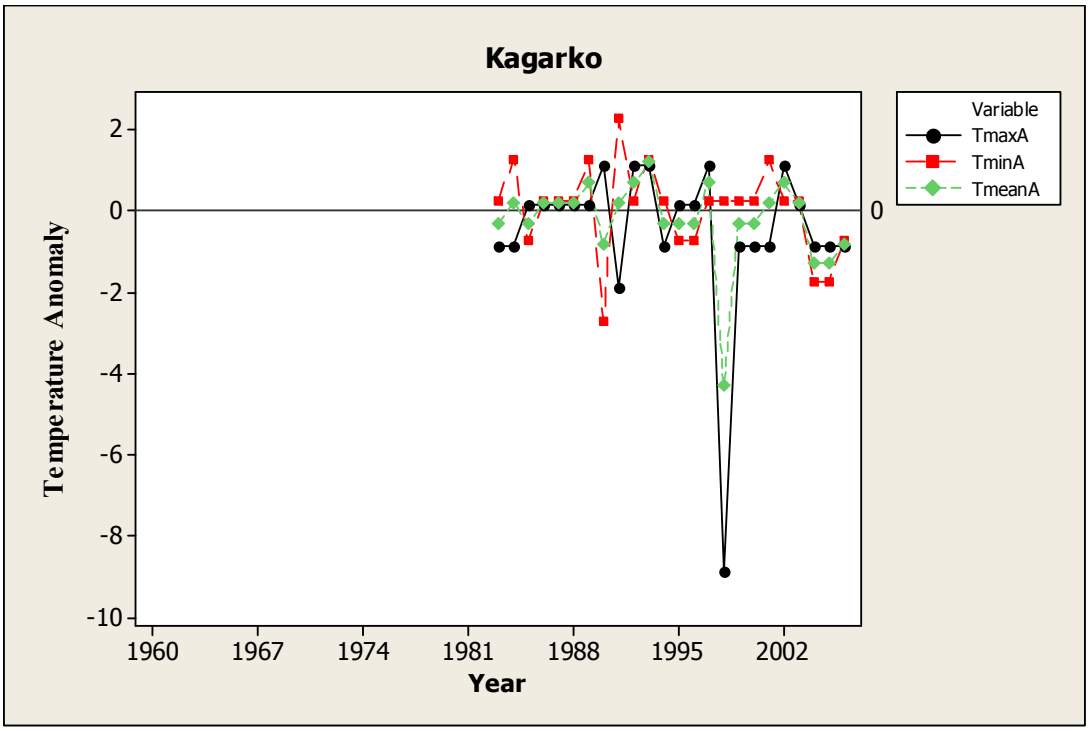


Figure A11c: Temperature Anomalies relative to 1961-1990

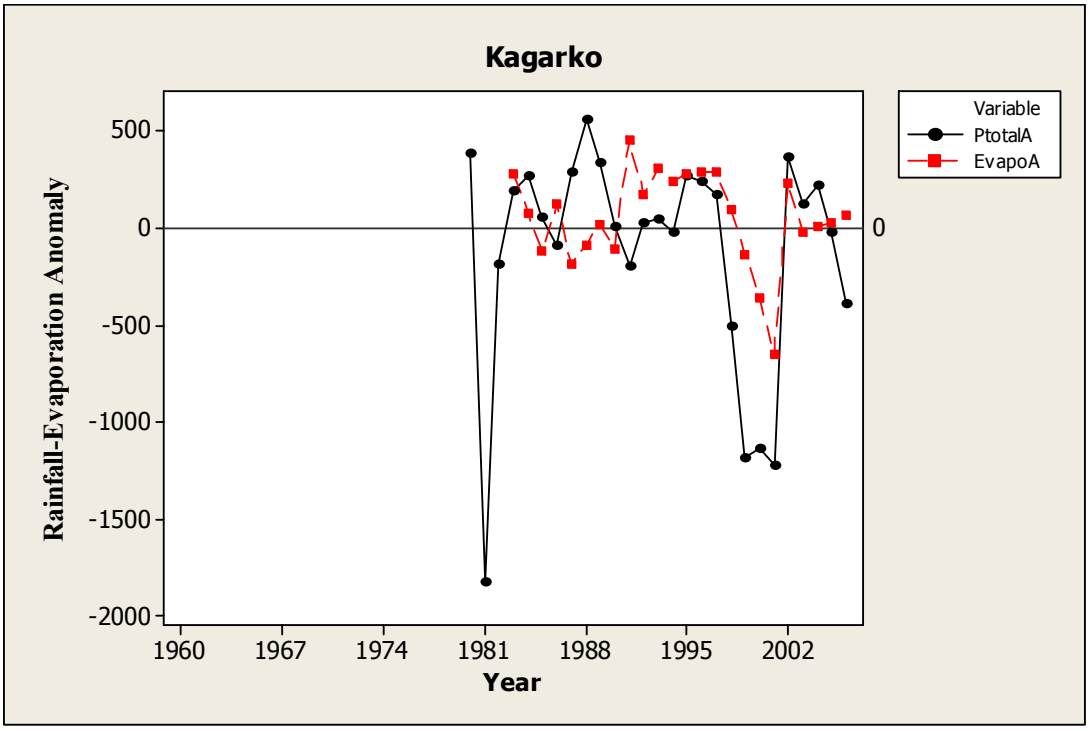


Figure A11d: Rainfall and Evaporation Anomalies relative to 1961-1990