**Sudan University of Science** 

 **and Technology**



# **College of Graduate Studies**

# **Application of Stochastic Models for Rainfall and Drought Frequency Analysis in Sudan**

# **تطبيق النماذج التصادفية للتحليل التكرارى للأمطار و الجفاف فى السودان**

**By:** 

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# **A Dissertation Submitted in Fulfillment of the Requirement for the Degree of Doctor of Philosophy in Civil Engineering**

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#### **بسم االله الرحمن الرحيم**

فَأَلَّا مَنْ جَآءَ بِالْحُسَنَةِ فَلَهُ عَشْرٌ أَمْثَالِهَا وَمَنْ جَآءَ بِالسَّيِّئَةِ فَلَا يُحْزَى إِلَّا مِثَّامَا وَهُمْ لَا يُظْلَمُونَ لَنَّايًا قُلْ إِنِّي هَدَىٰ رَبِّي إِنَّى صِرَطٍ مُّسْتَقِيمٍ دِينًا قِيَمًا مِّلَّةَ إِبْرَهِمَ جَنِيفًا وَمَاكَانَ مِنّ ٱلْمُشْرَكِينَ لِلِّنَّايَّ قُلْ إِنَّ صَلَاتِي وَنُسُكِي وَتَحْيَايَ وَمَمَاتِ لِلَّهِ رَبِّ ٱلۡعَـٰلَمِينَ لِّنَّآيَا لَا شَرِيكَ لَهُ ۚ وَبِذَٰلِكَ أُمِّرَتُ وَأَنَاْ أَوَّلُ ٱلۡسُّلِمِينَ أَنَّ أَغَيْرَاللَّهِ أَبْغِي رَبَّا وَهُوَرَبٌّ كُلِّ شَيْءٍ وَلَا تَكْسِبُكُّ نَفَّسٍ إِلَّا عَلَيْهَا وَلَا نَزِرُ وَازِرَةٌ وِزْرَ أُخْرَىٰ ثُمَّ إِنَّى رَبِّكُمْ تَرْجِعُكُمْ فَيُبَّتُكُمُ بِمَاكَنَتُمْ فِيهِ تَخْلِفُونَ إِنَّهُ وَهُوَ ٱلَّذِى جَعَلَكُمْ خَلَيْفَ أَلَأَرْضِ وَرَفَعَ بَعْضَكُمْ فَوْقَ بَعْضٍ دَرَجَتِ لِيَبْلُوَكُمْ فِي مَآءَاتَكُمْ إِنَّ رَبَّكَ سَرِيعُ ٱلْعِقَابِ وَإِنَّهُ لَغَفُورٌ رَّحِمُ الْأَنَّةُ

**صدق االله العظيم**

**سورة الانعام من الآية (١٦٠– ١٦٥ )**

# **DEDICATION**

**To the memory of my father** 

**To my mother, wife and children** 

**(Mahgoub, Mohamed and Wagd)** 

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# **Abstract**

Sudan is one of the countries which economy depends on rain- fed agriculture with recurring cycles of natural drought. The drought phenomenon has significant widespread impacts on the community, environment and economy.

The main objectives of this research are to study the characteristics of rainfall in Sudan, find suitable tools for drought characterization to be used during drought periods and propose monthly rainfall forecasting methods accuracy with inspection of the model forecasting ability.

As time series analysis and forecasting have become a major tool in different applications in hydrology and environmental management fields, linear stochastic models known as ARIMA and multiplicative Seasonal Autoregressive Integrated Moving Average (SARIMA) models were used to simulate droughts based on the procedures of the models developments. The models were applied to simulate droughts using standardized precipitation index (SPI) series in many rainfall stations in the Sudan. The SPI index was used as a drought indicator for drought forecasting due to its advantages over other drought indices. These models were also used for simulating and forecasting the monthly rainfall in many rainfall stations across Sudan.

The results of this research proved that the linear stochastic models (ARIMA) can be used for the rainfall stations for predicting SPI time series of multiple time scales to detect the drought severity in future. A time series model for monthly rainfall stations across Sudan, taking Gadaref station as a typical station was adjusted, processed, diagnostically checked and a typical SARIMA  $(0, 0, 0)$   $(0, 1, 1)_{12}$  model was established. The model was used to forecast three years monthly rainfall values.

The stochastic models developed for the stations can be employed for the development of a drought emergency management plan so as to ensure sustainable water resources management in these stations. The model was found appropriate to forecast the monthly rainfall in Gadaref station and assist decision makers to establish priorities for water demand, storage, distribution, and disaster management.

#### **الملخص**

 يعد السودان من الدول التي تعتمد اقتصاديا على الزراعة المطرية مع تكرر دورات الجفاف.وللجفاف تأثيرات واسعة ومهمة على المجتمع والبيئة والاقتصاد.

 يهدف هذا البحث إلى دراسة خواص المطر في السودان وإيجاد أدوات مناسبة لمحاكاة الجفاف فيه. كما يهدف لاقتراح طرق تنبؤ المطر الشهري، مع التأكد من قدرة و كفاءة النموذج على التنبؤ.

 إن تحليل وتنبؤ المتوالية الزمنية أصبحا أداة رئيسة في دراسة الموارد المائية ومجالات الإدارة البيئية. ولمحاآاة الجفاف تم استخدام نموذجي الانحدار الذاتي التكاملي المتوسط المتحرك (ARIMA (و الانحدار الذاتي التكاملي المتوسط المتحرك الموسمي (SARIMA (اللذين استخدما متوالية دليل المطر القياسي (SPI (آمؤشر تنبؤ للجفاف لتفوقه على غيره من المؤشرات.كما استخدمت الدراسة أيضا هذه النماذج لتنبؤ المطر الشهري في العديد من محطات المطر في السودان.

 أثبتت نتائج الدراسة أن نموذج الانحدار الذاتي التكاملي المتوسط المتحرك يمكن أن يستخدم في محطات المطر لتوقع متوالية دليل المطر القياسي الزمنية لاكتشاف شدة الجفاف في فترات زمنية متعددة مستقبلا كما استطاعت الدراسة اصطناع نموذج 1, 1, 1) ARIMA (0, 0, 0) (0, 1, 1) لوصف المطر الشهري في محطة القضارف كمحطه مرجعيه ثُم تَمَّ استخدامه لتوقع المطر الشهري بالمحطة نفسها لمدة ثلاث سنوات.

 خلصت الدراسة إلى أن النماذج التي تم اصطناعها يمكن أن تستخدم لتطوير خطة إدارة كوارث الجفاف في المحطات لضمان إدارة مصادر مياهها.وُجِدَ نموذج القضارف ملائما لتوقع المطر الشهري فيه مما يساعد صانعي القرار في تأسيس الأولويات لمطالب المياه (خزن – توزيع- إدارة كوارث).

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# **CHAPTER ONE**

# **Introduction**

## **1.1 Background**

Drought is one of the most serious problems for human societies and ecosystems arising from climate variability. It means scarcity of water, which adversely affects many sectors of human society, e.g. water supply, agriculture, hydropower generation. The major causes of drought are anomalies in the weather or climates that lead to less precipitation than normal for meeting water demands. Drought is one of the world's costliest natural disasters, causing an average of 6 to 8 billion US \$ in global damages annually, and affecting more people than any other form of natural catastrophe (Keyantash and Dracup, 2002). The World Meteorological Organization (WMO) reported that during 25 years from 1967 to 1991about 1.4 billion people were affected by drought and 1.3 million people were killed due to the direct and indirect cause of drought (Obasi, 1994).

The prime cause of drought is the occurrence of precipitation below normal, which is affected by various natural phenomena. Precipitation can reduce due to over-seeding of clouds by dust particles from the Earth's surface, an increase in albedo, a decrease in the availability of biogenic nuclei for rain drop formation caused by reduced plant cover and similar factors (Beran and Rodier, 1985). Another important causative factor of droughts is the oceanic circulations, which have average patterns of current and heat storage that affects the weather and climate. The most well-known classification of drought is the classification proposed by Dracup et al. (1980). These are based on the nature of the water deficit classified as, hydrological, meteorological, agricultural and socio-economic drought.

Stochastic simulation of hydrologic processes such as rainfall and stream flow has become standard tool for analyzing many water related problems. It enables to obtain probable occurrence of future hydrologic processes, used for estimating drought properties, such as duration, severity and intensity at the key points in the water supply system. Statistical techniques dealing with the duration aspect of drought are reasonably well developed, whereas techniques for severity aspects are less satisfactory and require considerable improvements and refinements (Panu and Sharma, 2002).

A lot of research has been on modeling for different aspects of drought, such as the identification and prediction of its duration and severity. Prediction aspects of drought duration are better developed than the drought severity aspects .There exist a variety of techniques and methods to analyze the duration and severity of droughts through time series methods, theory of runs, Standardized Precipitation Index (SPI),multiple regression, group theory and neural network methods.

Meteorological drought is defined as a period when rainfall is significantly less than the long-term average or some designed percentages, or less than some fixed value (Linsley et al., 1982).Research on estimation of drought frequency, duration and severity will provide basis for future agricultural insurance resource management decisions.

The study area is the Sudan with its new political boundaries as in figure (1.1).The Sudan is one of the largest African countries, with a total area of about 1.9 million km²; has a population of about 40 million people. The Sudan is rich in natural resources such as oil and gold, but agriculture is the most important sector that employs nearly 80% of the workforce. However, the Sudan is one among the world's poorest countries with only \$1360 GPD/capita (Hinderson, 2004).

Sudan is located in an ecological zone, exposed to specific forms and types of disasters such as drought, desertification, and floods. Its climate varies from desert at the North to poor Savannah in the middle and rich Savannah at the South, therefore rain varies from one region to another. The main water resources in Sudan are the surface water of the Nile River and its tributaries, which is also shown in figure (1.1).The Nile water is shared among eleven riparian countries which now became twelve after the recent separation of the South Sudan. Groundwater is another water source but rainfall is the most important water resource in central and western Sudan.

Due to population growth, expansion of agriculture and industrial sectors, the water demand has been increased in many parts of the world. Many other factors such as climate change and contamination of water supplies contributed in the scarcity. Drought events have been experienced in many part of the world, with a higher severity levels. Sudan crops are produced under stream flow and rain fed conditions. In last decades, huge areas have experienced significant drought. This phenomenon requires the attention of those involved in the formulation of agricultural policies. Drought has

occurred in various parts of Sudan many times seriously affecting crop production, and human living.

The climate in the Sudan varies greatly between the North and South directions. The rainfall decreases from South to North. The decrease in rainfall is associated with increased evaporation. The temperatures also increase in variability, and reach substantially higher levels. Sennar region, located in the southeastern part of the Sudan, experiences evaporation rates that totals to 2500 mm per year, yet only receives 500 mm of rain annually. The mean daily temperatures in the region approach 30°C. Monthly precipitation records indicate a summer monsoon season, with highest totals in the June-September months.

## **1.2 Droughts, Famines and Displacement in Sudan**

Sudan similar to other Sahel countries suffered from drought. The climate and environment in the Sudan have shown localized changes during the course of this century, and recurrent droughts in the last 30 years (Richards, 1994). It is estimated that 60% of the country is affected by desert or desertification. In 1984/5, Sudan experienced a particularly severe drought and famine (de Waal, 1989), resulting in widespread deaths. Despite this, there is little available information to monitor drought and environmental changes. There is a need in the Sudan, for a system which can provide timely, reliable and useful information for decision makers on the risk of drought and environmental change.

Periods of drought have occurred throughout the history of Sudan. In most cases these have been followed by famine and outbreaks of disease. Ibrahim (1985) findings concur with historical records that 1913, 1914, and 1927 were drought years, as shown in table (1.1), but these droughts actually spread from the eastern border of Sudan westward to Kordofan and Darfur regions. Moreover, Ibrahim (1985) added 1935, 1937,1942,1949,1951, and 1957 as years of severe drought in Sudan. Sudan largely escaped the worst years of the Sahelian drought of 1968-73 but experienced a major droughtrelated famine in 1984-85, about 100 years after the major drought of 1888-89.

Famine has persisted in Sudan through the 1980s and into the 1990s. Studies on the 1984-85 famine in Sudan converge on two key facets. First, famine is an outcome of a long process. The main contributing components are

drought and desertification, lack of or misguided government food and agricultural policies (Abdel Ati 1988), and absence of institutional capacity and political will to respond effectively to famine and economic crises (Shepherd 1988). Second, the outcome of such a process is often articulated in declining regional food availability, which, because of extreme infrastructural deficiencies, results in mass starvation and excess deaths due to hunger and diseases.



#### **Table No. (1.1): Historical Years of Famine and Drought in Sudan**

Source: Teklu et al., 1991

Western Sudan, particularly its northern part, experienced extremely low rainfall in the years between 1982 and 1984. The effects of these drought years precipitated a large drop in agricultural production and income.

High rates of displacement and migration were recorded in Kordofan (western part of Sudan). Large-scale movements involving whole families were also evident in other parts of the region. A study among sedentary farmers in eastern Kordofan revealed that, from a low percentage of 14.7 in 1980/81, the percentage of households that migrated with whole families



increased to 45.9 percent in the peak drought year of 1984/85 (Tesfaye et al., 1991 1).

**Fig. No. (1.1): Recent Map of the Sudan** 

## 1.3 Statement of the Problem

- Droughts are one of the main natural hazards and can have significant environmental and economic impacts. Compared with other natural hazards, such as floods and hurricanes, the spatial extent of droughts is usually much greater, as well the impacts of droughts are generally nonstructural and difficult to quantify (Obasi, 1994).
- $\bullet$ Droughts are very complex phenomena related to long sustain periods with scarce water availability and abnormal decrease in precipitation.
- The Sudan, similar to other Sahel countries suffered from drought. Severe droughts occurred in 1983–1984, causing population displacement and famine. It is estimated that 60% of the country is affected by desert or desertification.
- There is little available information about how to monitor drought and environmental changes. The climate and environment in the Sudan have shown localized changes during this century.

# **1.4 Objectives**

#### **1.4.1 General Objective**

The main or general objective is to apply a stochastic model to forecast the drought and monthly rainfall in the Sudan. This will facilitate water resources management under drought conditions, particularly for irrigation and agricultural purposes.

#### **1.4.2 Specific Objectives**

The specific objectives are:

1. Application of mathematical model adopting Autoregressive Integrated Moving Averages (ARIMA) techniques, based on Box–Jenkins models.

- Fit the Sudan rainfall data to represent drought events, estimate its parameters and check its goodness of fit.
- Simulating and forecasting the monthly rainfall at 12 rainfall stations across Sudan

2. Investigate rainfall drought properties such as magnitude, intensity, duration and severity for various return periods.

## **1.5 Structure of the Thesis**

The thesis is structured into five chapters, a reference list and annexes. Chapter one covers the importance of drought analysis, some background knowledge useful in the domain of drought analysis followed by brief

statements of the encountered drought problems and the research objectives. In chapter one, general description of the study area is also depicted. In chapter two an extensive literature review related to the study topic is given. This includes definitions and types of drought, time scales of droughts, drought variables, drought parameters and drought indices. Chapter two also reviews the various work and research conducted by previous researchers in both theory and modeling techniques. The third chapter addresses the description of the equipments, the methodology and the materials used in the research, including Standardized Precipitation Index (SPI) and ARIMA models description. Chapter four explains the results and discussions based on the rainfall characteristics and variability in Sudan. Chapter four also deals with the temporal and spatial characteristics of meteorological drought in Sudan using the Standardized Precipitation Index (SPI). This Index aims to provide a good picture of drought, regardless to the actual probability distribution of the observed cumulative amounts of rainfall for a given time scale. Further more, linear stochastic models known as ARIMA was used to simulate droughts based on the procedure of model development is also included in this chapter. The models were applied to forecast droughts using standardized precipitation index (SPI) series in Sudan. A univariate Box-Jenkins methodology was also used to build Seasonal SARIMA model to analyze and forecast monthly rainfall in Sudan. Chapter five is the part dealing with the conclusions and recommendations in general and for future research in the area.

# **CHAPTER TWO**

## **Literature Review**

## **2.1. Droughts and Floods**

Droughts and floods are extreme hydrological events which cause severe damage to the environment. According to UNEP (2002), the major environmental disasters in Africa are recurrent drought and floods. Their socio-economic and ecological impacts are devastating to African countries, because most of them do not have real time forecasting. Drought and floods affect many sectors in society and there is a need for different ways of defining or characterizing these extreme events. Data availability and climatic regional variations influence the definition. Neither a single drought nor flood characteristics are suitable to assess and describe hydrological extremes for any type of analyses in any region. It is important to understand how various ways characterize drought or floods leading to different conclusions regarding the hydrological extreme phenomenon. Maxx Dilley and Barry N. Heyman, of U.S. Agency for International Development (2012) indicated that the connection between El Nino and Southern Oscillation (ENSO) has been linked to droughts and flooding. Using the disaster history database of the U**.** S. Agency for International Development's Office of U. S. Foreign Disaster Assistance they examined the link between ENSO events and droughts or floods of sufficient magnitude to trigger international disasters. Worldwide, disasters triggered by droughts are twice as frequent during ENSO warm event than during other years. No such relationship is apparent in the case of flood disasters. Drought disasters that occurred during ENSO warm events are significantly more frequent than in other years in Southern Africa and Southeast Asia. No regional pattern emerges from a comparable analysis of flood disasters. However, the dividing line between floods and droughts can be presented by the classical curve depicting the relation between temperature and vapor pressure which involve evaporation as shown in figure (2.1).The zone above the curve is the wet area which is liable to flooding while the area below the curve is the dry area which liable to drought.



Fig. No. (2.1): Saturated Vapor Pressure Curve

## 2.2 Drought Components

In literature review about drought it is necessary to define drought and its types. The components of drought include its parameters and variables as well as quantification. It also necessarily includes drought complexity associated with its environmental, economic and social impacts. Furthermore study of drought will be incomplete without the consideration of hydrological stream flow properties. Time resolution of the data series, methods of characterizing hydrological droughts flow duration curve (FDC) and percentiles together with threshold level method are important components in studying drought. Coping with future droughts alternative water supply strategies, such as, developing more water supplies, reducing demand on fresh water, increasing irrigation system efficiency, developing innovative solutions to increase the water supply and adopting real- time management of water supplies are all inherently knitted with drought comp ponents.

#### 2.2.1 Drought Definition

The definition of the drought can be categorized broadly as either conceptual or operational (Wilhite and Glantz, 1985). The encyclopedia of Climate and Weather defines drought as "an extended period - a season, a year, or several

years – of deficient rainfall relative to the statistical multi-year mean for a region". Operational definitions attempt to identify the onset, severity and termination of drought accident. Another classification, based on an another perspective can be found in Dracup et al.(1980), where droughts are related to precipitation (meteorological), streamflow (hydrological), soil moisture (agricultural) or any combination of the three. According to Wilhite and Glantz (1985) four commonly used definitions of drought are as follows:

- 1. Meteorological drought is defined as a period when rainfall is significantly less than the long-term average or some designed percentages, or less than some fixed value (Linsley *et al*., 1982).
- 2. Hydrological drought is defined as a deficit of water supply in time, in area or in both, with deficit magnitude and deficit duration taken into account (Yevjevich, 1967).
- 3. Agricultural drought is defined as "a deficit of rainfall with respect to the long-term mean, affecting a large area for one or several seasons or years, that drastically reduce primary production in natural ecosystems and rainfed agriculture" (WMO, 1975). It is typically defined as a period when soil moisture is incomplete adequate to meet evapotranspirative demands so as to initiate and sustain crop growth.
- 4. Socio-economic drought occurs when water supply is insufficient to meet water consumption for human activities such as agricultural activities, industry, urban supply, irrigation etc. (Gibbs, 1975).

A similar, classification is used by Tate and Gustard (2000) who categorized droughts into climatologically, agro meteorological, river flow and groundwater droughts. Yevjevich (1967) indicated that drought occurs when the magnitude of a discrete series of variable X (e.g., river flow) that occurs at a given time, is smaller than some predefined arbitrary level. The demand time series is called "truncation level" and its value XT may be defined based on single-purpose water use for agriculture, for continuous irrigation, hydropower, water supply, low flow augmentation for quality control or a combination of various uses. The period of drought can vary from a month to years which makes the analysis of droughts somehow difficult, therefore, based on the study various time intervals of monthly, seasonally, or annually can be selected. Due to seasonal variation of the streamflow, use of a variable truncation level as shown in figure (2.2) was suggested in Kjeldsen et al. (1999).

Examples of applied truncation level are the mean, the median, mean and 75% of the mean and lower percentage exceedances, e.g., 90 or 95% flows found from flow duration curves (Zelenhasic and Salvai 1987). Modarres (2007) used the standardized streamflow index (SSFI) as a drought index. This index is statistically similar to the standardized precipitation index (SPI) defined by McKee et al. (1993) for meteorological drought analysis. The SSFI for a given period is defined as the difference between streamflow from mean divided to standard deviation (Modarres 2007). Streamflow classification based on SSFI is shown in Table (2.1).



**Fig. No. (2.2): Varying truncation level (Kjeldsen et al.1999)** 

#### **2.2.2 Drought Variables**

The sequences of the stream flows or rainfalls that are used to characterize droughts are known as drought variables. A drought variable can be defined as a prime variable responsible for assessing drought effect, and is considered a key element in defining drought and deciding on the techniques for its analysis (Panu and Sharma, 2002).

Values	Class
>2	Extremely wet
$1.55 - 1.99$	Very wet
$1.0 - 1.49$	Moderately wet
$-0.99$ to 0.99	Near normal
$-1$ to $-1.49$	Moderately dry
$-1.5$ to $-1.99$	Severely dry
$> -2.0$	Extremely dry

**Table No. (2.1) Stream flow Classification Based on SSFI** 

The determinant variable for the meteorological drought is precipitation/rainfall, whereas for the hydrological drought it is either river runoff / stream flow or reservoir levels and/or groundwater levels.

It is very important, for the analysis of droughts, to detect several drought parameters. The important parameters quantifying a drought are Duration, Severity, Areal coverage , the onset and end time of drought and Ratio of severity to duration (called magnitude or intensity).

Drought parameters are very important for planning and management of water resources system. For example, the design of water supply capacity of a city may be based on meeting water demands during a critical drought that may occur in a specified planning horizon (Frick *et al.*, 1990).

#### **2.2.3 Drought Quantification**

Droughts are the world's costliest natural disasters, causing an average of \$6–\$8 billion in global damages annually. The precise quantification of drought is a difficult endeavor. Numerous specialized indices have been proposed to do this.

A drought index is usually a single number, derived from stream flow, rainfall and other water supply indicators, which is more useful than raw data for decision making. Drought indices provide decision makers with an opportunity to place the current drought conditions into historical perspective. The most commonly used meteorological and hydrological drought indices are:

- 1. Discrete and cumulative precipitation anomalies.
- 2. The Palmer Drought Severity Index (PDSI)
- 3. The Rainfall Anomaly Index (RAI)
- 4. Rainfall deciles (DI)
- 5. The Bhalme Mooley Drought Index (BMDI)
- 6. The Standardized Precipitation Index (SPI)
- 7. The Z-score or Standardized Rainfall Anomalies
- 8. Reconnaissance Drought Index (RDI)
- 9. Standardized stream flow index (SSFI)

Different indices have been proposed to identify and monitor drought events. Some of the indices refer to meteorological drought and others describe hydrological or agricultural drought or water shortages in urban water supply systems. Table (2.2) presents a summary of main indices that can be applied to drought characterization and monitoring.



#### **Table No. (2.2) Drought Indices and Their Characteristics**



#### **2.2.4. Complexity of Drought**

Water scarcity means that water demand exceeds the water resources exploitable under sustainable conditions. Nowadays water scarcity is one of the major problems around the world, particularly in Africa. A country is said to experience water stress when its exploitable renewable water resources fall under  $1,700 \text{ m}^3$  per capita per year. This is a threshold quantity needed to satisfy a country's requirements in the household, agricultural, industrial and energy sectors, as well as the quantity needed to maintain basic ecological and hydrological requirements. When supply falls below 1,000 m<sup>3</sup> per capita per year, a country is said to experience water scarcity, and when this figure falls below  $500 \text{ m}^3$  per capita per year, the country is undergoing absolute scarcity.

#### **2. 2.5 Environmental, Economic and Social Impacts of Drought**

Drought represents a significant threat to our social and economic life and causes damage to natural resources. It reduces not only the primary production of crops, grass and fodder, that is essential to maintain human health and animal production, but also jeopardizes the constant supply of good quality water.

Drought, leads to degradation of the environment. It results in soil exposure, erosion, land degradation and, finally, desertification. The risk of land degradation and desertification is already taking place under the present climatic pattern and human activities. This is clearly depicted in reduced water levels; increased livestock and wildlife mortality rates and damage to wildlife and fish habitat. Environmental losses are the results of damages to plant and animal species, wildlife habitat and air and water quality; forest and range fires; degradation of landscape quality; loss of bio diversity and soil erosion.

The economic impacts occur in agriculture and related sectors, including forestry and fisheries, because of the reliance of these sectors on surface and subsurface water supplies.

Reduced income for farmers has a significant effect. Consequently, retailers and others who provide goods and services to farmers face reduced business and income. This leads to unemployment, increased credit risk for financial institutions, capital shortfalls, and loss of tax revenue for the government.

Reduced water supply affects the navigability of rivers and results in increased transportation costs because products must be transported by rail or truck. Hydropower production may also be stopped or reduced significantly.

Social impacts mainly involve public safety, health, conflicts between water users, reduced quality of life, and inequities in the distribution of impacts and disaster relief.

#### **2.2.6 Time Resolution of the Data Series**

Selecting an appropriate concept to study droughts depends on the time resolution of the available data and vice versa the most favorable time resolution depends on the purpose and outline of the study.

The most commonly used time scale in drought analysis is the year followed by the month (Sharma, 1997). Although the yearly time scale is rather long, it can be used to abstract information on the regional behavior of droughts. The monthly time scale is more appropriate for monitoring drought effects in situations related to agriculture, water supply and groundwater abstractions.

## **2.2.7 Coping with Future Droughts**

Coping with hydrological extremes, droughts, has been a major concern. Freshwater, a necessary condition of life and a raw material used in very high volumes in virtually every human activity is becoming increasingly scarce. Water use has risen considerably in the last hundred years at a pace exceeding the population growth. Therefore, societies are increasingly vulnerable to droughts and water deficits. Advanced drought preparedness systems can save lives and reduce human suffering. Fighting with droughts has not been quite successful. Humans have to get used to the fact that drought events are natural phenomena that will continue to occur. While doing one's best to improve the preparedness systems, it is necessary to learn to live with drought.

#### **2.2.8. Alternative Water Supply Strategies**

This is based on developing more water supplies such as construction of dams, reservoirs, wells and canals, controls flooding and captures water otherwise lost to the sea and other sinks, more efficient use of existing water recourses and use of non-conventional water resources (treated wastewater, desalination of saline water, wastewater treatment and reuse), water transfers, artificial precipitation, and conjunctive use of surface and groundwater.

Reducing demand on fresh water by directing water policies toward cutting the demand using the advanced technology is another alternative. This is associated with prevention of leaks, evaporation and water wastage, whether in industrial or urban water-distribution networks.

Another alternative is by increasing irrigation system efficiency This achieved by using new technologies such as new sprinkler design with low- energy application can increase efficiency from 60%-70% to 90% as high as the drip irrigation.

Alternatively developing innovative solutions to increase the water supply can be achieved by rainwater harvesting, desalination of seawater by reverse osmosis or evaporation using solar /wind energy. Use of treated waste water for irrigation and other purposes is another significant water supply that is always available.

Adopting real- time management of water supplies is an important alternative. Improved joint operation of basin wide facilities and reallocation of supplies among different users is a key factor to ease water constraints. In order to combat drought, there are major challenges ahead that would require: to shift from water policies based on water supply management to new policies that favor the management of water demand; to shift from preoccupation with development of water resources by major construction programs towards a more balanced approach that should emphasize: water demand management; water conservation and efficient use of water; water pricing and cost recovery; sustainable use of non-conventional water resources; water quality management; capacity building development; and tailored education and training.

## **2.3 Analysis of Meteorological Drought Using the Standardized Precipitation Index (SPI)**

The Standardized Precipitation Index (SPI) is a tool developed by McKee *et al*. (1993) for the purpose of defining and monitoring local droughts. The SPI is simply the transformation of the precipitation time series into a standardized normal distribution. McKee *et al*. (1993) defined the criteria for a "drought event" for any of the time scales. Definitions of the degree of wetness or dryness of weather on the basis of SPI values are shown in Table (2.3). A drought event occurs any time the SPI is continuously negative and reaches intensity where the SPI is -1.0 or less. The event ends when the SPI becomes positive.

<b>SPI Values</b>	<b>Classifications</b>
2.0 and more	Extreme Wet
1.5 to 1.99	Very Wet
1.0 to 1.49	Moderately Wet
$0.99 - t_0 0.99$	Near Normal
$-1.00$ to $-1.49$	Moderate Drought
$-1.50$ to $-1.99$	Severe Drought
$-2.0$ and less	<b>Extreme Drought</b>

**Table No. (2.3): Standardized Precipitation Index Classification** 

The SPI is an index based on the probability distribution of precipitation. This index depends on the distribution function, on the sample used to estimate the parameters of the distribution, and on the method of estimation. The nature of the SPI allows an analyst to determine the rarity of a drought or a wet event at a particular time scale for any location that has a precipitation record. Among others, the Colorado Climate Center, the Western Regional Climate Center, and the National Drought Mitigation Center use the SPI to monitor current states of drought in the United States.

The calculation of SPI requires that there is no missing data in the time series. The data record length is required to be at least 30 years. A number of advantages arise from the use of the SPI index. First of all, the index is
simple and is only based on the amount of precipitation so that its evaluation is rather easy. Also the SPI index can be computed for multiple time scales (i.e.,  $1, 2, 3, \ldots$  72 months), thus allowing the comparison between different time periods. In addition, these various time scales can be useful in assessing effects on different components of the hydrologic system (e.g., streamflow, reservoir levels and groundwater levels).

Many researchers have employed SPI to examine numerous problems such as, drought, stream flow and floods. Szalai and Szinell (2000) assessed the utility of the SPI for describing drought in Hungary. They concluded that the SPI was suitable for quantifying most types of drought event. Stream flow was described best by SPIs with time scales of 2–6 months. Strong relationships to ground water level were found at time scales of 5–24 months. Agricultural drought was replicated best by the SPI on a scale of 2– 3 months. Lana et al. (2001) recently used the SPI to investigate patterns of rainfall over Catalonia, Spain. Seiler et al. (2002) used SPI to study the recurrent floods affecting Argentina, as a tool for monitoring flood risk. SPI satisfactorily explains the development of conditions leading up to the three main flood events in the region during the past 25 years. They proposed applying SPI as an effective tool for regional climate risk monitoring system. Mishra and Desai (2005) studied the spatial and temporal variation of drought over Kansabati basin in India using SPI as the drought index.

## **2.4 Stream Flow Hydrological Drought**

The design of water supply capacity of a given city may be based on meeting water demands during a critical drought that may occur in a specified planning horizon. Moreover, the estimation of return periods associated to severe droughts can provide useful information in order to improve water systems management under drought condition.

Stream flow drought properties of various return periods, for example, are needed to assess the degree to which power generation ,agriculture, water supply and so on will be able to cope with future droughts and, accordingly, to plan alternative water supply strategies. They can be determined from the historical record alone by using nonparametric methods but, because the number of drought events that can be drawn from the historical sample is generally small, the historical drought properties have a large degree of uncertainty. Consequently, the stochastic models are used to generate long series of data so that adequate characteristics of the drought can be captured.

Stochastic simulation of hydrologic processes like stream flow has become standard tool for analyzing many water related problems. Simulation signifies the behavior of the underlying process so that realistic representations of it can be made. Stochastic simulation enables one to obtain equally likely sequences of hydrologic processes that may occur in the future , which are used for estimating drought properties , such as drought duration , severity and intensity at the key points in the water supply system among others.

#### **2.4.1 Methods of Characterizing Hydrological Droughts**

There are diverse methods of characterizing hydrological droughts. Most frequently noticed methods include the Flow duration curve (FDC) and percentiles. Flow duration curve (FDC) is a plot of the stream flow in ascending or descending order (as ordinate) and its frequency of occurrence as a percentage of the time covered by the record (as abscissa). The shape of the FDC can indicate the hydro geological characteristics of a watershed.

Low flow indices derived from the FDC are the percentiles which indicate a high frequency of exceedance and therefore present the low flow period of a regime. Common percentiles used as low flow indices are between *Q*95, and *Q*70. They are also frequently chosen as value for the threshold level in drought event definitions (Zelenhasic and Salvai, 1987). The exceedence probability (P) is given by the equation:

$$
P = 100 \left(\frac{M}{n+1}\right) \tag{2.1}
$$

 $P$ =The probability that a given flow will be equaled or exceeded (% of time)  $M$ =The ranked position on the listing (dimensionless)  $n=$ The number of events for period of record (dimensionless)

Alternatively, the threshold level method originates from the theory of runs introduced by Yevjevich (1967), who originally defined droughts as periods during which the water supply does not meet the current water demand. Both the water supply,  $I(t)$ , as well as the water demand,  $D(t)$ , were expressed as time series with the same temporal resolution, as shown in figure (2.3), and a drought event was defined as an uninterrupted sequence of negative values in the supply-minus-demand series,

$$
Y(t) = I(t) - D(t) \tag{2.2}
$$



**D Droughts ( (Yevjevich h, 1983).** 

## 2.5. Stochastic Models

A model is defined as a simplified representation of a complex system, and hence a hydrological model is a model of a hydrological system. A hydrological system is a set of physical, chemical and / or biological processes which act upon an input variable (or variables) to convert it (them) into an output variable (or variables). This variable is a characteristic of a system which may be measured and which assumes different values when measured at different times. Hydrological models may be physical, analog or mathematical. Mathematical models may be either deterministic or stochastic.

A time series is a set of observations  $(X_t)$ , each one being recorded at a specific time *t*. For example,  $(X_t)$  can be river flow (daily, monthly, etc.) measurements at time *t*. In general, a collection of random variables, indexed by  $t$  is referred to as a stochastic process. The observed values of a stochastic process are referred to as a realization of the stochastic process.

A mathematical model representing a stochastic process is called a stochastic model or time series model. The model consists of a certain mathematical form or structure and a set of parameters. Such models are built to resemble the main statistical characteristics of the time series. Several stochastic models have been used for modeling hydrological time

series in general and stream flow time series in particular (Salas et al., 1980). Unfortunately, the exact mathematical model of a hydrological time series is never known. The exact model parameters are also never known, they must be estimated from limited data.

Time series analysis and modeling is an important tool in hydrology and water resources. It is used for building mathematical models to generate synthetic hydrologic records, to determine the likelihood of extreme events, to forecast hydrologic events, to detect trends and shifts in hydrologic records, and to fill in missing data and extend records.

Stochastic simulation of stream flow time series has been widely used for solving various problems associated with the planning and management of water resources systems for several decades. Typical examples are the determination of a reservoir capacity, determining the risk of failure of dependable capacities of hydroelectric systems, evaluation of adequacy of a water resource management strategy under various potential hydrologic scenarios, hydrological drought analysis, and for many other purposes (Salas, 1993).

## **2.6. ARIMA Technique**

## **2.6.1 General**

A time series is a sequence of observations on a variable, usually taken at equally spaced intervals over time. It is generally viewed as a single realization of a stochastic process. A stochastic process is not a single function of time, but an infinite number of possible realizations. A time series analysis or modeling can be done either in the time domain or in the frequency domain. The autocorrelation function and the partial autocorrelation function are time domain concepts, while the spectral density and the power spectral function are frequency domain concepts. In the time domain, the autocorrelation of observations is focused. In the frequency domain, the cyclical movement is concentrated. The Wiener- Khinchine theorem indicates that the analyses in the two domains are equivalent (Gottman, 1981). The two domains are linked through the Fourier transformation. The same information of a discrete stochastic process can be presented for different insights, and the two forms of time series analysis and modeling are complementary to each other (Harvey, 1981).

The main purpose of modeling a time series is to forecast future values of the time series based on present and past values of the time series. There are two basic types of forecasting techniques; qualitative methods and quantitative methods (Bowerman and O'Connell, 1987).

Qualitative forecasting methods include the subjective curve fitting method, the Delphi method, time independent technological comparison, and the cross-impact method.

Quantitative forecasting methods include the univariate method and the causal method. For a univariate model, future values for a time series only depends on the past values of the time series. An ARIMA model (Box and Jenkins, 1970) is a univariate model. An ARIMA model relies on autocorrelation to predict future values and non stationary is a natural assumption. If a time series is not stationary, there is the assumption that the time series can be reduced to stationary by differencing or by detrending. In a causal model, dependent variables are related to explanatory variables. The relationship between dependent variables and explanatory variables are statistically constructed and then used to forecast future values of dependent variables (Bowerman and O'Connell, 1987). The linear least squares regression method belongs to the causal method.

### **2.6.2 Review of Previous Studies**

Drought is considered as the most complex natural phenomenon and, at the same time, the least understood among natural hazards with different temporal and spatial characteristics, ( Modarres , 2007). Drought generally involves long and sustained periods with insufficient precipitation, soil moisture or water resources for supplying the socio-economic activities in a region. Wilhite and Glantz (1985) have shown that the lack of a precise definition of drought has been an obstacle in understanding drought. This has led to indecision and inaction on the part of managers and policy makers.

Early studies by Yevjevich (1967) showed the feasibility of using statistics and probability theory in analyzing drought. These studies were among the first at attempting a prediction of properties of droughts using the geometric probability distribution, defining a drought of k years as k consecutive years when there are no adequate water resources. Saldariaga and Yevjevich (1970) continued the development of run theory, incorporating concepts of

time series analysis in formulations to predict drought occurrence. Rao and Padmanabhan (1984) investigated the stochastic nature of yearly and monthly Palmer's drought index (PDI) and to characterize those using valid stochastic models to forecast and to simulate PDI series. McKee et al. (1993) used the Standardised Precipitation Index (SPI) for the purpose of defining and monitoring local droughts. Lohani and Loganathan (1997) used Palmer drought severity index (PDSI) in a non-homogenous Markov chain model to characterize the stochastic behavior of drought and based on these drought characterizations an early warning system is used for drought management .Chung and Salas (2000) used low-order discrete autoregressive moving average models for estimating the occurrence probabilities of drought events. Kim and Valdes (2003) used PDSI as drought parameter to forecast drought in the Conchos River basin in Mexico using conjunction of dyadic wavelet transforms and neural network. Recently, Mishra and Desai (2005) applied seasonal autoregressive integrated moving average model (SARIMA) to forecast standardized precipitation index (SPI).

The popularity of ARIMA model in many areas resulted from having quite flexible of the model, due to the inclusion of both autoregressive and moving average terms. The ARIMA model approach has several advantages over others such as moving average, exponential smoothing, neural network and fuzzy logic, in particular, its forecasting capability and its richer information on time-related changes. In most time series, there is a serial correlation among observations. This characteristic is effectively considered by ARIMA model (Yurekli et al. 2005). Also, few parameters are required for describing time series, which exhibit non-stationary both within and across the seasons. This model also provides systematic searching in each stage (identification, estimation and diagnostic check) for an appropriate model (Chatfield, 1996).

Researchers have used this approach, ARIMA, for many different scientific and technical applications. Ahlert and Mehta (1981) examined the stochastic structure of flow data for the Upper Delaware River to describe the random component of streamflow time series by ARIMA model. Fernando and Jayawardena (1994) used various ARMA models in forecasting monthly rainfall records. Yurekli et al. (2005) applied the ARIMA model to monthly data from Kelkit Stream watershed. Yurekli et al. (2005) analyzed the residuals from the ARIMA models fitted to monthly streamflow data for three gauging stations located on Çekerek stream watershed by alternatives methods.

Characteristic of many types of hydrologic time series has periodically varying components. Data of this type may be modeled using a linear stochastic model that is commonly referred to as autoregressive integrated moving average (ARIMA) model (Lewis and Ray 2002). An inherent advantage of the SARIMA family of models is that few model parameters are required for describing time series, which exhibit non-stationary both within and across the seasons.

The SARIMA model was used by Mishra and Desai (2005) to develop a SPI –based drought forecasting model by removing seasonality. The technique was also used by Durdu (2010) in the Buyuk Menderes river basin, Western Turkey to forecast drought conditions using several time scales SPI time series. Both Mishra and Desai (2005) and Durdu (2010) found that their SARIMA models were able to give reasonably good results up to 2 month a head drought forecasts. Mishra and Desai (2005) also recommended that the SARIMA models can be used in other river basins for forecasting SPI series of multiple time scales.

Some useful applications of these models in seasonal river flow forecasting and drought forecasting are reported in Mishra and Desai (2005), Yurekli et al. (2005) and Modarres (2007). Hydrologists have also widely used stochastic analogy for the analyzing and modeling of hydrologic time series. It is observed from literature that the type of model fits to a particular time series is problem dependent. The ARIMA models seem to offer a potential to develop reliable forecasts towards prediction of drought duration and severity (Mishra and Desai 2005; Modarres 2007).

## **2.7. Water Resources Planning and Drought**

Adam et al. (2013), conducted study of drought duration analysis of Blue Nile using piecewise linear model. Sudan suffered its second most extreme drought on records in year 1984 which had a severe impact on its human, animal and vegetal populations. An approach developed for frequency analysis of drought duration of annual stream flow series, with a special reference to the Blue Nile in Sudan was developed. The procedure followed can be summarized as follows:

1. Smoothing of data by pre-whitening to eliminate the cause effect dependence and to make the frequency – curve of drought duration regular.

2. Piecewise linear model is used to represent the duration – dependent termination rate of drought data set.

3. The model parameters are estimated using least - square method.

Model estimates of exceedance probability R (t) are tested for confidence interval of 95 % assuming normality for distribution of the parameters. The historical data of the Blue Nile River annual stream flow at Ed Deim gauging station is used to demonstrate the methodology.

The results obtained showed that one year drought of the Blue Nile River has a return period of five years and nine year's drought has a return period of 370 years.

Drought duration (D) is defined as any year or consecutive number of years during which the annual stream flow is continuously below a given threshold level. The long term mean annual stream flow X, severity of drought (S) is the cumulative deficit of stream flow for that drought duration as shown in figure (2.4). The magnitude M is defined as the average deficit of stream flow for that duration:

$$
M = \frac{S}{D} \tag{2.3}
$$

From the above relation one of the parameters is completely determined by the other two. Duration (D) and severity (S) can be considered the two primary parameters which depend directly on annual stream flow: magnitude (M) is regarded as a secondary parameter which depends on duration and severity. The historical annual stream flow data of the Blue Nile River at Ed Deim gauging station for the period 1912 to 1987 is used to demonstrate the methodology.

The statistics and the first serial correlation for the historical data of the Blue Nile River at Ed Deim gauging station from the years 1912 to 1989, are calculated by the method of moments as shown in table (2.4).The lag one serial correlation of the historical data was found to be 0.196 which is too small to indicate a useful dependence, although due to effect of subsurface storage there may be some dependence. This could be concluded out of the positive value of the lag one serial correlation r (1).



Fig. No. (2.4): Definition of Parameters of Drought (Adam et al. 2013)





To estimate such cause and effect dependence of the series prewhitening process is done applying first order linear autoregressive model to have pure stochastic variable, and autocorrelation coefficient " $\varepsilon$ ". The coefficient " $\varepsilon$ " is estimated by the serial correlation coefficient  $r(1)$ . The series is assumed to follow the first order linear autoregressive model, as the prewhitening process does not change the properties of the historical data as shown in table (2.4), mainly the variability (standard deviation and coefficient of variation), which is the most important property for frequency analysis than the central tendency (mean).

Figure  $(2.5)$  shows how the prewhitening procedure smoothes out the irregularity and stretches out the realization in the drought duration (random

variable D) frequency curve  $Pr(D=1)$  of the annual stream flow series Figure  $(2.6)$  shows the shape of the drought duration termination rate for the smoothed data. The termination rate curve shown in figure (2.6) has a Vshape. This is called "Bathtub" hazard function. There are some hazard models to simulate or to fit this curve. A well known method of approximation is to divide the curve into a number of regions; this method is known as piecewise linear analysis. flow series.<br>
n rate for the<br>
6) has a V-<br>
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d



Fig. No (2.5): Frequency of Drought Duration of **Historical Data (Adam et al. 2013)** 





Banafsheh et al.(2011),in study of basin scale meteorological drought forecasting using Support Vector Machine (SVM) developed models for forecasting seasonal Standardized Precipitation Index (SPI),which has been widely used as an index for assessing the severity of meteorological drought events in different countries. The case study consists of basins of four major dams, namely Latyan, Karaj, Taleghan, and Mamloo, supplying domestic water demands of Tehran, the capital city of Iran.

Mutual Information (MI) index has been used for feature selection among the predictors. The selected predictors in the months of April to August have been used as the inputs of the SVM. The model has been trained to predict seasonal SPIs in autumn, winter, and spring seasons. The results have shown that the seasonal SPI values can be predicted by the proposed model with two to five months lead-time with enough accuracy to be used in long-term water resources planning and management in the study area.

There have been a limited number of studies related to the application of data mining and statistical learning methods for prediction of Standardized Precipitation Index (SPI). This index can be categorized as the most popular index for quantifying severity of meteorological droughts. The major differences between this research and the previous works include utilizing SVM model for seasonal SPI prediction in watershed scale and huge systematic data processing to achieve suitable meteorological features.

SVM is a new method which aim to recognize the data structures. Transformation of original data from input space to a new space (feature space) with new mathematical paradigm entitled Kernel function is the main SVM feature in detecting the data structure . Nonlinear transformations function  $\phi(x_i)$  is defined to map the input space to a higher dimension feature space,  $K^{nh}$ . A linear functions,  $f(x_i)$ , can be formulated in the high dimensional feature space to represent a non-linear relation between the inputs (xi) and the outputs (yi) as follows:

$$
y_i = f(x_i) = (w, \emptyset(x_i)) + b \tag{2.4}
$$

Where:

w and  $b =$  are the model parameters.

Shiva et al.(2013), studied drought management strategies adopted in arid and semi arid regions of Asia, which is vulnerable to water-related disasters, accounting for more than 50% of fatalities and more than 90% of the people affected by disasters. In India, areas prone to drought are characterized by low annual rainfall (approx. 750 mm) with high evaporation, high variation in annual rainfall, and lack of assured water availability. Drought prone areas comprise about 16 per cent of the geographical area and account for 11 per cent of the country's population. Drought reduces the country's food grains production to as much as 15-20 per cent of the yield of a normal year.

Africa had the maximum number of droughts, as also the maximum deaths due to droughts, but Asia suffered the maximum economic loss as also the maximum number of persons affected due to droughts as shown in table (2.5). Drought in developing countries will severely harm countries' development, affect millions of people and contribute to malnutrition, famine, loss of life and livelihoods, emigration and conflict situations including economic losses. UN Framework Convention on Climate Change (UNFCCC) also advises the countries to cooperate in preparing for adaptation to the impacts of climate change and to develop appropriate plans for various areas including water resources, agriculture and rehabilitation of regions affected by drought and desertification.

**Table No. (2.5): Number of Persons Affected By Droughts in Africa and Asia (1970-2009) (Shiva et al.2013)** 

	Events	Total Killed	Average Killed	Total Affected	Average Affected	Damage (1000US\$)
Asia	100	5308	53	1292962442	12929624	27619641
Africa	184	553095	3006	266806719	1450073	4816693

Drought management is the systematic process of using administrative directives, organizations and operational skills and capacities to implement strategies, policies and measures for improved coping capacities in order to lessen, i.e., prevent, mitigate and prepare for, the adverse impacts of drought and the possibility of disaster.

Drought Management depends on how exactly early signs of the impending disaster are picked up, assessed and evaluated, based on which appropriate steps are taken for managing the crisis situation. India has the following strengths to manage the drought.

1. Elaborate institutional structure for drought management.

2. Active research program, using remote sensing techniques.

3. Financial support offered for projects relevant to drought mitigation.

4. New technologies for multipurpose tree species, crop production, horticulture, are developed.

5. Social forestry, fuel wood and fodder programs being undertaken on degraded forest.

# **CHAPTER THREE**

# **Methodology**

## **3.1. Road Map**

The plan is the road map for the methodology which comprises the main objective and secondary objectives studies. Further details about the Sudan will be conducted including materials and equipment used in data collection and data analysis. The description of the equipment, the applied methodology and materials used are presented. Standardized Precipitation Index (SPI) with other indices and ARIMA models are described.

## **3.2. Applied Methodology**

According to the geographical consideration the area of this study was divided into three regions. Each region has a group of four to seven rainfall gauging stations. These gauging stations are previously shown in figure  $(1.1).$ 

- i. The northern and eastern region (hyper-arid zone of Sudan, lying nearly from latitude  $16^{\circ}$ N to around latitude  $22^{\circ}$ N), which incorporates three administrative states, namely River Nile State, Northern State and Red Sea State (region I). Four meteorological stations were selected to represent the States. The locations of the rainfall data points are Wadi Halfa, Dongola, Atbara and Port Sudan.
- ii. This region extends between  $13^{\circ}$ N and  $16^{\circ}$ N and from the main River Nile, Blue Nile to the borders with Ethiopia in the east (region II). Five meteorological stations were selected to represent the States. The locations of the rainfall data points are Khartoum, Kassala, Medani, Gadaref and Sennar.
- iii. The region of central and western of Sudan which incorporates three administrative states, namely White Nile, Kordfan and Darfur. Seven meteorological stations were selected to represent the States (region III). The locations of the rainfall data points are kosti, Obeid, Nahud, Kadugli, Fasher, Geneina and Nyala.

## **3.3. Data Analysis**

The data analysis covers the missing data calculation methods, mainly including Multiple Discriminant Analysis (MDA), and Qureshi and Khan Method.

#### **3.3.1. Missing Data Calculation Methods**

In order to preserve continuity of the monthly precipitation time series for this study, estimates of missing data were made. The missing data could be a result of the following:

- Any interruption at the rain-gauge stations.
- The absence of observer.
- Instrumental failure.

Different methods can be applied to fill the missing data, such as:

- Simple Arithmetic Average.
- The Normal- Ratio Method.
- Multiple discriminant analysis (MDA).
- Linear regression (LR).
- Oureshi and Khan Method.

Different methods were tried for filling in missing data points. Most of the missing data points were filled by Qureshi and Khan Method (1994). Kruskal-Wallis test was also used to test the null hypothesis that *k*  independent random samples (stations) come from identical populations (region).

#### **3.3.1.1 Multiple Discriminant Analysis (MDA)**

A modified version of the Normal-Ratio Method that was introduced by (Paulhus and Kohler, 1952) was one of the methods used to make the

estimations. The Normal-Ratio Method uses the mean annual precipitation at the target station divided by the mean annual precipitation at the nearest neighbor (index station) as a weighting factor. (Paulhus and Kohler, 1952) used three index stations. This method was modified to use mean monthly precipitation values instead of mean annual values since mean annual values mask the distribution of precipitation throughout the year (Edwards and McKee, 1997).

$$
p_{x} = \frac{1}{3} \left[ \left( \frac{N_{x}}{N_{1}} \right) P_{1} + \left( \frac{N_{x}}{N_{2}} \right) P_{2} + \left( \frac{N_{x}}{N_{3}} \right) P_{3} \right]
$$
(3.1)

where:

 $P_X$  = Estimated precipitation at the target station for a given month/year  $P_1$ ,  $P_2$  and  $P_3$  = Precipitation at a respective index station for a given month/year  $N_x$  = Mean precipitation at the target station for a given month  $N_1$ ,  $N_2$  and  $N_3$  = Mean precipitation at respective index station for a given month

In the instance when rainfall data from only one station or a poor degree of correlation among stations, in the region, the missing data for a given month were filled in from other methods.

### **3.3.1.2 Qureshi and Khan Method**

The missing data for a given month were filled in from the neighboring values, by taking the average of the three preceding and the three following year's records for that specific month(Qureshi and Khan,1994).

### **3.3.1.3 Kruskal-Wallis Test for the Stations**

Every geographical region was divided into different sub-region according to the values of these parameters namely, the mean of the annual rainfall series, the coefficient of variation and the nonparametric Kruskal-Wallis test.

The Kruskal-Wallis test or H test enables to test the null hypothesis that *k*  independent random samples come from identical populations. It is a nonparametric test. The method assumes that the variable has a continuous distribution, but nothing is said about the form of the population distribution or distributions from which the samples were drawn. The test is based on the statistic:

$$
H = \frac{12}{n(n+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(n+1)
$$
 (3.2)

Where:

 $K =$ The number of station in a region  $R_i$  = The sum of the ranks in the *i* th station  $n_i$  = The number of observation in the *i* th station n = The total number of observations, i.e.  $n = \sum n_i$ .

When  $n_i > 5$  for all *i* and the null hypothesis is true, the sampling distribution of the *H* statistic is well approximated by the chi-square distribution with  $k - 1$  degrees of freedom. The null hypothesis of equal means will be rejected for a given significance level,  $\alpha$ , if computed *H* is bigger than  $\chi^2_{1-\alpha, k-1}$ .

### **3.3.2. Homogeneity Test**

The reliable measurements of the climate data are the essential foundation for the quantitative climate analyses. In fact, there are several factors affecting the quality of the climate data and these factors must be understood and considered both for scientific and climatic analyses. Although there are universally accepted standards for instrument installation and observations, the practiced instruments measurements may differ from station to station in a given country, and also there may be changes in an individual station from time to time. As a result, these factors cause variations in station time series (Sahin, etal, 2010).

A homogeneous climate time series can be defined as one where variations are caused only by variations in weather and climate (Keiser and Grieffiths, 1997). If a precipitation or a temperature time series is homogeneous, all variability and changes of the series can be considered due to the atmospheric processes. The factors causing variations in long-term time series are, location of the stations, instruments, formulae used to calculate means, observing practices and station environment.

A rainfall record can be considered homogeneous when a sequence of monthly or annual rainfall amounts is stationary (Buishand, 1981). Stationarity means that the statistical properties of the rainfall amount do not change with time (Thompson, 1984). The rainfall records over a long period of time may reflect non-uniform conditions (non homogeneity). Nonhomogeneity can lead to serious bias in the analysis of the rainfall data i.e. slippage of mean, trend or some oscillation that may lead to misinterpretations of the climate being studied (Buishand, 1977).

The homogeneity tests of a climatic time series could be classified into two groups; absolute tests and relative tests. The absolute tests depend on the use of a single station's records, whereas relative tests depend on the use of neighboring station data that are supposedly homogeneous (Karabork et al., 2007).

## **3.3.2.1 Absolute Homogeneity Tests**

The most common tests which could be used to test the departure of homogeneity of a given time series are the Standard Normal Homogeneity Test (SNHT) for a single break, the Buishand range test, the Pettitt test and the Von Neumann ratio test. All four tests suppose under the null hypothesis that the annual values *Yi* of the testing variable *Y* are independent and identically distributed. Under the alternative hypothesis, the SNHT, the Buishand range and the Pettitt test assume that a step-wise shift in the mean -a break- is present (Yesilirmak et al., 2009). The fourth test, the Von Neumann ratio test, assumes under the alternative hypothesis that the series is not randomly distributed. This test is not location specific, which means that it does not give information on the year of the break.

### **3.3.2.1.1 Von Neumann Ratio Test**

In this research study, the Von Neumann ratio  $(N_V)$  test has been applied to all time series for annual rainfall. The Von Neumann's ratio has used in homogeneity testing of rainfall from India, Indonesia and Surinam (Buishand, 1977). The well-known Von Neumann ratio is defined as:

$$
N_V = \frac{\sum_{i=1}^{n-1} (Y_i - Y_{i+1})^2}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2}
$$
(3.3)

Where:

 $Y =$  Amount of rainfall (mm)  $\overline{Y}$  = Average of the  $Y_i$  s  $i = i<sup>th</sup>$  year  $n =$  Number of years

If the sample contains a break, then the value of  $N_V$  tends to be lower than this expected value (Buishand, 1981). If the sample has rapid variations in the mean, then values of  $N_V$  may rise above 2 (Sahin et al, 2010). Only this test does not give information on the year of break. The Von Neumann's ratio tends to be smaller than the critical values for a non-homogenous rainfall series with a jump in the mean. Table (3.1) gives critical values for *NV*.

**Table No. (3.1): Von Neumann ratio**  $(N_V)$  **Critical Values** 

		20   30   40   50   70   100		
1 %   1.04   1.20   1.29   1.36   1.45   1.54				

Table  $(3.1)$ :1% Critical values for N<sub>V</sub> of the Von Neumann ratio test as a function of n. For  $n \leq 50$  these values are taken from (Owen, 1962); for n  $= 70$  and  $n = 100$  the critical values are based on the asymptotic normal distribution of n (Buishand, 1981).

#### **3.3.2.1.2 Homogeneity of Single Stations (Hartley's Test for Equality of K Samples Variances)**

The annual rainfall data in each station were investigated for homogeneity by using the maximum F-ratio test of (Hartley, 1950). Annual rainfall series of each station were divided into two parts and the largest F-ratio was computed as

$$
F_{max} = \left(\frac{S^2_{MAX}}{S^2_{MIN}}\right) \tag{3.4}
$$

Where:

 $S<sup>2</sup>_{MAX}$  = the largest of the *K* sample variances  $S^2$ <sub>MIN</sub> = the smallest of the *K* sample variances.  $F_{max}$  = The maximum F-ratio.

The maximum F-ratio  $(F_{max})$  compared with the percentile values given in a special probability table (Sendil.U, and Salih 1986). If the observed ratio  $(F_{max})$  exceeds this critical value, the null hypothesis of equal variances should be rejected.

## **3.3.2.2 Relative Homogeneity Tests (Test for Consistency of Data)**

Rainfall data reported from a station may not be consistent always. Over the period of rainfall record, there could have been:

- 1) Unreported shifting of the rain gauge site.
- 2) Significant construction work in the area.
- 3) Change in observational procedure.
- 4) A heavy forest fire, Earth quake or landslide.

Such changes are likely to affect the consistency of data from a station. One may like to test the hypothesis that a given data set is consistent. Rejection of this hypothesis will imply that the data are inconsistent and accordingly one must adjust the records. Conversely, non-rejection of the hypothesis will imply that the data set is consistent and no adjustment is necessary. There are a number of methods and procedures that can be utilized for testing the consistency hypothesis of a given data set. Some of them are simple graphical procedures while others are statistically based. Sometimes both graphical and statistical procedures can be combined. Among the graphical procedures the so-called double mass method is the traditional one and perhaps the most widely used in practice (Salas, 2006).

## **3.3.2.2.1 Double Mass Curve Method**

In this study, the consistency of precipitation has been examined using the double mass curve test. It is essentially a simple graphical method but statistical concepts and tests can be also utilized.

Let be assume that one wish to check whether the data  $x_1, x_2,..., x_N$  (*N*= sample size) are consistent data or not. For this purpose use another data set  $y_1, y_2, ..., y_N$ , which is known to be reliable. The latter data set could be data measured at another gauge or more generally the average of the data records available at several sites located in the same region as the suspected gauge *x*.

The theory behind double mass curves is that by plotting the accumulation of two quantities, the data will plot as a straight line and the slope of this line will represent the constant of proportionality between the two quantities.

A break in slope indicates a change in the constant of proportionality. The main purpose of these curves is to check the consistency of data over time. The steps involved are as outlined below:

1) The doubtful station, say X, is marked.

2) A table is prepared in which the first column represents the yearly precipitation records of station X.

3) Yearly precipitation records of station Y are written in the second column.

4) In the third column, the cumulative rainfall of the first column is entered.

5) In the forth column, the cumulative rainfall of the second column is entered.

6) A graph is plotted taking cumulative rainfall of station X as the abscissa and cumulative rainfall of station Y as the ordinate. A straight line joins consecutive points.

7) If the consistency of the station X has undergone changes from any year, it can be noticed from the slope of the plot. The line joining the initial points of the graph is extended by a dotted line and correction factor  $(S_1)$  $S<sub>2</sub>$ )computed.

Where:

 $S_1$ - is the slope of the curve before change in the trend and

 $S_2$ - is the slope of the curve after a change in trend of the curve.

8) Rainfall records of subsequent years from the year of deviation are corrected by multiplying with the correction factor.

## **3.3.2.2.2 Single Mass Curve Method**

In the instance when rainfall data from only one station, in the region, is available, a Single Mass Curve is used to check for consistency and carry out the necessary corrections if any (Rugumayo and Mwebaze, 2002).

## **3.3.2.2.3Statistical Tests**

A number of statistical tests can be applied for consistency analysis of rainfall data. In fact, the double mass method as described above can be used in conjunction with a statistical method. For example one could test whether

the slope  $S_2$  is different than the slope  $S_1$ . Other tests that can be applied include the t-test, F-test, and a number of non-parametric tests.

### **3.3.3The Selected Probability Distributions of Annual Rainfall**

The amount of rainfall received over an area is an important factor in assessing the amount of water available to meet the various demands of agriculture, industry, and other human activities. Annual rainfall is probably the most important simple climatic indicator of productivity**.** Therefore, the study of the distribution of rainfall in time and space is very important for the economy. Many applications of rainfall data are enhanced by knowledge of the actual distribution of rainfall rather than relying on simple summary statistics.

A huge number of studies investigating the use of particular distributions to represent the actual rainfall patterns have been employed. The gamma distribution has been widely used in climatology and hydrology. Rainfall probabilities for durations of days, weeks, months and years have been documented using the gamma distribution (Haan 1977). The annual rainfall distribution, at locations where the mean exceeds 500 mm, is among the several climate parameters which are distributed normally (Linacre 1992). Eltahir (1992) found in central and western Sudan, that in cases in which the normal distribution did not adequately describe annual rainfall, the gamma distribution was a possible alternative. Waylen et al. (1996), in a study of spatial variability of annual rainfall in Costa Rica for 100 stations, found that rainfall frequency can be represented by a normal distribution. They used a goodness- of-fit procedure to test the significance of the distribution using the Kolmogorov-Smirnov test. They also, reported that the normal distribution provides an adequate description of annual rainfall frequency at different sites.

There are two ways of judging whether or not a particular distribution adequately describes a set of observation .Both of these methods require a visual judgment of goodness of fit. One method was to compare the observed relative frequency curve with the theoretical relative frequency curve. The second method was to plot the data on appropriate probability paper and judge as to whether or not the resulting plot is a straight line. Statistical tests corresponding to these visual tests are checked (Hann 1977). These Statistical tests can be obtained automatically by using EViews-7 statistical packages software.

A standard analytical procedure is followed for annual rainfall frequency analysis. This includes selection of an appropriate probability distribution that fits the observed data. Six frequency distribution functions are used, namely:

- Normal Distribution
- Log-Normal Distribution
- Exponential Distribution
- Gamma Distribution
- Extreme value Distribution
- Weibull Distribution

To compute parameters of a distribution for a particular set of data, the maximum likelihood method is used.

The selection of the class interval and the location of the first class mark can appreciably affect the appearance of a frequency histogram. The appropriate width for a class interval depends on the range of the data, the number of observations and the behavior of the data. Hann (1977) recommended that the number of classes be determined using Sturges' equation:

$$
m = 1 + 3.3 * \log N \tag{3.5}
$$

Where

 $m =$  the number of classes  $N =$  the number of observations

The annual rainfall data are grouped into  $m$  classes, as considered above. The relative frequency for each class  $(f_{xi})$  is given by the relation:

$$
f_{xi} = \frac{r_i}{N} \tag{3.6}
$$

Where

 $r_i$  = number of the observation in the *i* th interval

Firstly, the relative frequency for each interval is plotted against the class mark (histogram). Secondly, tests whether the rainfall data series comes from normal distribution. Jarque-Bera is a test statistic for testing whether the series is normally distributed. The test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution. The statistic is computed as:

$$
Jarque - Bera = \frac{N}{6} \left( S^2 + \frac{(K-3)^2}{4} \right) \tag{3.7}
$$

Where

S= the skewness (the skewness of the normal distribution is zero)  $K=$  the kurtosis, the kurtosis of the normal distribution is 3. If the kurtosis exceeds 3, the distribution is peaked (leptokurtic) relative to the normal; if the kurtosis is less than 3, the distribution is flat (platykurtic) relative to the normal.

Under the null hypothesis of a normal distribution, the Jarque-Bera statistic is distributed as  $\chi_c^2$  with 2 degrees of freedom. The reported Probability is the probability that a Jarque-Bera statistic exceeds (in absolute value) the observed value under the null hypothesis—a small probability value leads to the rejection of the null hypothesis of a normal distribution. For the time series displayed, one rejects the hypothesis of normal distribution at the 5% significance level.

EViews statistical packages provide built-in Kolmogorov-Smirnov, Lilliefors, Cramer-von Mises, Anderson-Darling, and Watson empirical distribution tests. These tests are based on the comparison between the empirical distribution and the specified theoretical distribution function.

Thirdly, using this software, EViews, one can test whether the series is normally distributed, or whether it comes from, among others, Log-Normal, an exponential, extreme value, or gamma distribution.

Finally, theoretical quantile-quantile plots, (Q-Q), are used to assess whether the data in a single series follow a specified theoretical distribution; *e.g.*  whether the data are normally distributed. If the two distributions are the same, the (Q-Q) plot should lie on a straight line. If the (Q-Q), plot does not lie on a straight line, the two distributions differ along some dimension. The pattern of deviation from linearity provides an indication of the nature of the mismatch.

#### **3.3.4 Cumulative Distribution Function (CDF)**

The Cumulative Distribution Function (CDF) provides a good estimate of probabilities. The CDF was determined by ranking the data in ascending order and calculating their associated cumulative probability of nonexceeding

$$
CDF = \frac{I}{(n+1)} * 100
$$
 (3.8)

Where:

 $I = rank position$  $n =$  total number of rainfall data points in series

The return period is the inverse of the probability of exceedance

$$
T_r = \frac{1}{(1 - F_i)}
$$
(3.9)

Where:

 $T_r$ = return period (year)  $F_i$  = relative frequency of occurrence for the classes of CDF

To test the degree at which the cumulative distributions are statistically different, the Kolmogorov-Smirnov (K-S) two-sample test was applied (Kanji 2006). According to the K-S test, two distribution functions are significantly difference if the maximum vertical deviation between them (D Statistic) exceeds the critical level at the specified significance level as 0.05.

Given samples of size  $n_1$  and  $n_2$  from the two populations, the cumulative distribution functions  $Sn_1(x)$  and  $Sn_2(y)$  can be determined and plotted. Hence the maximum value of the difference between the plots can be found and compared with a critical value obtained. If the observed value exceeds the critical value the null hypothesis that the two population distributions are identical is rejected.

## **3. 4 Analysis of Hydrological Time Series**

A sequence of values collected over time on a particular variable is a time series. Records of rainfall form data sequence can be studied by the methods of time series analysis. The tools of this specialized topic in mathematical statistics provide valuable assistance to engineers in solving problems involving the frequency of occurrences of major hydrological events (Shaw, 1994).

A time series may be composed of only deterministic events, only stochastic events or a combination of the two. Most generally a hydrologic time series is usually composed of a stochastic component superimposed on a deterministic component. The deterministic component may be classified as a periodic component, a trend, a jump or a combination of these (Hann, 1977).

If a hydrological time series is represented by  $X_1, X_2, X_3, \ldots, X_t, \ldots$ , then symbolically, one can represent the structure of the  $X_t$  by:

$$
X_t \Longleftrightarrow [T_t, P_t, E_t]. \tag{3.10}
$$

Where

 $T_t$  = The trend component.  $P_t$  = The periodic component.  $E_t$  = The stochastic component.

The first two components are specific deterministic features and contain no element of randomness. The third, stochastic, component contains both random fluctuations and the self-correlated persistence within the data series. These three components form a basic model for time series analysis. Tasks of time series analysis include:

(1) Identification of the several components of a time series

(2) Mathematical description (modeling) of different components identified.

## **3. 5 Trend Component**

This may be caused by long-term climatic change or, in river flow, by gradual changes in catchments response to rainfall owing to land use

changes. Many hydrological time series exhibit trending behavior. In fact, the trending behavior is a type of nonstationarity. But in this present research, they are treated separately. The purpose of a trend test is to determine if the values of a series have a general increase or decrease with the time increase. A time series is said to be stationary when its statistical properties such as mean, variance, autocorrelation, etc. are all constant over time. Most statistical forecasting methods are based on the assumption that the time series can be rendered approximately stationary (i.e., "stationarized") through the use of mathematical transformations.

#### **3. 5.1 Methods of Trend Identification**

Trend analysis of a time series consists of the magnitude of trend and its statistical significance. Obviously, different workers have used different methodologies for trend detection. In general, the magnitude of trend in a time series is determined either using regression analysis (parametric test) or using Mann-Kendall Test (non-parametric method). Both these methods assume a linear trend in the time series. In this study the Linear Regression Method has been applied to identify the trend in the time series. This method will be discussed briefly in the following section.

#### **3. 5.1.1 Linear Regression Method:**

Regression analysis is conducted with time as the independent variable and rainfall as the dependent variable. The regression analysis can be carried out directly on the time series or on the anomalies (i.e. deviation from mean).

The linear trend method simply involves the application of a simple, twovariable, regression technique:

$$
Y_t = a + bX \tag{3.11}
$$

Where:

 $Y_t$  = Trend values of the variable *Y* 

 $x =$  Point in time

*a* = The intercept or estimated value when *x* equal to zero

*b* = Slope of line or average change in *Y* per unit of time

The linear trend value represented by the slope of the simple least-square regression line provided the rate of rise/fall in the variable. A two tailed test

follows Student's t-distribution with n−2 degrees of freedom was used to investigate the significance of the regression coefficient of *y* on *x* (Kanji, 2006). All the time-series of monthly and annual rainfalls have been investigated for their direction and statistical significance of trend by the nonparametric Spearman rank correlation test (Kanji, 2006) using the Statistical Package for the Social Sciences (SPSS19 ), taking into account the common data period of1971–2010.

## **3.6 Materials Description and Indices**

This involves the description of material used with the different indices. These are namely; rainfall seasonality index, precipitation concentration index, modified Fournier index, and standardized precipitation index (SPI).

#### **3.6.1 Rainfall Seasonality Index**

Seasonality index helps in identifying the rainfall regimes based on the monthly distribution of rainfall. In order to define the seasonal contrasts, the seasonality index (SI) (Walsh and Lawler 1981), which is a function of mean monthly and annual rainfall, is computed using the following formula:

$$
SI_{i} = \frac{1}{R} \sum_{n=1}^{n=12} \left| X_{n} - R /_{12} \right| \tag{3.12}
$$

Where:

 $X_n$  = Rainfall of month n  $R =$ Annual rainfall

This index can in theory vary from zero (if all the months have equal rainfall) to 1.83 (if all the rainfall occurs in a single month). In table (3.2) a qualitative classification of degrees of seasonality is suggested, although the precise divisions selected have no intrinsic significance .This index is closely related to that proposed by Ayoade (1970) but computation of the former is marginally easier and its expanded scale is advantageous for descriptive purposes (Walsh and Lawler 1981). This index permits a quantification of the variability of rainfall through the year, but should be complemented by a detailed analysis of monthly rainfall .The index has been used by several investigators (Sumner et al., 2001; Pryor and Schoof, 2008 and Elagib, 2010).

Since the data contain no rain in some years (Atbara, Port Sudan and Dongola), the value of the denominator in equation (3.12) is zero in these cases. Thus, no values have been calculated due to corresponding division by zero in those years with no rain.

SI.	<b>Rainfall regime</b>		
< 0.19	very equable		
$0.20 - 0.39$	equable but with a definite wetter season		
$0.40 - 0.59$	rather seasonal with a short drier season		
$0.60 - 0.79$	Seasonal		
$0.80 - 0.99$	markedly seasonal with a long drier season		
$1.00 - 1.19$	most rain in 3 months or less		
>1.20	extreme seasonality (almost all rain in $1-2$ months)		
$S_{\text{out}}$ (Welsh and Lawlar, 1001)			

**Table No.(3.2): Suggested Qualitative Classification Seasonality Degrees** 

Source (Walsh and Lawler, 1981)

A long-term mean  $\overline{SI}_i$  for each site may subsequently be calculated directly from the accumulated  $SI<sub>i</sub>$  over a longer period, *j*, N years in the current study:

$$
SI_{i} = \frac{1}{N} \sum_{j=1}^{J=N} SI_{ij}
$$
 (3.13)

An alternative index using a similar formula may also be calculated using long term average monthly precipitation data directly  $(\overline{SI})$ , but the resulting index will possess a lower magnitude, since the process of averaging smoothes year-to-year 'noise' in the monthly precipitation values (Sumner et al., 2001).

One of the important restrictions of the index is that it does not indicate when or how wetter periods are distributed through the year.

Walsh and Lawler (1981) used the ratio  $(\overline{SI}/\overline{SI}_i)$  as a 'replicability index' to indicate whether or not the wettest period occurs over a small range of

months, or whether it may occur in any month during the year. Higher values of the replicability index indicate that the wettest month of the year generally occurs in only the same few months every year. Lower values indicate that the wettest month of the year tends to be more evenly spread amongst a larger number of different months. For example, areas with very pronounced wet and dry seasons will tend to have the wettest months in individual years concentrated during the period of the wet season: a high replicability index.

#### **3. 6.2 Precipitation Concentration Index**

The Precipitation Concentration Index (PCI) is a powerful indicator of the temporal distribution of precipitation. Traditionally it was applied at annual scales; as the value increases, the more concentrated the precipitation. Furthermore PCI is a part of the well-known Fournier index, with a long tradition on natural system analyses, as for example soil erosion.

The Precipitation Concentration Index, proposed as an indicator of rainfall concentration (Oliver, 1980) and rainfall erosivity (Michiels et al., 1992), was calculated on an annual scale for each grid point according to the equation:

$$
PCI = 100 \times \sum_{n=1}^{12} \left(\frac{X_n^2}{R^2}\right) \tag{3.14}
$$

Where:

 $X_n$  = Rainfall of month n  $R =$ Annual rainfall

The PCI ranges and corresponding descriptions are uniform (PCI=8.3–10), moderately seasonal (PCI=10–15), seasonal (PCI=15–20), highly seasonal (PCI=20–50) and irregular (PCI=50–100). This index was utilized by Apaydin et al. (2006).

#### **3.6.3 Modified Fournier Index**

Fournier (1960) devised an index, which was modified by Arnoldus (1980), referred to as modified Fournier index and denoted by MFI. It is defined by the following equation:

$$
MFI = \sum_{n=1}^{12} \left(\frac{X_n^2}{R}\right) \tag{3.15}
$$

where:

 $X_n$  = Rainfall of month n  $R =$ Annual rainfall

It assesses the effect of erosion by rainwater. Higher index values indicate a greater aggressivity while lower values indicate lower aggressivity of rainfall. The MFI has erosivity categories as very low (MFI=0–60), low (MFI=60–90), moderate (MFI=90–120), high (MFI=120–160) and very high (MFI>160). The calculation of this index has been found valuable in determining the erosive potential of rainfall by providing information on the long-term variability (Apaydin et al., 2006).

In the rank statistical methods, the applications of the rank correlation tests are more common. The rank correlation tests use a nonparametric (distribution-free) measure of correlation based on ranks. The most common of these methods are the Mann- Kendall and the Spearman rank tests. The Spearman rank correlation test has been used in this study. All the annual rainfalls time-series of SI, PCI and MFI have been investigated for their direction of trends by the nonparametric Spearman rank correlation test (Kanji, 2006) using the Statistical Package for the Social Sciences (SPSS), taking into account the common data period of1971–2010. The test was applied on the SI, PCI and MFI series for the common data period with the years of no rain being excluded.

## **3.7 Standardized Precipitation Index (SPI) Computation Methodology**

McKee et al., (1993) developed the Standardized Precipitation Index (SPI) for the purpose of defining and monitoring drought. Among others, the Colorado Climate Center, the Western Regional Climate Center and the National Drought Mitigation Center use the SPI to monitor current states of drought in the United States. The nature of the SPI allows the analyst to determine the rarity of a drought or an anomalously wet event at a particular time scale for any location in the world that has a precipitation record. The SPI based drought classification is demonstrated in table (2.3).

In most cases, the Gamma distribution is the distribution that best models observed precipitation data. Thom (1966) found the gamma distribution to fit climatological precipitation time series well. The gamma distribution is defined by its frequency or probability density function:

$$
g(x) = \frac{1}{\beta^{\alpha} \Gamma(\alpha)} x^{\alpha - 1} e^{-\frac{x}{\beta}} \qquad \text{for} \quad x > 0 \quad (3.16)
$$

where

 $\alpha > 0$  = A shape parameter

 $\beta > 0$  = A scale parameter

 $x>0$  = The amount of precipitation.

 $\Gamma(\alpha)$  = The gamma function, which is defined as

$$
\Gamma(\alpha) = \int_0^\infty y^{\alpha - 1} e^{-y} dy \tag{3.17}
$$

Computation of the Standardized Precipitation Index (SPI) involves fitting a gamma probability density function to a given frequency distribution of precipitation totals for a station. The alpha and beta parameters of the gamma probability density function are estimated for each station, for each time scale of interest (3 months, 12 months, 48 months, etc.), and for each month of the year. Edwards & McKee (1997) suggest estimating these parameters using the approximation of Thom (1958) for maximum likelihood as follows:

$$
\alpha = \frac{1}{4A} \left( 1 + \sqrt{1 + \frac{4A}{3}} \right) \tag{3.18}
$$

$$
\beta = \frac{\bar{x}}{\alpha} \tag{3.19}
$$

Where:

$$
A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \tag{3.20}
$$

#### n = number of precipitation observations

The resulting parameters are then used to find the cumulative probability of an observed precipitation event for the given month and time scale for the station in question. Integrating the probability density function with respect to *x* and inserting the estimates of *α* and *β* yields an expression for the cumulative probability *G(x)* of an observed amount of precipitation occurring for a given month and time scale:

$$
G(x) = \int_0^x g(x) dx = \frac{1}{\beta^{\alpha} \Gamma(\alpha)} \int_0^x x^{\alpha - 1} e^{-x} / \beta \, dx \tag{3.21}
$$

Putting  $t = \frac{x}{\beta}$ , this equation becomes the incomplete gamma function:

$$
G(X) = \frac{1}{\Gamma(\alpha)} \int_0^x t^{\alpha - 1} e^{-t} dt
$$
 (3.22)

This is the incomplete gamma function. Values of the incomplete gamma function are computed using an algorithm taken from Press et al. (1986).

 $\mu = 0$ 

Since the gamma distribution is undefined for

And 
$$
q = P(x=0) > 0
$$

Where:

 $P(x = 0)$  = The probability of zero precipitation.

The cumulative probability becomes

$$
H(x) = q + (1 - q)G(x)
$$
 (3.23)

If m is the numbers of zeros in a precipitation series, Thom (1966) states that q can be estimated by m / n.

The cumulative probability,  $H(x)$  is then transformed to the standard normal random variable Z with mean zero and variance one, which is the value of SPI. Following Edwards and McKee (1997), an approximate conversion is used in this research, as provided by Abramowitz and Stegun (1965) as an alternative:

$$
Z = SPI = -\left(K - \frac{c_0 + c_1 K + c_2 K^2}{1 + d_1 K + d_2 K^2 + d_3 K^3}\right) for \quad 0 < H(x) \le 0.5 \tag{3.24}
$$

$$
Z = SPI = +\left(K - \frac{c_0 + c_1 K + c_2 K^2}{1 + d_1 K + d_2 K^2 + d_3 K^3}\right) for \quad 0.5 < H(x) < 1.0 \quad (3.25)
$$

Where

$$
K = \sqrt{\ln \frac{1}{(H(x))^{2}}} \quad \text{for} \quad 0 < H(x) \le 0.5 \tag{3.26}
$$

$$
K = \sqrt{\ln \frac{1}{(1 - H(x))^{2}}} \quad for \quad 0.5 < H(x) < 1.0 \tag{3.27}
$$

Where:

 $x = \text{Precipitation}$  $H(x)$  = The cumulative probability of precipitation observed.  $c_0$ ,  $c_1$ ,  $c_2$ ,  $d_1$ ,  $d_2$  and  $d_3$  = Constants with the following values:<br>  $c_0$  = 2.515517  $c_1$  = 0.802853  $c_2$  = 0.010328  $c_0$  = 2.515517  $c_1$  = 0.802853<br>  $d_1$  = 1.432788  $d_2$  = 0.189269  $d_3 = 0.001308$ 

The definition of drought thus far has included a beginning date, ending date, and current drought intensity. Duration of drought can be either a current duration since the beginning or the duration of a historic drought event from beginning to ending. Peak intensity can easily be determined from the SPI. A measure of the accumulated magnitude of the drought can be included. Drought Magnitude (DM) is defined as:

$$
DM = -\left(\sum_{j=1}^{n} SPI_{ij}\right) \tag{3.28}
$$

Where:

 $j =$  Starts with the first month of a drought and continues to increase until the end of drought.

 $n =$  End of the drought.

 $i =$ Time scales  $(1,3, 6, 9, 12, 24, or 48$  months).

The DM has units of months and would be numerically equivalent to drought duration if each month of the drought has  $SPI = -1.0$ . In fact, many droughts will have a DM very similar to the duration in months since most of the SPI values are between 0 and -2.0 (McKee et al., 1993).

In this study a program called "SPI\_Analysis" was used to calculate and analyze the SPI values. This program has been developed by the National Drought Mitigation Center - United States.

## **3.8 Building ARIMA Models**

For more than half a century, Box–Jenkins ARIMA linear models have dominated many areas of time series forecasting. The Box-Jenkins approach to modeling ARIMA processes was described by statisticians George Box and Gwilym Jenkins in 1970. An ARIMA process is a mathematical model used for forecasting. Box-Jenkins modeling involves identifying an appropriate ARIMA process, fitting it to the data, and then using the fitted model for forecasting. One of the attractive features of the Box-Jenkins approach to forecasting is that ARIMA processes are a very rich class of possible models and it is usually possible to find a process which provides an adequate description to the data (Rob Hyndman, 2001). An ARIMA model means an integrated autoregressive moving average model, and is written as  $ARIMA(p,d,q)$ :

where:

p = The number of autoregressive terms

 $d =$ The number of difference steps to become stationary from nonstationary

q =The number of lagged forecast errors.

 $AR(p)$ ,  $MA(q)$ , and  $ARMA(p,q)$  models are some special cases of  $ARIMA(p,d,q)$  models.

In essence, ARIMA models are finely-tuned random walk and random-trend models. Lags of the differenced time series are called "autoregressive" terms, lags of forecast errors are called "moving average" terms, and the difference steps by which the time series becomes stationary from nonstationary are called "integrated" terms (Box and Jenkins, 1976). Considering seasonal adjustment to eliminate a seasonal component of periods, seasonal ARIMA models are written as SARIMA models, or seasonal ARIMA(p,d,q) x (P,D,Q)s models.

Where:

P, D and  $Q =$  Nonnegative integers for adjustment. Typically, D is 0 or 1, and P and Q are less than 3 (Brockwell and Davis, 2002).

The Box and Jenkins (1976) modeling approach involves the following three steps:

## **1. Model Identification**

In this step, the model that seems to represent the behavior of the series is searched, by the means of autocorrelation function (ACF) and partial autocorrelation function (PACF), for further investigation and parameter estimation. The behavior of ACF and PACF, is to see whether the series is stationary or not, seasonal or non-seasonal. Differencing is done to make non-stationary time series to stationary time series. A stationary time series has the property that its statistical characteristics such as the mean and the autocorrelation structure are constant over time.

### **2. Parameter Estimation**

After choosing the most appropriate model, the model parameters are estimated by using several estimation procedures. These parameters should satisfy two conditions namely stationary and invertibility for autoregressive
and moving average models, respectively (Box et al., 1976). The parameters should also be tested whether they are statistically significant or not.

# **3. Goodness-of-Fit Test**

Goodness-of-fit tests verify the validity of the model by some tools. The residuals of the model are usually considered to be time-independent and normally distributed over time. The most common tests applied to test timeindependence and normality is the *Q* statistics (Port mantateau lack-of-fit test), the Serial Correlation LM Test and the non-parametric Kolmogorov– Smirnov test.

The last two columns reported in the correlogram are the Ljung-Box *Q* statistics (Port mantateau lack-of-fit test) and their *p-* values. The *Q*-statistic at lag *k* is a test statistic for the null hypothesis that there is no autocorrelation up to order *k* and is computed as:

$$
Q(r) = n(n+2) \sum_{k=1}^{k} (n-k)^{-1} r_k^2
$$
 (3.29)

Where:

 $r_k$  = The *k*-th autocorrelation n = Number of observations

EViews software displays the autocorrelation and partial autocorrelation functions of the residuals, together with the Ljung-Box *Q*-statistics for highorder serial correlation. If there is no serial correlation in the residuals, the autocorrelations and partial autocorrelations at all lags should be nearly zero, and all *Q*-statistics should be insignificant with large *p*-values.

The serial correlation LM Test is an alternative to the *Q*-statistics for testing serial correlation. The statistic labeled "Obs\*R-squared" is the LM test statistic for the null hypothesis of no serial correlation. The (effectively) zero probability value strongly indicates the presence of serial correlation in the residuals.

This three-step model building process is typically repeated several times until a satisfactory model is finally selected. The final selected model can then be used for prediction purposes.

The two general forms of ARIMA models are non-seasonal ARIMA (p, d, q) and multiplicative seasonal ARIMA  $(p, d, q) \cdot (P, D, Q)$  are described below.

#### **i. Non Seasonal Models**

Autoregressive (AR) models can be effectively coupled with moving average (MA) models to form a general and useful class of time series models called autoregressive moving average (ARMA) models (Mishra and Desai 2005). In ARMA model the current value of the time series is expressed as a linear aggregate of p previous values and a weighted sum of q previous deviations (original value minus fitted value of previous data) plus a random parameter. However, they can be used when the data are stationary. This class of models can be extended to non-stationary series by allowing differencing of data series. These are called autoregressive integrated moving average (ARIMA) models. Box and Jenkins (1976) popularized ARIMA models. The general non-seasonal ARIMA model is AR to order p and MA to order q and operates on *d*th difference of the time series  $Z_t$ ; thus a model of the ARIMA family is classified by three parameters (p, d, q) that can have zero or positive integral values. The differencing operator that is usually used in the case of non-stationary time series is

$$
\nabla = 1 - B \tag{3.30}
$$

Where:

B =Backward shift operator

This form of non-seasonal ARIMA (p, d, q) is written as

$$
\phi(B)\nabla^d Z_t = \theta(B)a_t \tag{3.31}
$$

Where:

 $\phi(B)$  and  $\theta(B)$  = Polynomials of order p and q, respectively.

$$
\phi(B) = (1 - \phi_1 B - \phi_2 B^2 - \cdots \phi_P B^p)
$$
\n(3.32)

and

$$
\theta(B) = \left(1 - \theta_1 B - \theta_2 B^2 - \cdots \theta_q B^q\right) \tag{3.33}
$$

# **ii. Seasonal Models**

Many time series contain cyclic features. Very often in hydrologic time series these features are of an annual cycle primarily due to the earth's rotation about the sun. Such series are cyclically non-stationary (Mishra and Desai 2005). Once the deterministic cyclic effects have been removed from a series, the ARIMA approach can be applied to obtain a linear model for the stochastic part of the series. Box et al. (1994) have generalized the ARIMA model to deal with seasonality, and define a general multiplicative seasonal ARIMA model, which are commonly known as SARIMA models. In short notation the SARIMA model described as ARIMA (p, d, q) (P, D, Q)s,

Where:

 $(p, d, q)$  = The non-seasonal part of the model  $(P, D, Q)$  = The seasonal part of the model. p = The order of non-seasonal autoregression  $d =$ The number of regular differencing q = The order of nonseasonal MA  $P =$ The order of seasonal autoregression  $D$  = The number of seasonal differencing  $Q =$ The order of seasonal MA  $s$  = The length of season.

In this case a multiplicative model given by the following equation:

$$
\phi_p(B)\Phi_p(B^s)\nabla^d\nabla^p_s(Z_t) = \theta_q(B)\Theta_Q(B^s)a_t \tag{3.34}
$$

Where:

 $\Phi_p$  and  $\Theta_Q$  = Seasonal polynomials of order P and Q, respectively.

This is the general form of the multiplicative seasonal ARIMA model of order  $(p, d, q) \cdot (P, D, Q)$ .

Several researchers have indicated key advantages of the state space form over the ARIMA models (Durbin and Koopman, 2001). A time series might have some special components, such as trend, seasonal cycle and calendar variations, together with the effects of explanatory variables and interventions. These components can be preprocessed separately, and for

different purposes for a state space model. In contrast, the Box-Jenkins ARIMA model is a black-box model, which solely depends on the data without knowledge of the system structure that produces the data. The second advantage is the recursive nature of the state-space model that obviously allows change of the system over time, while ARIMA models are homogeneous through time, based on the stationary assumption.

Hence, due to the important role of drought forecasting in water resources planning and management and the stochastic behavior of drought, an autoregressive integrated moving average (ARIMA) model is applied to the rainfall in Sudan. The three phases of modeling which are used for stochastic modeling of hydrologic time series namely model identification, parameter estimation and diagnostic checking of the recommended ARIMA model are presented. SPSS and Eviews software were used to simulate the ARIMA samples.

# **CHAPTER FOUR**

# **Results and Discussion**

# **4.1 Rainfall Data Analysis**

In this chapter, rainfall data from sixteen meteorological stations across the country from 1971 to 2010 was obtained and missing values is filled before carrying out homogeneity and consistency tests. The main objective of this chapter is to study the characteristic of rainfall in the considered regions. A set of data, containing monthly and annual rainfall data, has been investigated to perform the required analysis. One of the main objectives of this chapter is the analysis of the rainfall variability, in Sudan, over both space and time during the last four decades. The analysis of variability of rainfall has been done by using the coefficient of variation. The coefficient of variation  $(C_V)$  was calculated as the ratio of standard deviation to the mean.

The nature of the seasonality of rainfall, in all regions, is examined using the rainfall seasonality index (SI). Seasonality index helps in identifying the rainfall regimes based on the monthly distribution of rainfall. Modified version of precipitation concentration index (PCI) was, also, used to estimate the monthly heterogeneity of rainfall. Understanding the rainfall characteristics, particularly its variability in time and space, is essential for the development of methods for estimating the risks due to erosion (Apaydin et al., 2006). The rainfall erosivity has been investigated using the Modified Fournier index (MFI) and annual rainfall.

# **4.1.1 Rainfall Record Used in the Study**

Sixteen meteorological stations across the country were selected with monthly and annually rainfall series during the period 1971 to 2010, as shown in appendix (1) and appendix (2) respectively. These Stations were selected on the basis of reasonably long records for the monthly data in locations that represent as many climatic zones as possible in Sudan. The rainfall data was obtained from the Sudan Meteorological Authority (SMA). All time series were checked to find out all missing data.

Table (4.1) contains information about stations, covered period and the fraction of missing data. These stations are classified by Elagib et al, (2000) and as follow:

- Kadugly, Nyala and Gedaref: semi-arid.
- Fasher, Genina, Obeid, Kosti, Nahud, Wad Medani, Sennar, Kassala and Khartoum :Arid
- Atbara, Dongola, Wadi Halfa and Port Sudan: hyper-arid.

	Latitude	Longitude	Period of	Missing data
<b>Station</b>	(N)	(E)	data	$(\%)$
Wadi Halfa	21.81	31.35	1974-2010	$0.009\%$
Port Sudan	19.58	37.22	1970-2010	$0.006\%$
Dongola	19.17	30.50	1971-2010	$0.000\%$
Atbara	17.7	33.97	1971-2010	$0.004\%$
Khartoum	15.60	32.55	1971-2010	$0.000\%$
Kassala	15.47	36.40	1971-2010	$0.000\%$
Medani	14.38	33.50	1971-2010	$0.002\%$
Gadaref	14.03	35.40	1971-2010	$0.000\%$
Fasher	13.62	25.33	1970-2010	$0.002\%$
Sennar	13.55	33.63	1971-2010	$0.000\%$
Geneina	13.48	22.45	1970-2010	$0.000\%$
Obaied	13.18	30.22	1970-2010	$0.006\%$
Kosti	13.16	32.66	1971-2010	$0.004\%$
Nahud	12.70	28.43	1971-2010	$0.002\%$
<b>Nyala</b>	12.05	24.88	1970-2010	$0.004\%$
Kadugli	11.00	29.72	1971-2010	$0.010 \%$

**Table No. (4. 1) List of Rain Gauge Stations Used in Sudan Study** 

# **4.1.1.1 In- Filling Missing Rainfall Records**

Sixteen meteorological stations across the country were selected with monthly precipitation series starting at 1971 and ending at 2010. Individual missing data for a given month were filled in from the neighboring values, by taking the average of the three preceding and the three following year's records for that specific month (Qureshi and Khan 1994).

### **4.1.2 Statistical Properties of the Annual Rainfall**

Using the sample data  $x_i$  (i=1,2,…,n) the basic statistical properties of the annual rainfall series, the mean  $\bar{X}$ , standard deviation *S*, coefficient of variation  $C_V$ , skew  $C_S$ , minimum and maximum values have been estimated for each station. The results obtained are given in table (4.2).



# **Table No. (4.2): Statistical Properties of Annual Rainfall Series for All Stations (1971-2010).**

# **4.1.3 Grouping of the Sub-Regions Stations**

The annual rainfall data in each geographical region were investigated to detect if the sample (station) are from same population (region), and to detect the homogeneity between stations in each region, by using the Kruskall–Wallis test. According to the values of the statistical parameters, in table (4.4), and the Kruskal-Wallis test, each region was divided into many sub-regions as considered in table (4.3).



# **Table No. (4.3) Grouping Of the Sub-Regions Using the Kruskall– Wallis Test for the Annual Rainfall Series**

\* Significant at  $(1 - \alpha = 0.01)$ ,  $\chi^2_{(0.01, l)} = 6.63$ 

(-) Not significant, at  $(1 - \alpha = 0.05)$ , with the others stations in same region

# **4.1.4 Test for homogeneity**

# **4.1.4.1 Von Neumann ratio test**

The results of the Von Neumann ratio test, table (4.4), indicate that the annual rainfall time series at all stations are homogeneous since the values of Von Neumann's ratio (N) are grater than the critical level.

# **4.1.4.2 Homogeneity of Single Stations (Hartley's Test for Equality of K Samples Variances)**

The results of the test as shown in table (4.5) indicate that the three stations namely Khartoum, Obaied and Port Sudan are in the critical region. In fact if one extreme value of annual rainfall is neglected that station will be out of the critical region. For example, if one neglect the extreme annual rainfall value in Khartoum station, year 1988 (415.5 mm), the  $F_{max}$  value reduced to

1.10 (less than critical level). The rest of stations have homogeneity of variance.

Station	Precipitation covered period	Von Neumann's ratio $(N)$	Critical level	Homogeneity Test at $1\%$
Wadi Halfa	1971-2010	1.48	1.29	Accepted
Port Sudan	1970-2010	2.03	1.29	Accepted
Dongola	1971-2010	1.87	1.29	Accepted
Atbara	19712-2010	1.76	1.29	Accepted
Khartoum	1971-2010	1.80	1.29	Accepted
Kassala	1971-2010	1.81	1.29	Accepted
Medani	1971-2010	1.94	1.29	Accepted
Gedaref	1971-2010	2.03	1.29	Accepted
Fasher	1970-2010	1.75	1.29	Accepted
Sennar	1971-2010	1.85	1.29	Accepted
Geneina	1970-2010	1.60	1.29	Accepted
Obeid	1970-2010	1.63	1.29	Accepted
kosti	1971-2010	1.75	1.29	Accepted
Nahud	1971-2010	1.95	1.29	Accepted
Nyala	1970-2010	1.72	1.29	Accepted
Kadugli	1971-2010	2.21	1.29	Accepted

**Table No. (4.4): Results of Von Neumann Ratio Test – Annual Rainfall Data Series.** 

# **4.1.4.3 Consistency of Rainfall Data**

In this study, the Consistency (relative homogeneity) of rainfall has been examined using the double mass curve test which is a commonly used data analysis approach. With the double mass curve technique, a data is consistent if the cumulative plot of the two quantities is a straight line.

<b>Station</b>	$N_1$ (years)	$\overline{X}_1$ (mm)	$S^2$ <sub>1</sub>	$N_2$ (year)	$\bar{X}_2$ (mm)	$S^2$ <sub>2</sub>	$F_{max}$	Critical Value*
Dongola	20	9.7	210.2	20	9.6	296.4	1.41	2.46
PortSudan	20	60.7	1946.9	20	99.6	7259.1	$3.73***$	2.46
Atbara	20	58.1	3005.2	20	47.5	1512.0	1.99	2.46
Khartoum	20	116.9	7333.5	20	127.9	2639.5	$2.78***$	2.46
Kassala	20	246.9	5990.8	20	240.1	8034.9	1.34	2.46
Madani	20	278.7	6906.7	20	298.5	6537.4	1.06	2.46
Sennar	20	422.7	12110.7	20	416.6	16993.1	1.40	2.46
Gadaref	20	603.6	14313.9	20	630.1	13534.9	1.06	2.46
Fasher	20	177.6	3618.3	20	213.3	4734.1	1.31	2.46
Kosti	20	342.3	9505.1	20	353.8	11847.1	1.25	2.46
Obeid	20	299.9	7048.7	20	396.8	18382.7	$2.61***$	2.46
Nahud	20	335.9	12483.5	20	378.1	12594.9	1.01	2.46
<b>Nyala</b>	20	358.8	8782	20	417.1	8773.2	1.01	2.46
Geneina	20	372.1	11850	20	480.2	12006.2	1.01	2.46
Kadugli	20	646.1	15208.4	20	716.6	16839.3	1.11	2.46

**Table No. (4.5) Homogeneity Test on Annual Rainfall Series for Single Stations** 

\* The critical value of  $F_{\text{max}}$ , at 5 percent level of significance, for  $N_1 = N_2$  = 20, K = 2 is 2.46 (Kanji, 2006).

N<sub>1</sub>: (1971-1990), N<sub>2</sub>: (1991-2010)

\*\* The observed ratio ( $F_{max}$ ) > the critical value (the null hypothesis of equal variances should be rejected).

Fig (4.1) presents a sample of the double mass curve for the rainfall data series (region II). The X axis presents the reference station (Medani), Y axis presents other stations (Khartoum, Kasala, Sennar and Gadaref). The results showed that all station did not provide any break in slope. This shows that rainfall data at these stations are consistent.

Fig  $(4.2)$  presents the reference station (Kosti) in X axis; Y axis presents other stations (Kadugli, obied and Nahoud). The results also showed that all station did not provide any break in slope. This shows that rainfall data at these stations are also consistent.

Fig (4.3) presents the reference station (Geneina) in X axis; Y axis presents other stations (Nyala and Fasher). The results also showed that all station did not provide any break in slope. This shows that rainfall data at these stations are also consistent.



**Fig No. (4.1): Cumulative Rainfall For Station Madeni Vs. Cumulative Rainfall For The Four Stations (Khartoum, Kasalla, Sennar and Gadaref)** 

With the single mass curve technique, a data is consistent if the cumulative plot of that data against the period (years) is a straight line. A Single Mass Curve diagram was drawn for Port Sudan meteorological station (winter rainfall) to see whether the data from this station was consistent. As seen in the Figure (4.4), the plot has provided many significant break in slope. This shows that rainfall data at this station is non-consistent. Table (4.6) presents the results of double mass curve for the rainfall data series of all stations.



**Fig No. (4.2): Cumulative Rainfall For Station Kosti Vs. Cumulative Rainfall For The Other Stations ( Kadugly, Nahoud and Obaied)** 



**Fig No.(4.3): Cumulative Rainfall For Station Geneina Vs. Cumulative Rainfall For The Other Stations ( Fasher and Nyala)** 



**Fig No. (4.4) Cumulative Rainfall For Port Sudan Station Vs. The Period (Years)** 

**Table No. (4.6): Results of Double Mass Curve for the Rainfall Data Series of All Stations (1971 - 2010).** 

<b>Stations</b>	<b>Double Mass Curve Test</b>
Wadi Halfa	non-consistent
Port Sudan	non-consistent
Dongola	non-consistent
Atbara	non-consistent
Khartoum	consistent
Kassala	consistent
Medani	consistent
Gedaref	consistent
Fasher	consistent
Sennar	consistent
Geneina	consistent
Obeid	consistent
kosti	consistent
Nahud	consistent
Kadugli	consistent

\*\* For Port Sudan meteorological station we used Single Mass Curve (winter rainfall data from only one station is available)

#### **4.1.5 Characteristics of the Rainfall in the Study Area**

Figure (4.5) shows the mean monthly rainfall for three stations namely Atbara, Dongola and Wadi Halfa (region I). The monthly mean approximately approach its maximum values in July and August for all stations. Atbara station is characterized by the highest annual rainfall followed by Dongola while Wadi Halfa receives the lowest annual rainfall (less than 1 mm per year) during the period from 1971 to 2010. For Port Sudan (winter rainfall) the monthly mean approaches its maximum values in October and November while the minimum (non zero) rainfall is in September.



**Fig No. (4.5) Mean Monthly Rainfall Totals Of The Stations Namely Atbara, Dongola And Wadi Halfa** 

For region II, the mean monthly rainfall is represented in Figure (4.6). The monthly mean approaches its maximum values in July and August for all stations. The minimum (non zero) rainfall value is in April and November at Gadaref, Medani and Kassala, while Sennar during April and October and Khartoum during May and October. Gadaref station is characterized by the highest annual rainfall followed by Sennar, Medani, Kasalla and finally Khartoum receives the lowest annual rainfall in this region as shown in figure  $(4.7)$ .



Fig No. (4.6) Mean Monthly Rainfall Totals Of The Stations Namely **K Khartoum, Kassala, M Madani, Se nnar And Gadaref** 



Fig No. (4.7) The Annual Total Rainfall For The Stations (Khartoum, **Kassala, Madani, Sennar And Gadaref)** 

Figure (4.8) presents the mean monthly rainfall for four stations namely Kosti, Obied, Nahoud and Kadugly. The monthly mean approaches its maximum values in July and August for all stations. The minimum rainfall value is in April and October at Nahoud, Obied and Kosti, while Kadugly during March and October. Kadugly station is characterized by the highest

annual rainfall followed by Nahoud, Obied and Kosti as shown in figure (4.9).



**Fig No. (4.8) Mean Monthly Rainfall Totals of the Stations Namely Kadugly, Obied, Nahoud and Kosti.** 



Figure (4.10) presents the mean monthly rainfall for three stations namely Fashir, Geneina and Nyala. The monthly mean approaches its maximum values in July and August for all stations. The minimum rainfall value is in April and October at all stations. Geneina station is characterized by the



highest annual rainfall followed by Nyala and Fashir as shownin figure (4.11).

**Fig No (4.10) Mean Monthly Rainfall Totals for The Stations Namely Genrina, Nyala And Fasher.** 



**Fig No. (4.11) The Annual Total Rainfall For The Stations (Genrina, Nyala and Fasher)** 

# **4.1.5.1 Results of the Selected Probability Distributions of Annual Rainfall**

The relative frequency for each interval is plotted against the class mark (histogram) for station, for instance, namely Port Sudan*,* Obeid and Geneina, are shown in figures (4.12) to fig (4.14).



**Fig No. (4.12): Relative Frequency Histogram for Port Sudan Station** 







#### **GENEINA**



**Fig No. (4.14): Relative Frequency Histogram for Geneina Station** 

Table (4.7) presents the Jarque-Bera values for testing whether the annual rainfall series is normally distributed. For the time series, one rejects the hypothesis of normal distribution at the 5% significance level ( $\alpha$  < 0.05).





Using the EViews software, all stations tested whether the annual rainfall series was normally distributed, or obtained from another distribution. Table (4.8, a through c) presents the EViews software tests results for Geneina stations, using three different distributions namely normal, gamma and exponential distribution. Theoretical quantile-quantile plots, (Q-Q), for the three considered distribution are used for Geneina station, table (4.9) and fig (4.15a through d).

From table (4.7), the Jarque-Bera test value for Geneina station is equal to (0.931646) - a high probability value leads to the accepting of the null hypothesis of a normal distribution. Also all the tests represented in table (4.8a) show that the hypothesis of normal distribution is accepted at the 5% significance level. The Q-Q plot using normal distribution at Geneina station lies on a straight line. The observed relative frequency histogram for Geneina station is superimposed onto the theoretical normal frequency distribution curve in figure (4.16). Using visual judgment the normal probability distribution is also, chosen as the best suitable probability distribution .Therefore normal probability distributions was select for annual rainfall at Geneina station. The selected probability distributions of annual rainfall for all stations are presented in table (4.10a).

### **Table No. (4.8a): Empirical Distribution Test For Geneina Station (Eviews Software – Normal Distribution)**









**\*\*EViews reports the Lilliefors test statistic instead of the Kolmogorov statistic since the parameters of the normal have been estimated**

### **Table No. (4.8b): Empirical Distribution Test For Geneina Station (Eviews Software – Gamma Distribution)**

<b>Empirical Distribution Test for GENEINA</b> <b>Hypothesis: Gamma</b> Date: 02/11/14 Time: 11:15 Sample: 1 40 Included observations: 40						
<b>Method</b>	Value	Adj. Value	<b>Probability</b>			
<b>Cramer-von Mises</b> (W2) Watson (U2) <b>Anderson-Darling</b> (A2)	0.071118 0.056463 0.457143	0.071118 0.056463 0.457143	> 0.25 > 0.25 > 0.25			

**Method: Maximum Likelihood (Marquardt) Convergence achieved after 8 iterations Covariance matrix computed using second derivatives** 



**\* Fixed parameter value** 

## **Table No. (4.8c): Empirical Distribution Test For Geneina Station (Eviews Software – Exponential Distribution)**





**Method: Maximum Likelihood (Exact Solution)** 

<b>Parameter</b>	Value	<b>Std. Error</b>	z-Statistic	Prob.
А MU	124.4000 301.7625	7.544063 48.32029	16.48979 6.245047	0.0000 0.0000
Log likelihood <b>No. of Coefficients</b>	-268.3856	Mean dependent var. S.D. dependent var.		426.1625 120.9195

800 700 600 Quantiles of Normal Quantiles of Normalفخو 500 400 300 200 100 100 200 300 400 500 600 700 Quantiles of GENEINA

**Fig No. (4.15a): Theoretical Quantile-Quantile Plots (Q-Q) (Hypothesis: Normal)** 



**Fig No. (4.15b): Theoretical Quantile-Quantile Plots (Q-Q) (Hypothesis: Gamma)** 



**Fig No. (4.15c): Theoretical Quantile-Quantile Plots (Q-Q) (Hypothesis: Exponential)** 







# **Table No. (4.9): Theoretical Values of Annual Rainfall Using Three Different Distribution Types (Geneina Station)**



# **Table No. (4.10a): Selected Probability Distributions for Annual Rainfall for All Stations**



For all stations in central and western Sudan it was found that in cases in which the normal distribution adequately describes annual rainfall, the gamma distribution was a second possible alternative.

For every station, the maximum monthly rainfall was selected for every year, forming the annual rainfall maximum series. The procedure, which adopted for annual rainfall, repeated again for the maximum annual rainfall. The selected probability distributions of maximum annual rainfall for all stations are recommended in table (4.10b).

# **Table No. (4.10b): Selected Probability Distributions for Maximum Annual Rainfall (Based On Maximum Monthly Rainfall)**



# **4.1.5.2 Cumulative Distribution Function (CDF)**

The cumulative probability of non-exceedence of the annual rainfall for Dongola and Atbara metrological stations, as a cumulative distribution function (CDF), represented in Figure (4.17). These stations are classified as a hyper – arid region (Elagib and Mansell 2000). Kolmogorov-Smirnov test proved that the cumulative distribution function of the annual rainfall of Dongola and Atbara stations were significantly different ( $D = 0.625$ ,  $\alpha =$ 0.000\*), Where (\*) = significant at  $\alpha$  = 0.05.



**Fig No. (4.17) Probability of Non-Exceedence As A Function of Ranked Annual Rainfall for Dongola and Atbara Stations (1971-2010)** 

The cumulative probability of non-exceedence of the annual rainfall for five metrological stations, namely Khartoum, Kasala, Medani, Sennar and Gadaref, as a cumulative distribution function (CDF), are represented in Figure (4.18). These stations are classified as follows Khartoum, Kasala, Medani and Sennar are arid, and Gadaref is semi-arid (Elagib and Mansell 2000).

The probability of the total annual rainfall not-exceeding 400 mm is 0.97, 0.92, 0.89, 0.36, and 0.06 for Khartoum, Kasala, Medani, Sennar and Gadaref respectively. It means that the return period to receive annual rainfall of less 400 mm is every year in Gadaref and once every 2 years in Sennar, while in Medani , Kasala and Khartoum it is once every 9 , 13 and 34 years respectively. Table (4.11) represents the 25th, 50th, and 75th percentiles of the annual rainfall for all stations.



# **Table No. (4.11) The 25th, 50th And 75th Percentiles of the Annual rainfall For All Stations (1971-2010).**



**Fig No. (4.18): Probability Of Non-Exceedence As A Function Of Ranked Annual Rainfall For Five Stations, Region II, (1971-2010)** 

Table (4.12) shows the Kolmogorov-Smirnov (K-S) test results for region II. The test proves that the cumulative distribution function of the annual rainfall of five stations namely, Khartoum, Kasala, Medani, Sennar and Gadaref are significantly different.

<b>Stations</b>	Khartoum	Kasala	Medani	Sennar
Kasala	$D = 0.725$ $\alpha = 0.000*$			
Medani	$D = 0.875$ $\alpha = 0.000*$	$D = 0.300$ $\alpha = 0.055$ **		
Sennar	$D = 0.925$ $\alpha = 0.000*$	$D = 0.650$ $\alpha = 0.000*$	$D = 0.575$ $\alpha = 0.000*$	
Gadaref	$D = 0.975$ $\alpha = 0.000*$	$D = 0.950$ $\alpha = 0.000*$	$D = 0.925$ $\alpha = 0.000*$	$D = 0.700$ $\alpha = 0.000*$

**Table No. (4.12) Kolmogorov-Smirnov Test Results for Region II** 

\* = significant at  $\alpha$  = 0.05

\*\*\* = significant at  $\alpha$  = 0.10 (not significant at  $\alpha$  = 0.05)

Table (4.13) shows the Kolmogorov-Smirnov test results for region III. The test proves that the cumulative distribution function of the annual rainfall of four stations namely, Fasher, Kosti, Geneina and Kadugly are significantly differentfig , which represented in Figure (4.19).

**Table No. (4.13) Kolmogorov-Smirnov Test Results for Region III** 

<b>Stations</b>	Fasher	Kosti	Geneina
Kosti	$D = 0.700$ $\alpha = 0.000*$		
Geneina	$D = 0.800$ $\alpha = 0.000*$	$D = 0.400$ $\alpha = 0.000*$	
kadugly	$D = 1.000$ $\alpha = 0.000*$	$D = 0.925$ $\alpha = 0.000*$	$D = 0.725$ $\alpha = 0.000*$

The Kolmogorov-Smirnov test proves that the cumulative distribution function of the annual rainfall between the stations namely Kosti, Obaied and Nahud are not different,  $(D (Obaied - Nahoud) = 0.175, Asymp. Sig. (2-$  tailed) =  $0.573 > \alpha$  (0.05)), where the mean annual rainfall for these stations is almost equal.



**Fig No (4.19) Probability of Non-Exceedence as A Function of Ranked Annual Rainfall for Four Stations, Region III, (1971-2010)** 

#### **4.1.6 Annual and Monthly Rainfall Trend**

Many authors have observed no established pattern of rainfall trends over various parts of Africa (Bunting et al. 1975and Ogallo 1979). The simple linear regression was used to obtain the trend rates of the time series of monthly and annual rainfall. The direction and statistical significance of trend was investigated by using *t*-test of a regression coefficient. Also, the time-series of monthly and annual rainfalls have been investigated for their direction and statistical significance of trend by the nonparametric Spearman rank correlation test (Kanji, 2006).

The results of this study indicate that of the about 16 rainfall stations examined; only two stations show significant annual rainfall trend during the period 1971-2010. These were the annual rainfall series at Geneina and Obaied, as shown in Figures (4.20) and (4.21). However, more analysis did show significant positive trend for the period 1975–2010 data in Nyala. A significant positive trend for the period 1980–2010 data in Kosti was detected as shown in table (4.14). The statistical analysis of the deviation from zero (Ho:  $b = 0$ ), using *t*-test, proved that the annual rainfall trend of Geneina, Obaied, Kosti and Nyala increase significantly as shown in table (4.14). The nonparametric Spearman rank correlation test proved the same results.



**Fig No. (4.20): Trend Analysis Of The Annual Rainfall** 

**For Station Geneina (1971-2010)** 



**Fig No. (4.21): Trend Analysis Of The Annual Rainfall For Station Obaied (1970-2010)** 

# **Table No. (4.14): The Trend Rates of the Annual Rainfall, Using** *t***-Test of a Regression Coefficient and Spearman Rank Correlation Test**



\* Significant at 0.05 ( $\alpha$  < 0.05); ns = not significant at 0.05 ( $\alpha$  > 0.05)

The global trend for a given data series may present a significant /insignificant increase/decrease within the study period. But locally, if the data series is divided into several parts the data series may contain local insignificant /significant decrease/increase and vice versa (Mosaad, 2011). Figure (4.22) displays an application for the pervious approach. The annual data series of Nyala was divided into two parts (1970-1989, 1990- 2010), results showed that an insignificant decrease in the annual rainfall has taken place within the period 1970-1989. Insignificant negative trend is detected in the first part and a significant positive trend (95 %) in the second part as shown in figure (4.23).

The results, also, indicate that only four stations show significant monthly rainfall trend during the period of study. These were the stations namely Gadaref (August), Nahoud (October), Geneina (July and August) and Kadugly (October) table (4.15).

**Table No. (4.15): Significant Month Trend Using Spearman Rank Correlation Test Rates of the Annual Rainfall** 

Station	Gadaref	Nahud	Geneina	Kadugli
Month		10		10
Spearman statistic	$+0.317$	$+0.320$	$+0.355$	$+0.322$
Significance level	$\alpha = 0.046$	$\alpha = 0.044$	$\alpha = 0.025$	$\alpha = 0.043$
Month				
Spearman statistic			$+0.34$	
Significance level			$\alpha = 0.027$	

Note: Only the significant results is given



**Fig No. (4.22): Trend Analysis of the Annual Rainfall For Station Nyala (1970-1989)** 



**Fig No. (4.23): Trend Analysis of the Annual Rainfall For Station Nyala (1990-2010)** 

### **4.1.7 Rainfall Variability**

In addition to mean rainfall pattern, the knowledge of variability of rainfall is of great use for hydrological planning and management. In this research, efforts have been made to model variability of rainfall. The analysis of variability of rainfall has been done by statistical tools. The extent of variability is expressed by the size of the departures from the mean, of which the standard deviation is a measure. The standard deviation divided by the mean yields a coefficient of variability. It can be expressed either as a fraction or a percent. The variability of monthly rainfall expressed by a coefficient of variation  $(CV)$  as:

 $CV=[(standard deviation / mean) \times 100]$ 

$$
CV(\%) = \left(\frac{\sqrt{\frac{\sum_{i=1}^{n} (x_i - \frac{\sum_{i=1}^{n} x_i}{n})^2}{n-1}}{\frac{\sum_{i=1}^{n} x_i}{n}}\right) * 100
$$
\n(4.1)

Where:

 $CV =$  the Coefficient of variation (percent)  $x_i$  = the value of sample (i)  $n =$  the number of samples

This makes it possible to compare the variability of rainfall in places with different mean annual rainfall. The coefficient of variation was calculated for the area of the study. Figure (4.24) represents the coefficient of variation (CV) for three stations namely, Atbara, Medani and Kadugly from 1971 to 2010. Comparing the annual rainfall and the variability of rainfall it can be found that the stations having lower mean rainfall have higher coefficient of variation as shown in figures (4.24) and (4.25). Table (4.16) represented the annual rainfall variability for all stations.

The results show that rainfall is highly fluctuated and varied over both space and time indicating a real variation in annual average rainfall values. Annual rainfall variability increases with decreasing mean rainfall. Among the study areas, the year-to-year variability in annual rainfall during 1971–2010, as measured by the coefficient of variation, ranges from 18.8 % in Kadugli to as high as 162.6% in Dongola as shown in table (4.16). In Sudan the CV decreases from north to south (more than 160% to less than 20%).This finding is in agreement with Elagib and Mansell (2000) who pointed out that the annual rainfall variability in Sudan increases with decreasing mean rainfall during 1961-1990, as measured by the coefficient of variability, ranges from 13.8% to 122.9%.

Among the all time-series of coefficient of variation (CV), only that for Nahud station has significant negative trend ( $\alpha = 0.011$ <sup>\*</sup>), Table (4.17).
<b>Stations</b>	<b>Annual Rainfall Variability</b> $(C_V)$
Port Sudan	86.2%
Dongola	162.6%
Atbara	89.4%
Khartoum	57.1 %
Kassala	33.9%
Wad Medani	28.2%
Gedaref	19.0 %
El Fasher	33.9%
Sennar	28.4%
Geneina	28.0%
El Obeid	34.7 %
Kosti	29.4 %
En Nahud*	31.1%
<b>Nyala</b>	25.2 %
Kadugli	18.8%

**Table No. (4.16): Annual Rainfall Variability**  $(C_V)$  **For the Precipitation Data Series of All Stations (1971 - 2010).** 

\* Significant at 0.05







### **Fig No.(4.25) Total Annual Rainfall For Stations (Atbara, Medani And Kadugly)**

### **4.1.8 The Rainfall Seasonality Index (SI)**

Seasonality index helps in identifying the rainfall regimes based on the monthly distribution of rainfall. Seasonality strongly affects annual variability and rain-use efficiency, particularly in arid, semi-arid and subhumid zones.

Extreme rainfall seasonality with almost all rainfall occurring during one to two in 1–2 months dominates region I, (Atbara, Dongola and Port Sudan), during the period of study (1971-2010). SI values exceeding 1.80 have occurred at the three stations in individual years. The values of SI varied from 1.25 in Port Sudan to 1.83 in both Dongola and Atbara, though the highest value registered for Port Sudan was as high as 1.81. Nonhomogeneous results can be noticed in terms of SI trends through the region, as shown in table (4.17). None of the trends in the region is found significant during the period of study. The behavior of SI in Atbara and Port Sudan through time is explained in figures (4.26) and (4.27).



Fig No.(4.26). Changes in Seasonality Index, (SI), Excluding **The Zero Rainfall Years, (Atbara Station)** 



**T The Zero Rainfall Y Years, (Po rt Sudan S Station).** 

For region II (Khartoum, kassala, Madani, Sennar and Gadref)), the behavior of SI through time is explained in figure (4.28). Extreme rainfall seasonality with almost all rainfall in 1–2 months dominates Khartoum during the period tudy (1971-2010). SI values exceeding 1.6 have occurred at Khartoum at

three individual years (1977, 1984 and 1990). SI values less than 1.2 have occurred at Khartoum at two individual years (2003 and 2008). The distribution of rainfall in kassala, Madani, Sennar and ElGadref is dominantly fluctuating between most rain in 3 months and extreme seasonality. None of the trends in the region is found significant during the period of study. However, the negative trend in SI through 1980–2010 for Sennar station is significant at  $\alpha$  of 0.022 and the positive trend through 1984–2010 for Kasalla station is significant at  $\alpha$  of 0.023.

For (Kosti, Obeid, Nahud and Kadugli), the behavior of SI through time is explained in figure (4.29). The distribution of rainfall in Kosti, Obeid and Nahud is dominantly fluctuating between most rain in 3 months and extreme seasonality. For Kadugli the rainfall seasonality is dominantly fluctuating between markedly seasonal with a long drier season and with most rain in 3 months or less.

For (Fasher, Geneina and Nyala), the behavior of SI through time is explained in figure (4.30). The rainfall seasonality is dominantly fluctuating between most rain in 3 months and extreme seasonality. Among the all timeseries of SI, table (4.17), only that for Nahud has significant trend ( $\alpha$  = 0.047).



**Fig No. (4.28) Changes in Seasonality Index, (Region I).** 



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### **Table No. (4.17): Trend Direction of**  $C_V$ **, SI, PCI and MFI Using Spearman Rank Correlation Test for the Common Data Period (1971–2010)**

 $(-)$ : Negative trend;  $(+)$ : Positive trend.

\*\* Trend is significant at the 0.01 level

\* Trend is significant at the 0.05 level

The values of the mean  $\overline{SI}_i$  for the full 40-year period, is well illustrated in table (4.18), the increased seasonality of northern areas of Sudan (hyper arid-region) when compared to the central and western region (arid and semi arid region), with indices of more than 1.7 at Dongola station, and exceeding 1.5 at Atbara and Port Sudan station. Elsewhere in western and central areas, the index is generally around 1.2. Mean values mask considerable annual variability in the  $\overline{SI}_i$ . In individual years, indices exceeding 1.4 or 1.5 have occurred within the study period along all regions. Lowest  $\overline{SI}_i$  values recorded for individual years are generally around 1.0 or 0.9 in the central and western region and about 0.8 in Kadogly and Genina station.

Replicability index  $(\overline{SI}/\overline{SI})$  at all stations, except Port Sudan, is high (0.75-0.96), which indicates that the wettest month of the year generally occurs in only the same few months every year. Table (4.18) summarizes the values of the mean  $\overline{SI}_i$ ,  $\overline{SI}$  and the replicability index  $(\overline{SI}/\overline{SI}_i)$  for the full 40-year period.

<b>Stations</b>	$\overline{SI}_i$	$\overline{SI}$	$\overline{\overline{SI}}/\overline{SI}_i$ )
Port Sudan	1.55	1.04	0.67
Dongola	1.74	1.30	0.75
Atbara	1.54	1.22	0.80
Khartoum	1.42	1.22	0.86
Kassala	1.30	1.17	0.90
Medani	1.23	1.11	0.90
Gedaref	1.18	1.13	0.96
Fasher	1.32	1.25	0.95
Sennar	1.22	1.15	0.94
Geneina	1.30	1.23	0.95
Obeid	1.26	1.13	0.90
Kosti	1.26	1.14	0.90
Nahud	1.21	1.13	0.93
Nyala	1.22	1.12	0.92
Kadugli	1.03	0.96	0.93

Table No. (4.18) Values Of The Mean  $\overline{SI}_i$  ,  $\overline{SI}$  And  $(\overline{SI}/\overline{SI}_i)$ **For The Full Period (1971-2010).** 

### **4.1.9 Precipitation Concentration Index**

The Precipitation Concentration Index (PCI) is a powerful indicator of the temporal distribution of precipitation, traditionally applied at annual scales; as the value increases, the more concentrated the precipitation. The PCI index was calculated for the period 1971-2010 to understand the changes with time.

The distribution of monthly rainfall in region (I) is dominantly irregular in Dongola and is fluctuating between highly seasonal and irregular classes in Atbara and Port Sudan. The values of PCI varied between 31 in Port Sudan to 100 in both Dongola and Atbara, though the highest value registered for Port Sudan was as high as 99.

For region II, (Khartoum, kassala, Madani, Sennar and Gadref), the behavior of PCI through time is explained in figure (4.31). The distribution of rainfall in the region is highly seasonal in kassala, Madani, Sennar and Gadref and is fluctuating between highly seasonal and irregular classes in Khartoum. The values of PCI varied between 19 in Gadref to 71 in Khartoum, though the highest value registered for Gadref was as high as 43.



**Fig No. (4.31) Precipitation Concentration Index, (Region I).** 

For region III (Kosti, Obeid, Nahud and Kadugli), the behavior of PCI through time is explained in figure (4.32) and figure (4.33) for three stations namely Fasher, Geneina and Nyala. The distribution of rainfall in the region is highly seasonal in Kosti, Naud, Geneina, Nyala, Obeid and Fasher, except in only 2 years (1991 and 2007) where the rainfall was irregular in Fasher and in Obeid (1977). In Kadugli the rainfall is fluctuating between seasonal and highly seasonal classes. The values of PCI varied between 15 in Kadugli to 74 in Fasher, though the highest value registered for Kadugli was as high as 27.

Among the all time-series of PCI, Ttable (4.17), only that for Nahud has significant trend ( $\alpha = 0.011$ ).



**Fig No. (4.32) Precipitation Concentration Index, (Region III).** 



**Fig No. (4.33) Precipitation Concentration Index, (Region III).** 

### **4.1.10 Modified Fournier Index (MFI) For Rainfall Erosivity**

According to the available data sets, two different procedures were used to calculate the Modified Fournier Index (MFI):

• In the first procedure the (MFI) is calculated from the monthly rainfall amounts of each individual year and the (MFI) averaged over a number of years. Those long term average values are reported as  $(MFI)$ <sub>1</sub>.

• In the second procedure the monthly rainfall amounts are averaged over a number of years. The (MFI) is then calculated from this averaged rainfall data set and reported as  $(MFI)$ <sub>2</sub>.

Figure (4.34) shows the time-series of the modified fournier index (MFI) for the three stations namely, Port Sudan, Atbara and Dongola. The rainfall in the region has very low to very high erosivity. Port Sudan and Atbara experienced MFI values of up to 212 and 200, respectively, compared with 51 for Dongola. The year-to-year values of MFI show highest variability for Port Sudan and lowest variability for Dongola. All the MFI cases for Dongola are in the very low class and most of those relating to Atbara fall in the categories of low and very low, while those pertinent to Port Sudan range in the classes from very low to very high. There were only two cases registered for Atbara where the rainfall erosivity was classified as moderate and very high.



**Fig No. (4.34). Changes In Rainfall Erosivity Index, (MFI), Excluding The Zero Rainfall Years.** 

For region II, the tendency of rainfall erosivity as measured by the modified fournier index (MFI) is illustrated in Figure (4.35) .The rainfall in the region has very low to very high erosivity. Khartoum, madani, Sennar and Gadaref experienced MFI values of up to 235, 273,228 and 310 respectively, compared to 166 for Kassala. All the MFI cases for Khartoum are in the range from very low to moderate class and most of those relating to Kassala and madani fall in the categories from low to high. There were only two

cases registered for Kassala and madani where the rainfall erosivity was classified as very high. Most of the MFI cases for Sennar are in the range from low to high, while those pertinent to Gadaref range in the classes from moderate to very high.



**Fig. No. (4.35). Changes In Rainfall Erosivity Index, (MFI), for Region II** 

For region III, the tendency of rainfall erosivity is illustrated in figures (4.36) and (4.37).The rainfall in the region has very low to very high erosivity. Kosti, Obeid, Nahud, Fashir, Nyala and Kadugli experienced MFI values of up to 177, 194,213, 163,194 and 219 respectively, compared to 247 for Geneina. Most the MFI cases for kosti, El Obeid, Nahud , Fashir and Nyala ,are in the range from very low to high class, while those pertinent to Geneina and Kadugli range in the classes from low to very high. Among the all time-series of MFI, table (4.17), only that for Geneina has significant trend  $(\alpha = 0.001)$ .



**Fig No. (3.36). Changes In Rainfall Erosivity Index, (MFI), for Region III** 



**Fig No. (4.37). Changes In Rainfall Erosivity Index, (MFI), for Region III** 

The method that calculated the MFI from the monthly rainfall amounts of each individual year and averaged over a number of years  $(MFI)$ <sub>1</sub> was compared with the method that calculated the MFI from the averages of ith monthly rainfall amounts and averaged over a number of years  $(MFI)_{2}$ . Results indicated that the  $(MFI)$ <sub>2</sub> led to the lower-risk MFI classes than the  $(MFI)<sub>1</sub>$ . This was attributed to the fact that the  $(MFI)<sub>2</sub>$  was statistically

unable to account for the year-to-year variability in the rainfall data, as shown in table (4.19).

<b>Station</b>	(MFI) Range	(MFI) <sub>1</sub>	(MFI) <sub>2</sub>
Dongola	$1 - 51$	10	4
Port Sudan	$3 - 212$	50	17
Atbara	$2 - 200$	31	16
Khartoum	$3 - 234$	53	35
Kassala	$22 - 166$	80	61
Madani	$35 - 273$	90	70
Sennar	$47 - 228$	119	101
Gadaref	$89 - 310$	168	147
Kosti	$24 - 177$	102	84
Obeid	$50 - 194$	104	87
Nahud	$39 - 213$	99	84
Nyala	$60 - 194$	108	89
Fashi	$24 - 163$	70	58
Geneina	$35 - 247$	141	125
Kadugli	$92 - 219$	140	120

Table No. (4.19) Range Of (MFI, The Values Of (MFI)<sub>1</sub> And (MFI)<sub>2</sub> **For All Meteorological Stations In Sudan (1971 – 2010).** 

Average rainfall aggressivity index  $(MFI)$ <sub>1</sub> is in the range from very low to moderate classes in most parts of study area, with higher values observed in Madani and very high value in Gadaref. The minimum and maximum values of  $(MFI)$ <sub>1</sub> was 1 in Dongola and 310 in Gadaref, respectively.

A linear relationship between annual rainfall and the Modified Fournier Index was found using linear regression method and Spearman rank correlation test. The annual rainfall, for all stations, had significant positive correlation with the MFI (Spearman correlation test), and the maximum and minimum determination coefficient  $(R^2)$  was 0.91 and 0.56 in Dongola and kosti, respectively as shown in table (4.20). Figures (4.38) and (4.39) represent the linear relation between annual rainfall and MFI for Port Sudan and Khartoum station.

## Table No. (4.20) Coefficient of Determination (R<sup>2</sup>)Between Annual **Rainfall And (MFI) For All Stations, With Spearman Correlation Coefficient.**



 $\overline{**}$  = significant (at  $p = 0.01$ )



**Fig No. (4.38): Relationship Between Annual Rainfall And Erosivity Modified Fournier Index (MFI) For Port Sudan Rainfall Station Data** 



### **Fig No. (4.39): Relationship Between Annual Rainfall And Erosivity Modified Fournier Index (MFI) For Khartoum Rainfall Station Data.**

Through a Spearman correlation coefficients, were highly significant linear correlations between SI and PCI for all stations , also significant linear correlations between PCI and MFI were found for all stations, except Atbara (significant at  $\alpha = 0.1$ ). For many stations a significant linear correlation between SI and MFI were also found, as shown in table (4.21).

<b>Station</b>	<b>SI-PCI</b>	<b>SI-MFI</b>	<b>PCI-MFI</b>
Dongola	$r_s = 0.982, \alpha = 0.000**$	$r_s = 0.498, \alpha = 0.001**$	$r_s = 0.525$ , $\alpha = 0.001**$
Port Sudan	$r_s = 0.820$ , $\alpha = 0.000**$	$r_s = 0.378$ , $\alpha = 0.016*$	$r_s = 0.579$ , $\alpha = 0.000$ **
Atbara	$r_s = 0.906$ , $\alpha = 0.000$ **	$r_s = 0.161$ , $\alpha = 0.321$	$r_s = 0.301$ , $\alpha = 0.059$ <sup>&amp;</sup>
Khartoum	$r_s = 0.843$ , $\alpha = 0.000**$	$r_s = 0.221, \alpha = 0.171$	$r_s = 0.353$ , $\alpha = 0.026*$
Kassala	$r_s = 0.785$ , $\alpha = 0.000$ **	$r_s = 0.440$ , $\alpha = 0.004**$	$r_S=0.457$ , $\alpha{=}0.003**$
Madani	$r_s = 0.762$ , $\alpha = 0.000**$	$r_s = 0.333$ , $\alpha = 0.036*$	$r_s = 0.559$ , $\alpha = 0.000**$
Sennar	$r_s = 0.679$ , $\alpha = 0.000**$	$r_s = 0.279$ , $\alpha = 0.081$	$r_s = 0.503$ , $\alpha = 0.001**$
Gadaref	$r_s = 0.688$ , $\alpha = 0.000**$	$r_s = 0.281, \alpha = 0.079$	r <sub>s</sub> = 0.618, $\alpha$ =0.000**
Kosti	$r_s = 0.703$ , $\alpha = 0.000$ **	$r_s = 0.379$ , $\alpha = 0.011*$	$r_s = 0.413$ , $\alpha = 0.008**$
<b>Obeid</b>	$r_s = 0.843$ , $\alpha = 0.000**$	$r_s = 0.302, \alpha = 0.059$	$r_s = 0.317$ , $\alpha = 0.046*$
Nahud	$r_s = 0.797$ , $\alpha = 0.000**$	$r_s = 0.479$ , $\alpha = 0.002**$	$r_s = 0.500$ , $\alpha = 0.001**$
Nyala	$r_s = 0.754$ , $\alpha = 0.000$ **	$r_s = 0.447$ , $\alpha = 0.004**$	$r_s = 0.561$ , $\alpha = 0.000**$
Fashir	$r_s = 0.731, \alpha = 0.000**$	$r_s = 0.322$ , $\alpha = 0.043*$	$r_s = 0.626$ , $\alpha = 0.000**$
Geneina	$r_s = 0.708$ , $\alpha = 0.000**$	$r_s = 0.492$ , $\alpha = 0.001**$	$r_s = 0.588$ , $\alpha = 0.000**$
Kadugli	$r_s = 0.499$ , $\alpha = 0.000**$	$r_s = 0.093$ , $\alpha = 0.566$	$r_s = 0.394$ , $\alpha = 0.012**$

**Table No. (4.21) Spearman Correlation Test Among (SI, PCI and MFI) for All Stations** 

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

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

 $\&$  Correlation is significant at the 0.1 level (2-tailed).

# **4.2 Drought Analysis Using the Standardized Precipitation Index (SPI)**

## **4.2.1 Introduction**

The SPI index is applied to long-term rainfall data, at all stations, for the period from January 1971 to December 2010. The occurrence in varying drought categories at 1, 3, 6, 9, 12 and 24 month time steps have been analyzed. The SPI values were calculated for the total period as well as for a specific month.

## **4.2.2 SPI Index of Consecutive Months**

Figures (4.40) through (4.45) explain the SPI values based on 3, 6 and 9 months time steps respectively for stations Atbara, Sennar, Gadaref, Nahoud, Kadugly and Geneina. . For illustration, the SPI\_3, SPI\_6, PSI\_9, SPI\_12 and SPI\_24 time series, for Gadaref station, were presented in annex (3). Appearance of drought is defined when SPI is negative and its intensity becomes -1.0 or lower. Several drought events have been detected. These events have also different durations. The duration of an event is defined as the time between the zero crossings that bound the events.

The 3-month SPI, (SPI\_3), may be misleading in stations where it is normally dry during any given 3-month period. Large negative or positive SPI may be associated with precipitation totals not very different from the mean, Figure (4.40a). A 6-month SPI, (SPI\_6), can be very effective in showing the precipitation over different seasons. Information from a 6 month SPI may also begin to be associated with anomalous stream flows and reservoir levels, depending on the region and time of year.



**Fig.No. (4.40a) SPI Time Series for Monthly Precipitation in Atbara Station (SPI\_3), (1971-2010)** 



**Fig.No. (4.40b) SPI Time Series for Monthly Precipitation in Atbara Station (SPI\_6), (1971-2010)** 



**Fig.No. (4.40c) SPI Time Series for Monthly Precipitation in Atbara Station (SPI\_9), (1971-2010)** 



**Fig.No. (4.41a) SPI Time Series for Monthly Precipitation in Sennar Station (SPI\_3), (1971-2010)** 



**Fig.No. (4.41b) SPI Time Series for Monthly Precipitation in Sennar Station (SPI\_6), (1971-2010)** 

**Sennar Station SPI\_9**



**Fig.No. (4.41c): SPI Time Series for Monthly Precipitation in Sennar Station (SPI\_9), (1971-2010)** 

**Gadaref Station SPI\_3**



**Fig.No. (4.42a): SPI Time Series for Monthly Precipitation in Gadaref Station (SPI\_3), (1971-2010)** 



**Fig.No. (2.42b): SPI Time Series for Monthly Precipitation in Gadaref Station (SPI\_6), (1971-2010)** 



**Fig.No. (4.42c): SPI Time Series for Monthly Precipitation in Gadaref Station (SPI\_9), (1971-2010)** 



**Fig.No. (4.43a): SPI Time Series for Monthly Precipitation in Nahoud Station (SPI\_3), (1971-2010)** 



**Fig.No. (4.43b): SPI Time Series for Monthly Precipitation in Nahoud Station (SPI\_6), (1971-2010)** 



**Fig.No. (4.43c): SPI Time Series for Monthly Precipitation in Nahoud Station (SPI\_9), (1971-2010)** 



**Fig.No. (4.44a): SPI Time Series for Monthly Precipitation in Kadugly Station (SPI\_3), (1971-2010)** 



**Fig.No. (4.44b): SPI Time Series for Monthly Precipitation in Kadugly Station (SPI\_6), (1971-2010)** 





**Genenina Station SPI\_3**



**Fig.No. (4.45a): SPI Time Series for Monthly Precipitation in Geneina Station (SPI\_3), (1971-2010) Months**

-4 -3 -2 -1 0 1 2 3 4 0 50 100 150 200 250 300 350 400 450 500 **SPI Months Genenina Station SPI\_6**

**Fig.No. (4.45b): SPI Time Series for Monthly Precipitation in Geneina Station (SPI\_6), (1971-2010)** 



**Fig.No. (4.45c): SPI Time Series for Monthly Precipitation in Geneina Station (SPI\_9), (1971-2010)** 

#### **4.2.3 Selection of the Driest Years**

The negative values of the SPI have been aggregated to be used as an indicator for dry years during the period 1971-2010 for Sennar and Gadaef station, tables (4.22) and (4.23) respectively. The accumulated values of the negative SPI based on 3, 6 and 9 months time scale for Sennar and Gadaref station are presented in figures (4.46) and (4.47). These figures can be used for the detection of the driest years and compare different drought magnitudes. As shown in Sennar Station, figure (4.46), several years such as 1982, 1984, 1990, 1997 and 2005, were exposed to sever drought and are selected as the driest years. Table (4.24) summarizes the results of the driest years of the other stations based on 6 months time scale (SPI\_6).

**Table No. (4.22): Summation of Negative Values of the SPI (1971-2010) (Sennar Station)** 

	Sum of	Sum of	Sum of		Sum of	Sum of	Sum of
Year	negative	negative	negative	Year	negative	negative	negative
	values of	values of	values of		values	values	values of
	SPI <sub>3</sub>	SPI <sub>6</sub>	SPI 9		of SPI_3	of SPI 6	SPI_9
1971	$-1.71$	$\theta$	$\theta$	1991	$-9.09$	$-9.04$	$-9.57$
1972	$-2.31$	$-3.45$	$-2.79$	1992	$-2.52$	$-5.3$	$-10.3$
1973	$-0.31$	$-1.01$	$-0.65$	1993	$-0.51$	$-2.33$	$-0.12$
1974	$-0.71$	$-0.35$	$-0.04$	1994	$-1.28$	$-1.83$	$-1.49$
1975	$-2.14$	$-0.47$	$-0.59$	1995	$-1.42$	$-0.64$	$-0.01$
1976	$-1.96$	$-3.07$	$-0.93$	1996	$-0.07$	$-0.61$	$\theta$
1977	$-0.93$	$-1.09$	$-0.93$	1997	$-6.18$	$-10.17$	$-10.57$
1978	$-2.14$	$-1.74$	$-1.77$	1998	$-5.77$	$-6.29$	$-8.63$
1979	$\theta$	$-1.82$	$-1.88$	1999	$-2.73$	$-2.91$	$-2.75$
1980	$-4.52$	$-0.58$	$-0.11$	2000	$\boldsymbol{0}$	$\overline{0}$	$\overline{0}$
1981	$-1.15$	$-4.8$	$-3.85$	2001	$-3.4$	$-3.73$	$-2.18$
1982	$-9.08$	$-11.68$	$-11.33$	2002	$-2.6$	$-3.23$	$-2.48$
1983	$-4.73$	$-6.55$	$-9.66$	2003	$-1.75$	$-1.56$	$-0.81$
1984	$-12.39$	$-18.36$	$-16.92$	2004	$-7.57$	$-11.34$	$-11.58$
1985	$-1.14$	$-4.84$	$-12.94$	2005	$-5.17$	$-7.85$	$-13.61$
1986	$-1.59$	$-2.02$	$\theta$	2006	$-4.56$	$-9.21$	$-11.93$
1987	$-1.92$	$-1.64$	$-0.81$	2007	$-1.44$	$-1.46$	$-0.81$
1988	$-0.33$	$-0.84$	$-0.73$	2008	$-1.7$	$-1.34$	$-0.86$
1989	$-1.91$	$-1.51$	$-1.46$	2009	$-5.59$	$-5.39$	$-6.43$
1990	$-7.51$	$-10.77$	$-9.79$	2010	$-0.2$	$-3.87$	$-5.83$

Year	Sum of negative values of	Sum of negative values of	Sum of negative values of	Year	Sum of negative values	Sum of negative values	Sum of negative values of
	SPI <sub>3</sub>	SPI <sub>6</sub>	SPI <sub>9</sub>		of SPI_3	of SPI 6	SPI <sub>9</sub>
1971	$-3.24$	$-1.38$	$-1.52$	1991	$-7.55$	$-12.06$	$-16.55$
1972	$-1.42$	$-2.49$	$-2.84$	1992	$-2.95$	$-6.78$	$-12.76$
1973	$-3.35$	$-5.04$	$-3.85$	1993	$-1$	$-0.03$	$-0.4$
1974	$-0.93$	$\overline{0}$	$-0.23$	1994	$-2.78$	$-1.84$	$-0.67$
1975	$-4.16$	$-4.69$	$-3.38$	1995	$-4.05$	$-5.98$	$-5.2$
1976	$-0.96$	$-1.61$	$-0.12$	1996	$-0.89$	$-1.34$	$-2.34$
1977	$-3.29$	$-2.71$	$-1.84$	1997	$-1.53$	$-1.94$	$-1.93$
1978	$-1.87$	$-1.21$	$-0.85$	1998	$-5.39$	$-7.92$	$-8.36$
1979	$-1.13$	$-1.35$	$-1.71$	1999	$-0.32$	$-0.5$	$-0.52$
1980	$-3.32$	$-1.98$	$-0.97$	2000	$-0.67$	$-0.5$	$\boldsymbol{0}$
1981	$-3.23$	$-2.84$	$-3.27$	2001	$-5.26$	$-8.26$	$-7.76$
1982	$-3.36$	$-4.93$	$-3.3$	2002	$-0.57$	$-0.56$	$-2.47$
1983	$-5.68$	$-8.76$	$-7.15$	2003	$-8.2$	$-8.47$	$-4.09$
1984	$-11.43$	$-18.84$	$-21.81$	2004	$-2.47$	$-2.73$	$-1.77$
1985	$-0.81$	$-4.54$	$-11.98$	2005	$-2.99$	$-3.57$	$-4.74$
1986	$-2.05$	$-2.32$	$-1.09$	2006	$-0.58$	$-2.47$	$-2.29$
1987	$-5.61$	$-8.02$	$-6.96$	2007	$-1.93$	$-1.39$	$-0.81$
1988	$-2.93$	$-3.33$	$-6.64$	2008	$-2.4$	$-1.59$	$\theta$
1989	$-1.38$	$-2.6$	$-1.19$	2009	$-4.27$	$-6.56$	$-6.73$
1990	$-10.52$	$-16.22$	$-15.58$	2010	$-0.67$	$-2.9$	$-3.14$

**Table No. (4.23): Summation of Negative Values of the SPI (1971-2010) (Gadaref Station)** 



**Fig. No. (4.46): Accumulated Magnitude of the Negative Values of the SPI (Sennar Station)** 



**Fig. No. (4.47): Accumulated Magnitude of the Negative Values of the SPI (Gadaref Station)** 



## **Table No. (4.24): Results of the Driest Years of the Stations Based on 6 Months Time Scale (SPI\_6).**

Based on the analysis of droughts across Sudan, SPI showed that throughout the entire regions extreme drought occurred during the years 1983, 1984, 1990 and 1991 while the drought during the years1973 and 1982 affected some parts.

### **4.2.4 Probability of Drought Occurrence**

Figure (4.48) shows the probability of the occurrence of dry and wet events, based on 6 months SPI, in Sennar station. Result of Sennar station showed that SPI defines mild drought in 31.9 % of the time, moderate drought in 7.4 % of the time, severe drought in 4.0 % of the time and extreme drought in 2.8 % of the time. Because the SPI is standardized, these percentages are expected from a normal distribution of SPI. Table (4.25) shows the probability of the occurrence of dry events, based on 6 months time scale, for the rest of stations.



**Fig.No. (4.48): Percentage Of Dry And Wet Events Based On SPI\_6 Values For Sennar Station** 

The occurrence in varying drought categories at 3, 6, 9 and 12months time steps has been analyzed for Gadaref station. The aim was to identify drought events at comparable time steps based on their occurrence frequencies. Figure (4.49) presents percentages of drought occurrence expressed at multiple-time steps for different drought severity types. Each percentage is calculated by taking the ratio of drought occurrence in each time step to the total drought occurrence in the same time step and drought category.

<b>Station</b>	Mildly drought $(\% )$ $SPI \ge -0.99$	Moderate drought $(\% )$ $-1.0 \ge SPI \ge -1.49$	Severe drought $(\% )$ $-1.5 \ge SPI \ge -1.99$	Extremely drought $(\% )$ $SPI \le -2.0$
Khartoum	31.4	4.7	2.3	2.5
Madani	32.9	7.6	3.2	2.8
Sennar	31.9	7.4	4.0	2.8
Gadaref	37.0	6.4	3.2	3.1
Obaied	32.0	9.3	3.7	1.4
Nehoud	31.9	8.9	2.1	3.0
Kadugly	37.6	7.4	4.7	1.7
Fasher	33.3	8.6	3.1	1.0
Geneina	32.4	4.0	3.7	2.5
<b>Nyala</b>	36.6	7.6	2.9	2.1

**Table No (4.25): Percentage of Dry Events Based On SPI\_6 Values** 





### **4.2.5 SPI for a Specified Month**

The monthly mean rainfall, across the Sudan, reaches its maximum value in August for all stations, except Port Sudan (winter rainfall). The SPI values for the month August has been calculated based on one month (SPI\_1) time step for the stations Madani, Sennar and Kadugly as shown in figures (4.50) ,(4.51),and (4.52).



**Fig. No. (4.50): SPI Time Series for Monthly Precipitation in Madani Station (SPI\_1\_August), (1971-2010)** 



**Fig. No. (4.51): SPI Time Series for Monthly Precipitation in Sennar Station (SPI\_1\_August), (1971-2010)** 



**Fig. No. (4.52): SPI Time Series for Monthly Precipitation in Kadugly Station (SPI\_1\_August), (1971-2010)** 

Further study, of the SPI values for the month August has been calculated based on three month (SPI\_3\_August) time step. The 3-month precipitation at month t was calculated using rainfall data at month's t - 2, t - 1 and t (Chen et al. 2009). Thus, the 3-month SPI value (SPI\_3) of August, was based on the sum of June–August rainfall. Figures (4.53),(4.54),and (4.55) illustrate the SPI values for the month August based on 3 months time steps for the stations Sennar, Kadugly and Fasher respectively. Figure (4.56) presents the time series of SPI data values of Port Sudan station based on 3 month time step (SPI 3 December).



**Fig. No. (4.53): SPI Time Series Based On the Total Monthly Rainfall in Sennar Station (SPI\_3\_August)**



**Fig.No. (4.54): SPI Time Series Based On the Total Monthly Rainfall in Kadugly Station (SPI\_3\_August)**



**Fig.No. (4.55): SPI Time Series Based On the Total Monthly Rainfall in Fasher Station (SPI\_3\_August)**


**Fig. No. (4.56): SPI Time Series Based On the Total Monthly Rainfall in Port Sudan Station (SPI\_3\_December)** 

The results show that in Geneina station, drought occurred in rainfall season, (June-August), although there was a significant increase in the annual rainfall as was demonstrated in table (4.14).It is clear from the figures that several severely and extremely drought events occurred in Sudan and the drought event in the year 1984 was the most extreme event.

#### **4.2.6 Trend of SPI Index for the Total Period**

The simple linear regression was used to obtain the trend rates of the time series of SPI. The direction and statistical significance of trend was investigated by using *t*-test of a regression coefficient, as shown in table (4.26). To examine the direction and statistical significance of trend in the SPI data series the non-parametric Spearman rank correlation test (Kanji 2006) was also performed to SPI 3, SPI 6 and SPI 9. Table  $(4.27)$ summarizes the results of the Spearman rank correlation test.

Significant positive and negative trends were detected, in figures (4.57),(4.58),and (4.59). It can be seen that there were considerably different trends for different stations.

<b>SPI</b> Category	SPI <sub>3</sub>			SPI 6		SPI 9
Station	Trend	$\alpha$	Trend	$\alpha$	Trend	$\alpha$
Port Sudan	$\pm$	ns	$\hspace{0.1mm} +$	ns	$^{+}$	ns
Atbara		ns		ns		ns
khartoum	$^{+}$	ns	$\hspace{0.1mm} +$	ns	$^{+}$	ns
Kassala		ns	$-0.001$	$0.009*$	$-0.001$	$0.004*$
Madani	$^{+}$	ns	$^{+}$	ns	$+0.001$	$0.039*$
Sennar		ns		ns		ns
Gadaref	$^{+}$	ns	$^{+}$	ns	$^{+}$	ns
Kosti		ns		ns		ns
Obaied	$+0.001$	$0.014*$	$+0.001$	$0.000**$	$+0.002$	$0.000**$
Nehoud	$^{+}$	ns	$^{+}$	ns	$+0.001$	$0.040*$
Kadugly	$^{+}$	ns	$+0.001$	$0.028*$	$+0.001$	$0.002**$
Fasher	$^{+}$	ns	$^{+}$	ns	$^{+}$	ns
Geneina	$+0.001$	$0.027*$	$+0.001$	$0.000**$	$+0.002$	$0.000**$
<b>Nyala</b>	$\hspace{0.1mm} +$	ns	$+0.001$	$0.018*$	$+0.001$	$0.000**$

**Table No. (4.26): Trend Analysis by Linear Regression Test** 

Note: only significant trend is given

(+) Positive trend; (-) Negative trend

\*\* Significant at  $(\alpha = 0.01)$ ; \* Significant at  $(\alpha = 0.05)$ ; ns= (not significant)





Note: Spearman coefficient value for only significant results is given



**Fig.No. (4.57): SPI Time Series Trend Based On the Total Monthly Rainfall in Kassala Station (SPI\_9)** 



**Fig.No. (4.58): SPI Time Series Trend Based On the Total Monthly Rainfall in Kadugly Station (SPI\_9)** 



**Fig. No. (4.59): SPI Time Series Trend Based On the Total Monthly Rainfall in Nyala Station (SPI\_3)** 

# **4.2.7 Trend of SPI Index of a Specified Month**

The spatial distribution patterns of the SPI\_1 and SPI\_3 of August trends, for all stations, are shown in table (4.28). Positive and negative trends, which represent trends toward wetter and drier conditions respectively, were detected as shown in figures (4.60),(5.61),(4.62),(4.63),and (4.64). It can be seen that there were considerably different trends for different stations.

The significant positive trend for Geneina station, in the SPI\_3 for the month August can be explained as due to the decrease of the number of drought events, which can be noticed from figure (4.64) that during the period 1985 to 2010 the number of drought events is very small compared with wet events. It can also be explained by the significant increase in the month August and annual rainfall as considered previously in table (4.14) and table  $(4.15)$ .



# **Table No. (4.28): Trend Analysis by Spearman Rank Correlation Test for Specified Month**



**Fig.No. (4.60): SPI Time Series Trend Based On The Total Monthly Rainfall In Gadaref Station (SPI\_1\_August)** 



 **Fig.No. (4.61): SPI Time Series Trend Based On The Total Monthly Rainfall In Nyala Station (SPI\_1\_August)**



**Fig.No. (4.62): SPI Time Series Trend Based On The Total Monthly Rainfall In Geneina Station (SPI\_1\_August)** 



**Fig.No. (4.63): SPI Time Series Trend Based On The Total Monthly Rainfall In Obaied Station (SPI\_3\_August)** 



**Fig.No. (4.64): SPI Time Series Trend Based On The Total Monthly Rainfall In Geneina Station (SPI\_3\_August)** 

#### **4.2.8 Severe and Extreme Drought Events**

Rainfall drought events which occurred in Sudan during the period 1971to 2010 have been detected. Table (4.29a) and table (4.29b) presented the Severe and extreme drought events based on 1, 3, 6, 9 and 12 months of SPI values in the stations of Gadaref. Table (4.30) and table (4.31) present the extremely drought events, only , based on 1, 3, 6, 9 and 12 months of SPI values in the stations Kadugly and Nyala. The results show that, all stations,

in Sudan, received severely and extremely drought events in the period 1971 to 2010.

These tables present the advantage of using several time steps when applying the SPI approach. For example if the SPI values are calculated based on one month time step, the detected event might be a drought event which cannot be detected if the SPI is calculated based on 3 months time step.

A good example for this fact is shown in table (4.29a), Gadaref station, when SPI based on one month time step, (SPI\_1), has been applied; the drought event which occurred in July 1982, which was a very dry month, has been detected. But with SPI\_3 this event has not been detected. Another example, is as shown, in the same table there was an extremely drought event in August 1990, this event has been detected by using SPI based on 3 months time step (SPI\_3) and did not appear in the results of SPI based on one month time step (SPI\_1).

	$SPI_1$			SPI_3			$SPI_6$			SPI <sub>9</sub>			<b>SPI_12</b>	
Year	Month	Value	Year	Month	Value	Year	Month	Value	Year	Month	Value	Year	Month	Value
1980	9	$-2.19$	1984	8	$-2.47$	1984	8	$-2.48$	1984	8	$-2.45$	1984	8	$-2.69$
1982	$\overline{7}$	$-2.27$	1984	9	$-2.32$	1984	9	$-2.69$	1984	9	$-2.66$	1984	9	$-2.57$
1984	8	$-2.15$	1984	10	$-2.36$	1984	10	$-2.93$	1984	10	$-2.95$	1984	10	$-2.95$
2003	6	$-2.9$	1987	9	$-2.30$	1984	11	$-2.88$	1984	11	$-2.94$	1984	11	$-2.93$
		$\overline{a}$	1990	8	$-2.44$	1984	12	$-2.65$	1984	12	$-2.95$	1984	12	$-2.93$
Ξ.		$\overline{\phantom{0}}$	1998	$\overline{7}$	$-2.14$	1985	$\mathbf{1}$	$-2.35$	1985	$\mathbf{1}$	$-2.88$	1985	$\mathbf{1}$	$-2.91$
		$\overline{\phantom{a}}$	2003	6	$-3.51$	1990	8	$-2.63$	1985	$\overline{2}$	$-2.84$	1985	$\overline{2}$	$-2.91$
		$\qquad \qquad -$	2003	$\tau$	$-2.41$	1990	9	$-2.05$	1985	3	$-2.64$	1985	3	$-2.94$
						1990	10	$-2.27$	1985	$\overline{4}$	$-2.44$	1985	$\overline{4}$	$-2.97$
				۰		1990	11	$-2.08$	1990	8	$-2.6$	1985	5	$-2.96$
				$\overline{\phantom{a}}$		1991	11	$-2.44$	1990	9	$-2.04$	1985	6	$-2.24$
		-			$\overline{a}$	1991	12	$-2$	1990	10	$-2.32$	1990	8	$-2.41$
		-	۳	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	1998	$\overline{7}$	$-2.14$	1990	11	$-2.32$	1990	9	$-2.11$
-	-	-	-	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	2003	6	$-3.57$	1990	12	$-2.32$	1990	10	$-2.31$
-	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	2003	$\overline{7}$	$-2.45$	1991	$\mathbf{1}$	$-2.24$	1990	11	$-2.31$
-	$\overline{\phantom{a}}$	-	$\overline{\phantom{0}}$	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	$\overline{\phantom{a}}$	1991	$\overline{2}$	$-2.05$	1990	12	$-2.31$
Ξ.	$\overline{\phantom{a}}$	Ξ.	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	$\overline{\phantom{0}}$	1992	$\overline{2}$	$-2.04$	1991	$\mathbf{1}$	$-2.29$
Ξ.	$\overline{\phantom{a}}$	Ξ.	$\overline{\phantom{a}}$	$\qquad \qquad -$	$\overline{\phantom{0}}$	$\overline{\phantom{a}}$	$\overline{a}$	$\overline{\phantom{a}}$	1998	$\overline{7}$	$-2.09$	1991	$\overline{2}$	$-2.29$
-	$\qquad \qquad -$	$\qquad \qquad \blacksquare$	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	$\qquad \qquad -$	2003	$\overline{\mathcal{L}}$	$-2.41$	1991	3	$-2.32$
Ξ.	$\overline{\phantom{a}}$	-	$\overline{\phantom{a}}$	Ξ.	$\overline{\phantom{a}}$	$\blacksquare$	$\qquad \qquad -$	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	$\overline{\phantom{a}}$	$\blacksquare$	1991	$\overline{\mathcal{A}}$	$-2.12$
												1992	5	$-2.69$
												1992	6	$-2.54$

Table (4.29a): Extremely drought events (SPI≤ -2.0) for Gadaref Station (1971-2010).

	$SPI_1$			SPI_3			$SPI_6$			SPI <sub>9</sub>			<b>SPI_12</b>	
Year	Month	Value	Year	Month	Value	Year	Month	Value	Year	Month	Value	Year	Month	Value
1973	6	$-1.6$	1973	8	$-1.69$	1981	$\overline{2}$	$-1.86$	1987	9	$-1.83$	1984	6	$-1.56$
1977	9	$-1.81$	1980	11	$-1.89$	1987	9	$-1.84$	1988	$\overline{3}$	$-1.58$	1984	$\overline{7}$	$-1.87$
1978	8	$-1.64$	1987	8	$-1.61$	1987	11	$-1.5$	1990	6	$-1.53$	1987	9	$-1.67$
1987	8	$-1.75$	1990	7	$-1.69$	1987	12	$-1.58$	1990	7	$-1.7$	1988	5	$-1.73$
1990	8	$-1.79$	1990	9	$-1.55$	1990	7	$-1.74$	1991	3	$-1.86$	1991	5	$-1.51$
1991	6	$-1.72$	1991	8	$-1.73$	1990	12	$-1.86$	1991	9	$-1.74$	1991	6	$-1.64$
1991	9	$-1.86$	1991	9	$-1.95$	1991	9	$-1.75$	1991	10	$-1.79$	1991	7	$-1.6$
1992	6	$-1.55$	1991	11	$-1.53$	1991	10	$-1.92$	1991	11	$-1.78$	1991	9	$-1.9$
1996	$\tau$	$-1.86$	1992	6	$-1.8$	1992	$\overline{2}$	$-1.5$	1991	12	$-1.78$	1991	10	$-1.8$
2001	7	$-1.72$	1998	6	$-1.72$	1992	6	$-1.68$	1992	$\mathbf 1$	$-1.89$	1991	11	$-1.77$
2002	5	$-1.51$	2001	8	$-1.83$	1998	6	$-1.76$	1992	3	$-1.95$	1991	12	$-1.77$
2003	5	$-1.96$	2003	$5\overline{)}$	$-1.96$	2001	8	$-1.74$	1992	5 <sup>5</sup>	$-1.78$	1992	$\mathbf{1}$	$-1.76$
2007	5	$-1.73$	2005	11	$-1.59$	2001	9	$-1.51$	1998	6	$-1.81$	1992	$\overline{2}$	$-1.76$
		$\overline{\phantom{a}}$	Ξ.	-	$\overline{\phantom{0}}$	2003	5	$-1.95$	2001	8	$-1.72$	1992	3	$-1.73$
۰.		-	۰.	۰.	-	2006	$\overline{2}$	$-1.57$	2001	9	$-1.51$	1992	$\overline{4}$	$-1.92$
		-	-		-	-		$\overline{\phantom{0}}$	2003	6	$-1.68$	1998	7	$-1.6$
									2009	6	$-1.51$	2001	8	$-1.53$

Table (4.29b): Severe drought events (-1.50 ≥SPI≥ -1.99) for Gadaref Station (1971-2010).

	$SPI_1$			SPI <sub>3</sub>			$SPI_6$			SPI 9			<b>SPI_12</b>	
Year	Month	Value	Year	Month	Value	Year	Month	Value	Year	Month	Value	Year	Month	Value
1976	6	$-2.55$	1973	6	$-2.2$	1973	6	$-2.25$	1973	7	$-2.57$	1973		$-2.01$
1997		$-2.06$	1973	7	$-2.46$	1973	7	$-2.59$	1973	8	$-2.42$	1973	6	$-2.49$
2007	9	$-2.08$	1984	11	$-2.02$	1973	8	$-2.45$	1980	5	$-2.08$	1973	7	$-2.91$
		$\overline{\phantom{a}}$	1987	10	$-2.38$	1984	3	$-3.26$	1986	6	$-2.28$	1973	8	$-2.45$
$\overline{\phantom{0}}$	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	1987	11	$-2.18$	1985	$\overline{2}$	$-2$	1988	4	$-2.28$	1980	8	$-2.23$
		$\overline{\phantom{a}}$	1992	9	$-2.12$	1988		$-2.4$	2000	7	$-2.38$	1984	9	$-2.34$
		$\overline{\phantom{a}}$	2000	7	$-2.51$	1988	$\overline{2}$	$-2.16$			$\overline{\phantom{a}}$	1986	6	$-2.24$
			$\overline{\phantom{0}}$		$\overline{\phantom{0}}$	2000	7	$-2.4$						

Table (4.30): Extremely drought events (SPI≤ -2.0) for Kadugly Station (1971-2010).

	SPI_1			SPI_3			SPI_6			SPI <sub>9</sub>			<b>SPI_12</b>	
Year	Month	Value	Year	Month	Value	Year	Month	Value	Year	Month	Value	Year	Month	Value
1977	9	$-2.94$	1977	11	$-2.17$	1978	$\overline{2}$	$-2.15$	1984	9	$-2.1$	1984	9	$-2.23$
1984	6	$-2.36$	1986	10	$-2.16$	1984	9	$-2.11$	1984	10	$-2.33$	1984	10	$-2.34$
1986	8	$-2.35$	1987	8	$-2.2$	1984	10	$-2.32$	1984	11	$-2.38$	1984	11	$-2.36$
1994	$\overline{7}$	$-2.44$	1990	6	$-2.16$	1984	11	$-2.54$	1984	12	$-2.37$	1984	12	$-2.36$
1995	6	$-2.02$	1991	11	$-2.01$	1984	12	$-2.04$	1985		$-2.35$	1985	$\mathbf{1}$	$-2.37$
$\overline{\phantom{a}}$		$\overline{\phantom{a}}$	2002	7	$-2.45$	1986	9	$-2.08$	1985	$\overline{2}$	$-2.52$	1985	$\overline{2}$	$-2.37$
$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	$\qquad \qquad \blacksquare$	$\overline{\phantom{a}}$	1986	10	$-2.03$	1986	9	$-2.06$	1985	3	$-2.21$
	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	$\blacksquare$	$\blacksquare$	$\blacksquare$	1987	1	$-2.14$	1986	10	$-2.05$	1985	4	$-2.17$
		$\blacksquare$		$\overline{\phantom{0}}$	$\overline{\phantom{0}}$	1990	6	$-2.29$	1986	11	$-2.10$	1985	5	$-2.63$
$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	$\overline{\phantom{0}}$	$\overline{\phantom{a}}$	2002	7	$-2.47$	1986	12	$-2.08$	1985	6	$-2.23$
	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	$\blacksquare$	$\qquad \qquad \blacksquare$	$\blacksquare$	$\blacksquare$	$\blacksquare$	$\blacksquare$	1987	$\mathbf{1}$	$-2.07$	1986	9	$-2.2$
	$\qquad \qquad -$	$\overline{\phantom{0}}$	۳	$\blacksquare$	$\blacksquare$	$\overline{\phantom{0}}$	۳	$\overline{\phantom{a}}$	$\blacksquare$	$\overline{4}$	$-2.20$	1986	10	$-2.06$
	$\overline{\phantom{a}}$	$\qquad \qquad \blacksquare$	$\qquad \qquad =$		$\qquad \qquad$		$\overline{\phantom{0}}$	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	5	$-2.02$	1986	11	$-2.08$
	$\overline{\phantom{a}}$	$\qquad \qquad \blacksquare$	$\overline{\phantom{0}}$	$\overline{\phantom{a}}$	$\qquad \qquad \blacksquare$	$\qquad \qquad$	$\overline{\phantom{0}}$	$\overline{\phantom{a}}$	$\qquad \qquad =$	7	$-2.44$	1986	12	$-2.08$
	$\overline{\phantom{a}}$	$\qquad \qquad \blacksquare$	$\qquad \qquad$	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	$\qquad \qquad \blacksquare$	$\blacksquare$	1987	$\mathbf{1}$	$-2.09$
	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	$\overline{\phantom{a}}$		$\overline{\phantom{0}}$	$\overline{\phantom{a}}$		$\overline{\phantom{a}}$	$\overline{\phantom{a}}$		$\overline{\phantom{0}}$	1987	$\overline{2}$	$-2.09$
	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	$\overline{\phantom{0}}$	$\overline{\phantom{0}}$	$\qquad \qquad \blacksquare$	$\overline{\phantom{0}}$	$\blacksquare$	$\qquad \qquad =$	$\overline{\phantom{0}}$	$\overline{\phantom{0}}$	$\blacksquare$	1987	3	$-2.1$
$\overline{\phantom{a}}$	$\blacksquare$	$\overline{\phantom{a}}$	$\blacksquare$	$\overline{\phantom{0}}$	$\blacksquare$	$\overline{\phantom{0}}$	$\blacksquare$	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	$\qquad \qquad =$	$\blacksquare$	1987	$\overline{4}$	$-2.1$
	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	$\overline{\phantom{a}}$	$\overline{\phantom{0}}$	$\overline{\phantom{0}}$	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	$\overline{\phantom{a}}$	1987	7	$-2.37$
												1987	8	$-2.22$

Table (4.31): Extremely drought events (SPI≤ -2.0) for Nyala Station (1971-2010).

### **4.2.9 Drought Periods with the Drought Magnitude**

The duration of drought event is obtained by counting the months from the beginning to the end of negative SPI values and magnitude by positive summing the SPI values of all months within drought event. Drought duration with the drought magnitudes for Gadaref station, based on 6-month months time steps (SPI 6) are shown in Table (4.32).



# **Table No. (4.32) Drought Duration with the Drought Magnitudes for Gadaref Station Based On 6-Month Time Step (SPI\_6)**

For the SPI at short time scales the precipitation (rainfall) of each new month has a substantial impact on the accumulative precipitation of that period, and thus has more chance to influence the value of SPI, making it fluctuate above and below zero frequently (Juan Du et al. 2012). As the time scale becomes longer, monthly precipitation makes less contribution to the total amount and also the value of SPI. Therefore, the SPI at short time scales reflects short-term precipitation and ignores the overall characteristics of precipitation within a relatively long period; while with long time scale, SPI value responses more slowly and stably to changes in daily precipitation, revealing clear periods of annual and multiple-year dry and wet conditions (Juan Du et al. 2012).

Figures (4.65.a), (4.65.b), (4.65.c), (4.65.d), and (4.65.e), show the variation of the SPI over 3, 6, 9, 12, and 24 months intervals from 1971 to 2010 at Gadaref station. At short time scales SPI shows a high frequency of change between dry and wet periods. With increasing time scales, the dry and wet periods show a lower frequency of change and a longer duration. At the time scale of 1 month, the average duration of dry periods in Gadaref station, as example, was 1.73 months. At the time scale of 3, 6 , 9 and 12 months, the average durations of dry periods were 2.5, 3.9,6.4 and 8.7 months, respectively. The longest average durations of dry periods were 11 months at the time scale of 24 months. The average duration of dry periods is calculated by dividing the ratio of the total number of drought months in each time step to the total number of drought spell (short or long) in the same time step and drought category. The results confirm the statements discussed above.











**Fig. No. (4.65, A Through E): SPI Time Series Based On the Total Monthly Rainfall in Gadaref Station** 

# **4.3 Drought Simulating Using Stochastic Models**

Linear stochastic models known as ARIMA models are used to simulate droughts based on the procedure of models developments. The models are applied to simulate droughts using standardized precipitation index (SPI\_6) series in many rainfall station in Sudan.

Time series model development consists of three stages identification, estimation, and diagnostic checking (Box and Jenkins, 1970). The identification stage involves transforming the data (if necessary) to improve the normality and stationary of the time series to determine the general form of the model to be estimated. During the estimation stage the model parameters are calculated. Finally, diagnostic test of the model is performed to reveal possible model inadequacies to assist in the best model selection.

# **4.3.1 Model Identification**

The drought events were calculated using the SPI. The data series from 1971 to 2010 were used for model development for SPI\_6 series, for all stations. For illustration, example Gadaref station is described briefly for SPI\_6. There are two software packages which are used for time series analysis. These programs are the SPSS package and Econometrics program Eviews7.

# **4.3.1.1 Preliminary Data Analysis**

Time series plot was conducted using the raw data, SPI 6 Gadaref, to assess its stability. The assessments results are shown in figure (4.66). It is clearly depicted that the time series are stationary.

In this step, the model that seems to represent the behaviour of the series is searched, by the means of autocorrelation function (ACF) and partial auto correlation function (PACF), for further investigation and parameter estimation. The behaviour of ACF and PACF is to see whether the series is stationary or not.



**Fig. No. (4.66): SPI 6 of Gadaref Station Time Series 1971-2010** 

Stationary is also confirmed by the Augmented Dickey-Fuller Unit Root Test (ADF test) on the data. The ADF test was conducted on the entire data. Table (4.33) shows ADF test results. ADF test value of -7.29548 is less than critical vales -3.9778, -3.4194, -3.1323 all at 1%, 5%, and 10% respectively. This indicates that the series is stationary. The ADF test proved that all SPI 6 time series, for all stations, were stationary.





For modelling by ACF and PACF methods, examination of values relative to auto regression and moving average were made. An appropriate model for estimation of SPI\_6 values for stations were finally found.

Figure (4.67) shows the ACF and PACF, which have been estimated for SPI-6 for Gadaref station. Many models for Gadaref stations, according to the ACF and PACF of the data, were examined to determine the best model .The model that gives the minimum Akaike Information Criterion (AIC) , Schwarz Criterion (SC) and Sum squared of residual is selected as best fit model, as shown in table (4.34).

	<b>Autocorrelation Partial Correlation</b>		AC		PAC Q-Stat Prob	
$.$ *****	. *****	1	0.710	0.710	240.58	0.000
$\cdot$ ****		2	0.515	0.021	367.28	0.000
$.$ ***	$\cdot$	3	0.381	0.016	436.84	0.000
. **		$\overline{\mathbf{4}}$	0.264	$-0.036$	470.20	0.000
.∣*	$*$ .	5	0.110	$-0.147$	476.05	0.000
*∣.	**∣.	6	$-0.087$	$-0.235$	479.71	0.000
* .	.∣*	7	$-0.095$	0.168	484.06	0.000
*∣.	$\cdot$	8	$-0.074$	0.065	486.67	0.000
* .	٠ .	9	$-0.074$	$-0.001$	489.31	0.000
٠ .		10	$-0.055$	0.042	490.78	0.000
$\cdot$ .		11	$-0.021$	$-0.004$	490.99	0.000
$\cdot$ .		12	0.032		$-0.028$ 491.49	0.000
$\cdot$ .	.∣.	13	0.071	0.066	493.93	0.000
$\cdot$ .	.∣.	14	0.046	$-0.063$	494.98	0.000
.∣.		15	0.030	$-0.030$	495.42	0.000
٠ .	$\cdot$ .	16	0.027	0.027	495.77	0.000
٠ .	$\cdot$ .	17	0.032	0.033	496.29	0.000
٠ .	$\cdot$ .	18	0.016	$-0.011$	496.42	0.000

**Fig. No. (4.67): ACF and PACF Plot for Gadaref Station (SPI\_6) Series** 

Variable	Station	Model	<b>AIC</b>	<b>SC</b>	Sum squared residual
		ARIMA(1,0,0)	2.108	2.126	226.15
		ARIMA(1,0,1)	2.112	2.138	226.05
		ARIMA(0,0,1)	2.339	2.357	285.63
SPI 6	Gadaref	ARIMA(0,0,2)	2.192	2.218	245.48
		ARIMA(0,0,3)	2.169	2.204	238.85
		ARIMA(0,0,4)	2.156	2.200	234.82
		ARIMA(0,0,5)	2.014	2.067	202.96

**Table No. (4.34) Comparison of AIC and SC for Selected Models, (SPI6\_Gadaref)** 

The ACF and PACF correlograms, figure (4.67), and the coefficient are analyzed carefully and the ARIMA model chosen is ARIMA (0,0,5), as shown in table (4.35).





# **4.3.2 Parameters Estimation**

After identifying models, it is needed to obtain efficient estimates of the parameters. These parameters should satisfy two conditions namely stationary and invariability for autoregressive and moving average models, respectively. The parameters should also be tested whether they are statistically significant or not. The parameters values are associated with standard errors of estimate and related t-values.

After the identification of the model using the AIC and SC criteria, estimation of parameters was conducted. The values of the parameters are shown, in table (4.35). The result indicated that the parameters are all significant since their p-values is smaller than 0.05 and should be used in the model. However, the constant  $(C)$  in the selected model is insignificant since its p-values is greater than 0.05. Therefore, it can be conclude that the constant should be omitted from the model.

# **4.3.3 Diagnostic Check**

As considered in table (4.35) the model ARIMA (0,0,5) has been selected as the one with min AIC and SC. The model has been identified and the parameters have been estimated. The model verification is concerned with checking the residuals of the model to see if they contain any systematic pattern which still can be removed to improve the chosen ARIMA. All validation tests are carried out on the residual series. The tests are summarized briefly in the following paragraph.

# **4.3.3.1 ACF and PACF of Residuals**

For a good model, the residuals left over after fitting the model should be white noise. This is revealed through examining the autocorrelations and partial autocorrelations of the residuals of various orders. For this purpose, the various correlations up to 24 lags have been computed. The ACF and PACF of residuals of the model are shown in figure (4.68).

Most of the values of the RACF and RPACF lies within confidence limits except very few individual correlations appear large compared with the confidence limits. The figure indicates no significant correlation between residuals.

#### **4.3.3.2 Portmantateau Lack-of-Fit Test (The Ljung–Box Test)**

The Ljung-Box Q-statistic is employed for checking independence of residual. From figure (4.68), ones can observe that the p-value is greater than 0.05 for all lags, which implies that the white noise hypothesis is not rejected.



# **Fig.No. (4.68): The ACF and PACF of Residuals For SPI6 For Gadaref Station Model**

#### **4.3.3.3The Breusch-Godfrey Serial Correlation LM test**

The Breusch-Godfrey Serial Correlation LM test accepts the hypothesis of no serial correlation in the residuals, as shown in table (4.36). Durbin

Watson statistic, (DW=1.999764), also indicated that there is no serial correlation in the residuals.

# **Table No. (4.36): The Breusch-Godfrey Serial Correlation LM test (SPI6\_Gadaref)**



The *Q*-statistic and the LM test both indicated that the residuals are none correlated and the model can be used. Since the coefficients of the residual plots of ACF and PACF are lying within the confidence limits, the fit is good and the error obtained through this model is tabulated in the table (4.37). The graph showing the observed and fitted values is shown in figure  $(4.69)$ .

# **Table No. (4.37): Errors Measures Obtained For the Model ARIMA (0,0,5) , (SPI6\_Gadaref)**





**Fig.No. (4.69): Graph of Observed and Fitted Values ARIMA (0, 0, 5), (Gadaref, SPI\_6)** 

Figure (4.69) shows a very close agreement between the fitted model and the actual data.

# **4.3.3.4 Histogram of Residuals**

Histogram of residuals for SPI 6 is shown in figure (4.70). This histogram shows that the residuals are normally distributed. This signifies residuals to be white noise.

#### **4.3.3.5 (Q-Q) Plot of Residuals**

The graph of the (Q-Q) plot for the residual data look fairly linear, the normality assumptions of the residuals hold, as shown in figure (4.71).



**Fig. No. (4.70) Histograms of Residuals for SPI\_6 Gadaref Station** 



**Fig. No. (4.71) (Q-Q) Plot of Residuals for SPI\_6 for Gadaref Station** 

#### **4.3.3.6 Kolgomorov–Smirnov (K–S) tests**

The K–S test is used to test the normality of residuals. It is observed that the  $D_{\text{cal}}$  is less than  $D_{\text{tab}}$  at 5% significant level, shown in table (4.38),  $(\alpha = 0.153 > 0.05)$ . This test satisfies that the residuals are normally distributed.

# **Table No. (4.38) K-S Test Calculation of Residuals for SPI\_6 Series, (Gadaref)**



One can note that all the model coefficients are statistically significant, each being more than twice its standard error. The regression is very highly significant with a p-value of 0.0000. As high as 55.5% of the variation in data is accounted for by the fitted model. Figure (4.68) shows that the residuals are uncorrelated. Figure (4.69) shows a very close agreement between the fitted model and the data. Therefore the fitted model is adequate. Fitted to the SPI 6 for Gadaref station is the ARIMA  $(0, 0, 5)$ model. Using various alternative arguments it has been shown to be adequate. Table (4.39), presents the selected ARIMA models for the rest of stations.

Therefore one can propose the ARIMA model

$$
X_t = \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \theta_3 \epsilon_{t-3} + \theta_4 \epsilon_{t-4} + \theta_5 \epsilon_{t-5}
$$
(4.2)

Where:

 $X_t$  = The SPI 6 for Gadaref station (Forecasted value)  $\theta_1$ ,  $\theta_2$ ,  $\theta_3$ ,  $\theta_4$ ,  $\theta_5$ =The optimum coefficients values of the model  $\epsilon_1$ ,  $\epsilon_{t-1}$ ,  $\ldots$ ,  $\epsilon_{t-5}$  = The errors values at time t, t-1,  $\ldots$ , t-5

The fitted model for Gadaref station (SPI\_6) is given by

$$
X_{t} = \varepsilon_{t} + 0.695606\varepsilon_{t-1} + 0.521462\varepsilon_{t-2} + 0.401594\varepsilon_{t-3} + 0.401325\varepsilon_{t-4} + 0.387663\varepsilon_{t-5}
$$
 (4.3)



# **Table No. (4.39) The best time series model, efficiency values, autocorrelation coefficients and the groups of the selected stations.**



# **4.4 Time Series Analysis of Monthly Rainfall Data for the Gadaref Rainfall Station**

Sudan is one of the countries which economy is highly dependent on rainfed agriculture. Rainfall is considered as the most important climatic element that influences agriculture. Therefore, monthly rainfall forecasting plays an important role in the planning and management of agricultural and water resource systems.

Linear stochastic models known as ARIMA and multiplicative Seasonal Autoregressive Integrated Moving Average (SARIMA) models were used to model and forecast monthly rainfall in Gadaref station based on the procedure of model development. The data set from 1971 to 2007 was used for model development for monthly rainfall time series. Gadaref region was selected because it is the most important agricultural productive areas, under rain-fed, in Sudan.

# **4.4.1 Model Identification of Gadaref Monthly Rainfall**

Time series plot was conducted using the monthly rainfall data for Gadaref station to assess the stability of the data, and figure (4.72) was obtained. Since the data is a monthly rainfall, Figure (4.72), shows that there is a seasonal cycle of the series and the series is not stationary. The seasonal fluctuations occur every 12 month, resulting in period of time series  $S = 12$ . The time-plot shows no noticeable trend.

Non-stationary is confirmed by the Augmented Dickey- Fuller Unit Root Test (ADF) on the monthly rainfall data is shown in table (4.40). The ADF Test was done on the entire rainfall data. Table (4.40) displays results of the test: statistic value of -0.75518 is greater than critical vales -2.5699,  $-1.9415$ ,  $-1.616244$  all at  $1\%$ ,  $5\%$ , and  $10\%$  respectively.

This indicates that the series is non- stationary and also confirm that the rainfall data needs differencing in order to be stationary.



**Fig. No. (4.72): Monthly Rainfall Data For Gadaref Station (1971-2010)** 

**Table. No. (4.40) ADF- Unit Root Test For Gadaref Monthly Rainfall** 

<b>Station</b>		Variable   ADF test	Level of Confidence	Critical   Value	Probability	Result
	Monthly		$1\%$	$-2.5699$		
Gadaref	rainfall	$-0.75518$	$5\%$	$-1.9415$	0.3889	Non- stationary
			10%	$-1.6162$		

If there is seasonality and no trend takes a difference of lag *S*=12, this occurs because it is a monthly data with seasonality. The monthly rainfall data was differenced by one seasonal degree of differencing to achieve stationary.

From the plot of the ACF of Gadaref monthly rainfall shown in figure (4.73), it has been also found that the monthly rainfall data must be differenced by one seasonal degree of differencing to achieve stationary. The ACF and PACF have been estimated as shown in figure (4.73).

<b>Autocorrelation</b>	<b>Partial</b> <b>Correlation</b>	<b>AC</b> <b>PAC</b> Q-Stat Prob
$.$ ****	. ****	0.000 $1\ \ 0.555\ \ 0.555\ \ 148.99$
.∣*	** .	0.000 $2\;0.145\; -0.237$ 159.15
* .	** .	173.81 0.000 $3 - 0.174 - 0.217$
$**$ .	*∣.	0.000 4 -0.342 -0.157 230.54
$***$ ]	*∣.	$5 - 0.395 - 0.169$ 306.35 0.000
*** .	$**$ .	0.000 $6 - 0.406 - 0.242$ 386.87
$***$	$**$ .	0.000 7 -0.390 -0.288 461.34
** .	**∣.	8 -0.322 -0.312 512.09 0.000
* .	$**$ .	0.000 9 -0.164 -0.300 525.27
.∣*	$*$ .	10 0.141 -0.103 535.07 0.000
. ****	•∣**	0.544 0.260 681.22 0.000 11
. *****	•¦***	0.756 0.369 963.71 0.000 12
. ****	.∣*	13 0.574 0.168 0.000 1127.2
.∣*	* .	14 0.147 -0.104 0.000 1137.9
* .	$\cdot$ .	0.000 15 -0.168 -0.029 1152.0
$**$ .	. .	0.000 $16 - 0.332 - 0.010$ 1207.1
*** .		$17 - 0.387 - 0.016$ 0.000 1282.0
*** .	$\cdot$ .	1360.6 0.000 18 -0.396 -0.037
$***$	.∣.	0.000 19 -0.379 -0.049 1432.7
** .	* .	0.000 20 -0.318 -0.074 1483.6
*∣.	* .	0.000 $21 - 0.162 - 0.094$ 1496.8
.∣*	$\cdot$ .	0.000 $22$ 0.143 -0.046 1507.1
$.$ ****	.∣.	23 0.514 0.043 1640.7 0.000
$\cdot$ *****	.∣*	0.726 0.143 1908.1 0.000 24

**Fig. No. (6.73): ACF and PACF Plot for Gadaref Station Monthly Rainfall Series** 

Augmented Dickey-Fuller Unit Root Test was done again on the seasonally differenced rainfall data (deseasonalized data).Table (4.41) displays the results of the test: statistic value of -7.7919 is less than critical vales -2.5700, -1.9415, -1.6162 all at 1%, 5%, and 10% respectively. This indicates that the series are stationary and confirms that the rainfall data needed to be differenced to be stationary.

#### Station Variable  $\left|$  ADF test  $\left| \right|$  Level of Confidence **Critical**  $\begin{array}{c|c}\n\hline\n\end{array}$  Probability Result Gadaref Monthly rainfall after difference -7.7919  $1\%$  | -2.5699  $5\%$   $\vert$  -1.9415  $\vert$  0.0000 stationary  $10\%$  -1.6162

# **Table No. (4.41) ADF- Unit Root Test for Gadaref Monthly Rainfall (After Seasonal Difference, Period=12)**

The optional models, the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC) values are shown in table (4.42). The model that gives the minimum AIC and SC is selected as best fit model. Obviously, model SARIMA  $(0,0,0)$   $(0,1,1)_{12}$  has the smallest values of AIC and then one would temporarily have a model SARIMA  $(0,0,0)$   $(0,1,1)_{12}$ .





After the identification of the model using the AIC criteria, estimation of parameters was conducted. The values of the parameters are shown in table (4.43).

Variable	<b>Coefficient</b>	<b>Std. Error</b>	t-Statistic	Prob.
MA(12)	$-0.970272$	0.012651	-76.69556	0.0000
<b>R-squared</b>	0.487472	Mean dependent var		0.110684
<b>Adjusted R-squared</b>	0.487472	S.D. dependent var		53.84589
S.E. of regression	38.54885	Akaike info criterion		10.14386
<b>Sum squared resid</b>	693968.6	Schwarz criterion		10.15273
Log likelihood	-2372.664		Hannan-Quinn criter.	10.14735
Durbin-Watson stat	2.062220			
<b>Inverted MA Roots</b>	1.00	$.86 + .50i$	.86-.50i	$.50 + .86i$
	.50-.86i	$.00 + 1.00i$	$-.00-1.00i$	-.50+.86i
	-.50-.86i	-.86-.50i	-.86+.50i	$-1.00$

**Table .No. (4.43): Summary of Parameter Estimates And Selection Criteria (AIC) For Gadaref Monthly Rainfall** 

# **4.4.2 Parameters Estimation**

After the identification of the model using the AIC criteria, estimation of parameters was conducted. The values of the parameters are shown in table (4.43). The result indicated that the parameters are significant since their pvalues are smaller than 0.05 and should be retained in the model. However, the constant (C) in the selected model is insignificant since its p-values are greater than 0.05. Therefore, it can be concluded that the constant should be omitted from the model.

# **4.4.3 Diagnostic Check**

The model verification is concerned with checking the residuals of the model to see if they contain any systematic pattern which still can be removed to improve the chosen SARIMA. All validation tests were carried out on the residual series. The tests are summarized briefly in the following paragraph.

#### **4.4.3.1 ACF and PACF of Residuals**

The ACF and PACF of residuals of the model SARIMA  $(0, 0, 0)(0,1,1)_{12}$  are shown in figure (4.74). As shown in figure (4.74), most of the values of the RACF and RPACF lies within confidence limits except very few individual correlations appear large compared with the confidence limits. The figures indicate no significant correlation between residuals.

	<b>Partial</b>		
<b>Autocorrelation</b>	<b>Correlation</b>	PAC Q-Stat Prob AC	
.∣.	$\cdot$ .	1 -0.031 -0.031 0.4614	
.∣.	$\cdot$ .	$2 -0.040 -0.041$ 1.1997	0.273
. .	٠ .	$3 - 0.011 - 0.013$ 1.2550	0.534
. .	.∣.	$4 - 0.019 - 0.021$ 1.4198	0.701
	$\cdot$ .	$0.000 - 0.002$ 1.4198 5	0.841
.∣.	٠ .	$6 - 0.003 - 0.005$ 1.4248	0.922
	٠ .	$7 - 0.011 - 0.012$ 1.4813	0.961
$\cdot$ .	$\cdot$ .	$0.023$ $0.021$ 1.7246 8	0.974
.∣.	$\cdot \cdot$	$9 - 0.004 - 0.004$ 1.7329	0.988
. .	.∣.	$10 - 0.052 - 0.051$ 3.0251	0.963
.∣.	$\cdot \cdot$	11 -0.024 -0.028 3.3090	0.973
.∣.	$\cdot$ .	$0.003 - 0.002$ 3.3136 12	0.986
$\cdot  ^*$	.∣*	0.097 0.094 7.8161 13	0.799
	$\cdot$ .	$14 - 0.021 - 0.017$ 8.0207	0.842
٠ .	$\cdot \cdot$	$15 - 0.007 - 0.002$ 8.0468	0.887
. .	.∣.	$16 - 0.016 - 0.017$ 8.1736	0.917
	$\cdot$ .	17 -0.003 -0.003 8.1796	0.943
. .	$\cdot \cdot$	18 -0.001 -0.001 8.1799	0.963
.∣.	.∣.	0.008 0.008 8.2075 19	0.975
. .	٠ .	20 0.003 0.002 8.2121	0.984
٠ .	$\cdot \cdot$	21 -0.017 -0.023 8.3472	0.989
. .	٠ .	$22 - 0.032 - 0.033$ 8.8610	0.990
*∣.	* .	23 -0.087 -0.082 12.578	0.944
٠ .	٠ .	24 -0.051 -0.058 13.886	0.930

**Fig.No. (4.74): ACF and PACF Plot of Residual of Gadaref Monthly Rainfall Station Model** 

# **4.4.3.2 Portmantateau Lack-of-Fit Test (The Ljung–Box Test)**

The Ljung-Box Q-statistic is employed for checking independence of residual. From figure (4.74), one can observe that the p-value is greater than 0.05 for all lags, which implies that the white noise hypothesis is not rejected.

# **4.4.3.3 The Breusch-Godfrey Serial Correlation LM test**

The Breusch-Godfrey Serial Correlation LM test accepts the hypothesis of no serial correlation in the residuals, as shown in table (6.44).

# **Table.No. (4.44): The Breusch-Godfrey Serial Correlation LM test**

#### **Breusch-Godfrey Serial Correlation LM Test:**



Durbin Watson statistic, (DW=2.062220), also indicated that there is no serial correlation in the residuals.

The *Q*-statistic and the LM test both indicated that the residuals are none correlated and the model can be used. Since the coefficients of the residual plots of ACF and PACF are lying within the confidence limits, the fit is good and the error obtained through this model, (1971-2007), is tabulated in the table  $(4.45)$ .

**Table.No. (4.45): Errors Measures Obtained For the Model SARIMA**  $(0.0.0)(0,1,1)_{12}$ 

<b>Error Measure</b>	Value
<b>RMSE</b>	38.80
MAF	19.99

Finally, this concludes that SARIMA  $(0, 0, 0)$   $(0, 1,1)<sub>12</sub>$  model identified previously is adequate to represent the monthly rainfall data and could be used to forecast the upcoming rainfall data.

#### **4.4.4 Forecasting of Monthly Rainfall**

Since the model diagnostic tests show that all the parameter estimates are significant and the residual series is white noise, the estimation and diagnostic checking stages of the modeling process are complete.

The SARIMA  $(0,0,0)$   $(0,1,1)_{12}$  model was also tested for its validity to forecast 36 observations obtained for the years 2008−2010 for Gadaref station. Forecasting refers to the process of predicting future rainfall values from a known time series. In this research forecasting is performed as follows:

According to Equation (3.34), the SARIMA  $(0, 0, 0)$   $(0, 1, 1)_{12}$  model could be written in the following form:

$$
(1 - B^{12})X_t = (1 - \theta_1 B^{12})\varepsilon_t
$$
\n(4.4)

Where:

 $X_t$  = The monthly rainfall at month t

 $X_{t-12}$ = The monthly rainfall at month t-12

 $\varepsilon_t$ ,  $\varepsilon_{t-12}$ = The errors values at time t and t-12

This equation can be multiplied out and written in a form that is used in forecasting as shown in equation (4.5):

$$
Xt - Xt-12 = \varepsilont - \vartheta1 \varepsilont-12
$$
  

$$
Xt = Xt-12 + \varepsilont - \vartheta1 \varepsilont-12
$$
 (4.5)

After substituting the estimated parameter value in Equation (4.5), one can obtain the following equation:

$$
X_t = X_{t-12} + \varepsilon_t + 0.970272\varepsilon_{t-12}
$$
 (4.6)

The results obtained using the equation (4.6) is shown in figure (4.75). The observed rainfall was found to be closely aligned to the forecasted values.


**Fig. No. (4.75): Actual and Forecast Plot for Monthly Rainfall of Gadaref Station, (2008-2010)** 

#### **4.4.4.1 Forecasting Accuracy**

If the fitted SARIMA  $(0, 0, 0)$   $(0, 1, 1)_{12}$  model has to perform well in forecasting, the forecast error will be relatively small. The accuracy of forecasts was measured using root mean square error (RMSE), mean absolute error (MAE), and Theil inequality coefficient .The results show that the Root mean square error (RMSE) turn out to be 24,06 mm which is relatively low and Theil inequality coefficient turn out to be 0.138509, which is relatively close to zero. The Theil inequality coefficient always lies between zero and one, where zero indicates a perfect fit. The bias and variance proportion are also very small, which are 0.012034 and 0.000011, respectively. Thus, the measurements indicated that the forecasting accuracy is very high, as shown in table (4.46). Table (4.47), presents the selected SARIMA models for all stations.

### **Table No. (4.46) Forecasting Accuracy for Gadaref monthly rainfall Station from January 2008 To December 2010**



### **Table No. (4.47) Presents the Selected SARIMA Models for Monthly Rainfall for All Stations**



## **CHAPTER FIVE**

## **Conclusions and Recommendations**

## **5.1 Conclusions**

- Normal distribution adequately described annual rainfall for 7 stations, while Gamma distribution adequately described annual rainfall for 5 stations. Exponential distribution adequately described annual rainfall for most stations in hyper arid zones.
- Forty years rainfall data, indicated that a significant increase in the annual rainfall in four stations. Significant decrease trend of 95% confidence level rainfall variability  $(C_V)$ , seasonality (SI) and precipitation concentration index (PCI), for one station only, and significant increase 99% confidence level in Modified Fournier index (MFI) in another one station, while the changes in the another stations were statistically insignificant.
- The Precipitation Concentration Index *PCI* for three stations indicated an irregular distribution of the rainfall within the year and a highly seasonal distribution for the rest of stations. The study suggests that the risk of water erosion may be greater in three stations, with three stations in the lowest aggressiveness in the hyper-arid zone. The annual rainfall had significant positive correlation with the MFI, for all stations, and the correlation coefficient between 0.97 to 0.52 at  $(\alpha \leq 0.01)$ .
- Through a matrix of Spearman correlation coefficients, highly significant linear correlations between SI, PCI and MFI, for all stations were obtained. Between SI and PCI, there was a correlation coefficient between ( $r_s$  = 0.906 to  $r_s$  = 0.499) and between PCI and MFI the correlation coefficient obtained was  $(r_s = 0.626$  to  $r_s = 0.317)$ .
- Using SPI for drought monitoring, the results indicated that the drought randomly affect the stations. Many drought events occurred during the period under study. Trend analysis reveals that a general wetting tendency can be observed in the autumn seasons in the most stations. Most of the stations, were characterized by increasing SPI

trends in autumn season (SPI\_3\_August), except four stations, were characterized by decreasing SPI trends in the autumn season. Three stations characterized by increasing significantly SPI trends in August (SPI\_1\_August),  $(\alpha < 0.05)$ . Also, two stations characterized by increasing significantly SPI trends in August (SPI\_3\_August), June– August,  $(\alpha < 0.05)$ .

 The tentative model of monthly rainfall for Gadaref station that best fits the criteria and meets the requirement is model SARIMA  $(0,0,0)$   $(0,1,1)_{12}$ . By analyzing the forecasted values, it was found that use of SARIMA model for forecasting monthly rainfall is admirably good.

## **5.2 Recommendations**

### **5.2.1 Recommendations for decision makers**

- The good fitting of stochastic ARIMA models to meteorological time series could result in a better tool which can be used for water resource planning.
- The stochastic ARIMA models can be used for the rainfall stations in Sudan for predicting SPI time series of multiple time scales to detect the drought severity.
- SARIMA model has the ability to predict accurately the future monthly rainfall for all stations in Sudan.

#### **5.2.2 Recommendations for future research**

 It is hoped that future works and studies concentrates on developing a drought mapping system to monitor drought using the Standardized Precipitation Index (SPI), drought early warning system using the Standardized Precipitation Index (SPI) as a tool, and study the occurrence probabilities, return periods and risk of drought events in Sudan.

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# **Appendix (1)**

# **Monthly Rainfall Data Records (in mm) for 16 stations**



**Dongola Monthly Rainfall in mms for the Period (1971-2010)** 



<b>YEAR</b>	JAN.	FEB.	MAR.	APR.	MAY.	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
1970	0.0	0.2	0.0	0.0	0.0	0.0	<b>11.0</b>	0.0	0.0	0.0	7.7	28.5
1971	51.3	4.1	0.0	0.0	0.0	0.0	12.7	0.0	0.0	25.2	15.0	0.3
1972	0.0	0.0	0.0	0.0	0.0	7.7	1.4	0.0	0.0	48.5	2.3	0.0
1973	1.5	0.0	0.0	0.0	0.0	0.0	1.4	0.0	0.0	0.3	5.2	0.3
1974	5.1	0.0	1.4	0.0	0.0	0.0	<b>19.0</b>	0.0	0.0	0.0	6.3	0.3
1975	0.2	0.0	0.0	0.6	0.0	0.0	0.0	0.0	0.0	0.0	61.1	1.9
1976	0.0	0.0	0.0	0.0	0.0	0.0	2.7	0.0	0.0	10.7	106.1	3.4
1977	0.0	0.0	0.0	0.0	0.1	0.0	3.0	0.0	0.0	64.0	5.3	0.0
1978	0.0	0.0	0.0	0.0	0.0	0.0	7.4	4.2	0.0	0.0	0.0	92.4
1979	2.3	0.0	0.0	0.0	0.0	0.0	0.0	8.7	0.3	80.7	2.6	0.0
1980	0.8	0.0	0.0	0.0	0.0	0.0	3.0	0.0	0.0	0.0	1.1	6.0
1981	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.7	5.5
1982	0.3	0.0	0.0	1.2	0.0	0.0	0.0	0.0	0.0	14.7	64.2	0.0
1983	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1984	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	53.4	6.0	23.5
1985	22.0	0.0	0.0	0.0	2.3	0.0	0.0	0.0	0.0	21.2	99.5	13.4
1986	34.5	0.0	24.4	0.0	0.0	0.0	0.0	0.3	0.0	7.0	0.4	0.0
1987	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	<b>10.0</b>	0.5	0.0
1988	0.5	0.0	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.1	9.3	0.0
1989	0.0	0.0	0.0	1.6	10.9	0.0	0.0	0.0	0.0	45.1	4.9	2.4

**Port Sudan Monthly Rainfall in mms for the Period (1970-2010)** 



<b>YEAR</b>	JAN.	FEB.	MAR.	APR.	MAY.	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
1971	0.0	0.0	0.0	0.0	0.3	0.0	0.0	3.8	7.3	0.0	0.0	0.0
1972	0.0	0.0	0.0	0.0	0.0	0.0	0.0	40.6	8.9	5.7	0.0	0.0
1973	0.0	0.0	0.0	0.0	0.4	0.0	3.3	0.3	3.6	4.3	0.0	0.0
1974	0.0	0.0	0.0	0.0	14.2	0.0	14.4	16.8	5.6	0.0	0.0	0.0
1975	0.0	0.0	0.0	0.0	0.0	0.0	3.5	88.7	0.0	0.0	0.0	0.0
1976	0.0	0.0	0.0	0.0	1.0	0.0	51.4	15.3	1.1	0.0	0.0	0.0
1977	0.0	0.0	0.0	0.0	9.0	0.0	52.2	27.1	0.0	23.4	0.0	0.0
1978	0.0	0.0	0.0	0.0	0.0	0.0	57.9	29.2	4.8	0.0	0.0	0.0
1979	0.0	0.0	0.0	10.4	0.0	0.0	0.1	14.2	65.6	15.6	0.0	0.0
1980	0.0	0.0	0.0	0.0	24.9	3.8	28.6	6.5	0.0	0.0	0.0	0.0
1981	0.0	0.0	0.0	1.5	0.0	0.0	10.7	2.0	12.8	0.0	0.0	0.0
1982	0.0	0.0	0.0	0.0	0.0	0.0	0.0	<b>18.0</b>	0.0	0.0	0.0	0.0
1983	0.8	0.0	0.0	0.0	0.0	8.3	6.4	0.0	0.0	0.0	0.0	0.0
1984	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.1	0.0	0.0
1985	0.0	0.0	0.0	0.0	15.5	0.0	2.0	9.1	6.7	0.0	0.0	0.0
1986	0.0	0.0	0.0	0.0	0.0	1.0	20.5	0.0	19.8	0.0	0.0	0.0
1987	0.0	0.0	0.0	0.0	1.1	0.5	0.0	52.4	<b>17.0</b>	0.0	0.0	0.0
1988	0.0	0.0	0.0	0.0	0.0	0.0	18.0	218.1	3.6	0.0	0.0	0.0
1989	0.0	0.0	0.0	0.3	16.0	5.0	0.0	5.0	24.2	0.0	0.0	0.0
1990	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

**Atbara Monthly Rainfall in mms for the Period (1971-2010)** 



<b>YEAR</b>	JAN.	FEB.	MAR.	APR.	MAY.	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
1971	0.0	0.0	0.0	0.0	0.0	0.0	53.8	33.2	31.9	1.6	0.0	0.0
1972	0.0	0.0	0.0	0.0	0.0	6.5	6.0	110.5	<b>10.0</b>	0.6	0.0	0.0
1973	0.0	0.0	0.0	0.0	14.2	0.0	74.6	0.0	34.3	51.6	0.0	0.0
1974	0.0	0.0	0.0	0.0	0.0	13.9	55.4	12.0	4.7	0.0	0.0	0.0
1975	0.0	0.0	0.0	0.0	4.2	0.0	0.9	50.1	47.8	0.0	0.0	0.0
1976	0.0	0.0	0.0	0.0	0.0	0.0	43.0	80.1	25.7	7.8	22.2	0.0
1977	0.0	0.0	0.0	0.0	0.0	0.0	37.4	125.6	2.9	0.8	0.0	0.0
1978	0.0	0.0	0.0	0.0	0.0	4.0	60.3	46.3	14.5	8.5	0.0	0.0
1979	0.0	0.0	0.0	0.0	3.2	12.1	2.7	62.3	<b>19.8</b>	0.0	0.0	0.0
1980	0.0	0.0	0.0	0.0	0.7	4.2	60.0	19.2	<b>11.0</b>	1.2	0.0	0.0
1981	0.0	0.0	1.4	0.0	1.2	1.7	86.9	30.7	12.9	6.3	0.0	0.0
1982	0.0	0.0	1.6	0.0	5.0	0.0	9.4	46.9	39.8	0.0	0.0	0.0
1983	0.6	0.0	0.0	0.0	1.1	46.5	23.2	6.8	5.8	0.0	0.0	0.0
1984	0.0	0.0	0.0	0.0	1.4	0.0	0.0	0.0	3.3	0.0	0.0	0.0
1985	0.0	0.0	0.0	0.0	9.1	3.1	16.4	0.3	9.9	0.0	0.0	0.0
1986	0.0	0.0	0.0	0.0	0.0	0.0	9.1	21.9	16.3	10.4	0.0	0.0
1987	0.0	0.0	0.0	0.0	21.1	23.0	22.0	48.9	0.0	0.6	0.0	0.0
1988	0.0	0.0	0.0	0.0	0.0	0.0	65.9	301.4	46.3	1.9	0.0	0.0
1989	0.0	0.0	0.0	0.0	5.8	1.3	0.0	24.7	48.0	0.0	0.0	0.0
1990	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0	2.4	0.0	0.0	0.0

**Khartoum Monthly Rainfall in mms for the Period (1971-2010)** 



<b>YEAR</b>	JAN.	FEB.	MAR.	APR.	MAY.	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
1971	0.0	0.0	0.0	6.8	0.3	5.2	128.5	95.8	117.9	0.0	0.0	0.0
1972	0.0	0.0	0.0	0.0	4.3	80.0	60.8	47.9	13.2	16.5	0.0	0.0
1973	0.0	0.0	0.0	0.0	30.4	14.3	133.1	21.2	51.6	8.2	0.0	0.0
1974	0.0	0.0	0.0	0.0	9.7	30.8	210.5	17.4	65.6	0.0	0.0	0.0
1975	0.0	0.0	0.0	0.8	0.2	48.5	<b>36.0</b>	103.3	106.9	0.0	0.0	0.0
1976	0.0	0.0	0.0	0.0	4.5	24.9	110.0	56.5	37.3	10.4	0.1	0.0
1977	0.0	0.0	0.0	0.0	0.1	3.1	94.3	108.6	0.0	6.2	0.0	0.0
1978	0.0	0.0	0.0	3.2	1.7	16.9	133.4	53.8	42.2	18.9	0.0	0.0
1979	0.3	0.0	0.0	1.3	17.8	14.5	59.9	136.9	47.3	2.1	0.0	0.0
1980	0.0	0.0	0.0	0.0	4.8	25.7	70.5	112.2	12.8	0.0	0.0	0.0
1981	0.0	0.0	0.0	6.2	15.1	7.0	66.9	81.9	54.3	8.4	0.0	0.0
1982	0.0	0.0	0.0	2.0	10.6	1.5	44.2	121.1	2.8	35.0	0.0	0.0
1983	0.0	0.0	0.0	0.0	22.8	106.1	10.9	103.3	6.3	0.0	0.0	0.0
1984	0.0	0.0	0.0	0.0	0.0	9.8	54.6	4.8	28.3	1.3	0.0	0.0
1985	0.0	0.0	0.0	0.8	17.8	20.8	41.7	40.2	21.9	2.7	0.0	0.0
1986	0.0	0.0	0.0	0.0	0.0	21.0	109.1	31.6	93.2	52.0	0.0	0.0
1987	0.0	0.0	0.0	0.0	45.1	29.9	30.7	151.8	1.8	12.5	0.0	0.0
1988	0.0	0.0	0.0	0.0	1.7	4.6	93.0	228.7	65.3	0.5	0.0	0.0
1989	0.0	0.0	0.0	3.4	2.2	65.2	37.8	43.5	47.5	40.2	0.0	0.0
1990	0.0	0.0	0.0	0.0	6.7	0.5	7.5	22.4	30.5	8.0	0.0	0.0

**Kasalla Monthly Rainfall in mms for the Period (1971-2010)** 



<b>YEAR</b>	JAN.	FEB.	MAR.	APR.	MAY.	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
1971	0.0	0.0	0.0	0.0	5.0	18.6	150.3	137.8	49.7	5.7	0.0	0.0
1972	0.0	0.0	0.0	0.0	3.9	3.3	44.8	102.4	42.5	8.2	0.0	0.0
1973	0.0	0.0	0.0	0.0	22.3	0.0	38.8	60.1	96.2	<b>18.0</b>	0.0	0.0
1974	0.0	0.0	0.0	0.0	7.6	48.6	96.0	46.5	87.2	5.4	0.0	0.0
1975	0.0	0.0	0.0	9.4	24.2	29.9	66.9	230.4	75.8	6.5	0.0	0.0
1976	0.0	0.0	0.0	14.6	7.0	58.9	89.1	34.2	61.7	2.0	5.0	0.0
1977	0.0	0.0	0.0	0.0	0.0	47.8	46.1	93.3	37.8	26.3	0.0	0.0
1978	0.0	0.0	0.0	$2.2\,$	27.1	38.8	158.4	93.1	23.8	2.2	0.0	0.0
1979	0.0	0.0	0.0	0.0	16.9	8.0	75.0	94.9	39.2	3.1	0.0	0.0
1980	0.0	0.0	0.0	0.0	12.7	22.3	177.9	71.3	15.2	5.6	0.0	0.0
1981	0.0	0.0	0.0	0.0	15.8	14.4	111.0	84.0	87.2	8.1	0.0	0.0
1982	0.0	0.0	0.0	0.0	1.0	15.8	30.5	105.0	39.6	29.4	0.0	0.0
1983	0.3	0.0	0.0	0.0	12.4	28.8	48.2	58.6	67.8	19.3	0.0	0.0
1984	0.0	0.0	0.0	0.0	7.4	12.5	39.0	8.2	80.1	0.0	0.0	0.0
1985	0.0	0.0	0.0	0.0	51.9	45.0	71.3	220.3	45.0	5.2	0.0	0.0
1986	0.0	0.0	0.0	2.2	0.0	24.3	65.7	81.7	44.8	29.9	0.0	0.0
1987	0.0	0.0	0.0	0.0	43.1	23.7	37.9	112.1	48.8	2.2	0.0	0.0
1988	0.0	0.0	0.0	0.0	13.9	43.9	77.9	161.8	40.4	1.6	0.0	0.0
1989	0.0	0.0	0.0	0.0	34.5	41.5	24.0	116.8	36.4	0.3	32.3	0.0
1990	0.0	0.0	0.0	0.0	0.0	7.7	38.9	0.3	27.6	40.9	0.0	0.0

**Madani Monthly Rainfall in mms for the Period (1971-2010)** 



<b>YEAR</b>	JAN.	FEB.	MAR.	APR.	MAY.	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
1971	0.0	0.0	0.0	0.0	28.0	52.0	117.0	199.0	31.0	8.0	0.0	0.0
1972	0.0	0.0	0.0	2.0	1.0	41.3	120.4	142.7	124.9	5.0	0.0	0.0
1973	0.0	0.0	0.0	0.0	28.0	23.0	143.8	114.1	131.9	27.0	0.0	0.0
1974	0.0	0.0	0.0	<b>18.0</b>	4.0	80.5	130.5	75.0	94.0	<b>13.0</b>	0.0	0.0
1975	0.0	7.0	0.0	<b>11.0</b>	0.0	43.0	120.3	264.7	69.4	0.0	0.0	0.0
1976	0.0	0.0	0.0	1.0	0.0	96.0	117.0	104.5	75.0	<b>10.0</b>	2.0	0.0
1977	0.0	0.0	0.0	0.0	6.0	75.0	159.0	126.0	33.0	48.0	0.0	0.0
1978	0.0	0.0	0.0	0.1	24.0	36.9	153.7	78.9	66.3	6.2	0.0	0.0
1979	0.0	0.0	0.0	0.0	37.4	117.8	149.6	233.8	85.3	20.7	0.5	0.0
1980	0.0	0.0	0.0	0.0	9.8	81.2	113.1	185.6	14.2	0.0	0.0	0.0
1981	0.0	0.0	0.0	0.7	19.9	18.2	135.1	138.2	104.6	6.6	0.0	0.0
1982	0.0	0.0	0.0	0.0	5.4	28.2	51.7	105.4	36.2	2.4	0.0	0.0
1983	0.8	0.0	0.0	0.0	6.8	122.9	71.1	88.9	54.3	0.0	0.0	0.0
1984	0.0	0.0	0.0	0.0	77.9	11.5	<b>14.0</b>	10.9	60.4	0.0	0.0	0.0
1985	0.0	0.0	0.0	0.0	20.7	50.2	76.3	149.4	111.3	3.8	1.7	0.0
1986	0.0	0.0	0.0	0.0	0.0	98.5	146.7	75.0	94.5	43.0	0.0	0.0
1987	0.0	0.0	0.0	0.0	31.4	0.8	110.1	208.2	36.3	29.4	0.0	0.0
1988	0.0	0.0	0.0	0.0	10.2	106.1	141.9	152.9	146.5	23.1	0.0	0.0
1989	0.0	0.0	0.0	0.0	19.3	47.5	28.8	327.2	137.0	7.0	0.0	0.0
1990	0.0	0.0	0.0	0.0	0.0	9.8	97.9	12.4	151.6	36.6	0.0	0.0

**Sennar Monthly Rainfall in mms for the Period (1971-2010)** 



<b>YEAR</b>	JAN.	FEB.	MAR.	APR.	MAY.	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
1971	0.0	0.0	0.0	1.6	22.2	25.9	248.4	168.6	76.1	6.9	0.0	0.0
1972	0.0	0.0	1.4	0.0	22.1	79.1	174.9	240.8	96.0	3.7	0.0	0.0
1973	0.0	0.0	0.0	0.0	45.4	20.0	159.5	104.8	217.6	50.5	0.0	0.0
1974	0.0	0.0	0.0	6.5	37.5	131.2	175.3	273.1	77.1	<b>11.3</b>	0.0	0.0
1975	0.4	0.0	0.0	0.4	7.2	76.7	125.2	187.1	207.7	1.7	1.3	0.0
1976	0.0	0.0	0.0	7.5	9.0	134.2	194.0	126.3	124.3	39.9	6.8	0.0
1977	0.0	0.0	0.0	0.0	12.4	130.3	179.3	127.1	30.7	98.2	30.8	0.0
1978	0.0	0.0	2.7	25.6	13.0	82.3	274.6	80.1	70.4	54.1	0.0	0.0
1979	0.0	0.0	0.0	19.6	82.2	181.0	254.9	134.5	80.1	19.7	3.3	0.0
1980	0.0	0.0	0.8	0.9	41.6	188.6	153.4	215.3	23.9	20.9	0.0	0.0
1981	0.0	0.0	0.0	4.4	35.4	41.4	305.8	204.4	67.3	0.0	0.0	0.0
1982	0.0	0.0	0.0	0.0	29.3	76.7	74.0	449.4	77.2	3.4	0.0	0.0
1983	0.0	0.0	0.0	0.0	4.6	87.6	169.9	155.1	42.3	22.6	0.0	0.0
1984	0.0	0.0	0.0	1.5	16.5	31.3	136.1	58.4	73.1	5.1	0.0	0.0
1985	0.0	0.0	0.0	0.0	24.1	81.0	348.0	136.8	71.1	67.7	16.0	0.0
1986	0.0	0.0	0.0	0.0	7.0	86.7	177.6	141.5	157.2	34.0	0.0	0.0
1987	0.0	0.0	0.0	0.0	54.1	65.6	150.8	75.1	42.4	85.0	0.0	0.0
1988	0.0	0.0	0.0	0.0	10.8	99.9	151.4	228.8	92.0	1.1	0.0	0.0
1989	0.0	0.0	0.0	1.0	14.1	132.2	158.3	354.2	90.1	<b>10.0</b>	1.4	0.0
1990	0.0	0.0	0.0	0.0	6.2	36.7	116.7	72.7	136.1	3.5	0.0	0.0

**Gadaref Monthly Rainfall in mms for the Period (1971-2010)** 



<b>YEAR</b>	JAN.	FEB.	MAR.	APR.	MAY.	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
1971	0.0	0.0	0.0	0.0	24.2	39.1	86.6	135.9	86.8	9.7	0.0	0.0
1972	0.0	0.0	0.6	0.0	6.3	95.2	183.6	64.4	65.6	2.8	0.0	0.0
1973	0.0	0.0	0.0	0.0	53.3	4.9	82.1	93.6	145.9	2.2	0.0	0.0
1974	0.0	0.0	0.0	0.0	4.6	93.7	111.7	103.7	31.4	0.0	8.0	0.0
1975	0.0	0.0	0.0	0.0	0.6	129.0	60.3	259.4	87.1	0.0	0.0	0.0
1976	0.0	0.0	0.0	12.0	21.4	28.5	70.7	107.2	67.0	28.3	0.0	0.0
1977	0.0	0.0	0.0	0.0	2.6	24.5	94.7	166.6	64.1	6.0	0.0	0.0
1978	0.0	0.0	0.0	7.4	45.3	46.2	108.8	134.3	70.9	28.8	0.0	0.0
1979	0.0	0.0	0.0	20.3	41.1	51.0	90.3	104.7	47.0	22.1	58.2	0.0
1980	0.0	0.0	0.0	0.0	12.0	45.8	158.2	132.4	8.6	25.1	0.0	0.0
1981	0.0	0.0	0.0	0.0	3.8	5.7	80.2	34.4	177.9	3.0	0.0	0.0
1982	0.0	0.0	0.0	0.0	42.9	4.0	48.8	143.7	57.4	17.0	0.0	0.0
1983	0.0	0.0	0.0	0.0	0.0	68.8	103.8	65.7	28.4	1.0	0.0	0.0
1984	0.0	0.0	0.0	0.0	3.9	28.2	12.4	26.6	24.9	0.0	0.0	0.0
1985	0.0	0.0	0.0	0.0	7.2	4.8	135.1	145.4	54.7	12.4	0.8	0.0
1986	0.0	0.0	0.0	0.0	0.0	11.5	78.8	79.2	64.9	0.3	0.0	0.0
1987	0.0	0.0	0.0	0.0	0.8	50.2	24.6	182.3	21.0	3.0	0.0	0.0
1988	0.0	0.0	0.0	4.0	2.4	70.2	99.4	131.9	66.4	12.9	0.0	0.0
1989	0.0	0.0	0.0	0.0	9.0	65.4	105.5	143.0	65.6	1.6	<b>1.0</b>	0.0
1990	0.0	0.0	0.0	0.0	0.0	14.4	98.0	22.3	48.1	1.0	0.0	0.0

**Kosti Monthly Rainfall in mms for the Period (1971-2010)** 



<b>YEAR</b>	JAN.	FEB.	MAR.	APR.	MAY.	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
1971	0.0	0.0	0.0	0.0	1.8	31.4	89.2	48.7	66.8	7.8	0.0	0.0
1972	0.0	0.0	0.0	9.1	<b>20.0</b>	15.7	127.4	143.1	81.0	26.5	0.0	0.0
1973	0.0	0.0	0.0	9.8	2.0	9.3	111.9	49.2	70.8	3.9	0.0	0.0
1974	0.0	0.0	0.0	0.0	0.0	28.6	185.4	78.1	94.9	0.0	0.0	0.0
1975	0.0	0.0	0.0	0.0	1.3	10.7	81.0	195.2	90.8	0.0	0.0	0.0
1976	0.0	0.0	0.0	0.0	1.2	15.9	100.2	91.8	62.4	14.9	0.0	0.0
1977	0.0	0.0	0.0	0.0	47.0	17.4	51.3	133.3	60.1	8.5	0.0	0.0
1978	0.0	0.0	$2.2\,$	0.0	2.5	25.9	112.8	160.7	48.7	38.9	0.0	0.0
1979	0.0	0.0	0.0	7.4	11.5	102.4	182.4	106.1	13.4	0.6	0.0	0.0
1980	0.0	0.0	6.0	0.0	54.8	151.0	244.6	169.3	41.7	13.6	0.0	0.0
1981	0.0	0.0	0.0	1.3	<b>11.0</b>	27.1	121.0	71.3	45.5	17.2	0.0	0.0
1982	0.0	0.0	0.0	5.0	3.8	26.5	45.9	197.5	57.3	27.1	0.0	0.0
1983	0.0	0.0	0.0	0.0	5.6	51.8	132.0	90.6	32.2	0.0	0.0	0.0
1984	0.0	0.0	0.0	0.0	7.3	2.9	79.1	32.0	13.6	4.0	0.0	0.0
1985	0.0	0.0	0.0	3.4	8.8	5.9	74.5	178.1	49.9	0.3	0.0	0.0
1986	0.0	0.0	0.0	0.0	0.0	21.5	80.4	55.9	107.2	9.7	0.0	0.0
1987	0.0	0.0	0.0	0.0	11.8	50.8	80.9	115.2	16.1	43.2	0.0	0.0
1988	0.0	0.0	0.0	0.0	0.0	144.7	56.3	100.0	81.4	0.0	0.0	0.0
1989	0.0	0.0	0.0	0.0	<b>33.2</b>	45.5	46.7	106.5	124.5	0.5	0.0	0.0
1990	0.0	0.0	0.0	0.0	9.5	6.2	62.7	21.5	29.3	35.4	0.0	0.0

**Nahoud Monthly Rainfall in mms for the Period (1971-2011)** 



<b>YEAR</b>	JAN.	FEB.	MAR.	APR.	MAY.	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
1970	0.0	0.0	0.0	0.5	0.0	0.0	98.9	72.7	75.1	14.2	0.0	0.0
1971	0.0	0.0	0.0	0.0	16.3	54.6	107.9	98.3	49.4	6.2	0.0	0.0
1972	0.0	0.0	0.0	0.0	14.1	42.2	50.9	148.0	18.3	63.4	0.0	0.0
1973	0.0	0.0	0.0	9.1	15.3	20.3	110.9	15.5	105.9	16.5	0.0	0.0
1974	0.0	0.0	0.0	0.0	0.0	6.8	208.1	93.0	38.4	0.3	0.0	0.0
1975	0.0	0.0	0.0	0.0	3.9	8.5	87.2	59.1	42.9	0.0	0.0	0.0
1976	0.0	0.0	0.0	2.3	0.0	6.0	176.8	135.2	89.2	23.1	0.0	0.0
1977	0.0	0.0	0.0	0.0	8.3	4.3	72.9	210.4	7.6	0.1	0.0	0.0
1978	0.0	0.0	0.0	7.7	42.5	9.5	130.5	164.1	77.1	36.8	0.0	0.0
1979	0.0	0.0	0.0	0.0	21.2	13.1	50.2	154.3	31.2	6.8	7.6	0.0
1980	0.0	0.0	4.6	0.0	12.0	40.0	138.0	75.4	87.5	7.4	0.0	0.0
1981	0.0	0.0	0.0	0.0	28.0	30.3	112.0	65.4	46.0	30.6	0.0	0.0
1982	0.0	0.0	0.0	2.0	0.7	1.2	40.8	89.7	27.8	39.7	0.0	0.0
1983	0.0	0.0	0.0	0.0	0.1	40.2	100.0	137.5	74.0	0.0	0.0	0.0
1984	0.0	0.0	0.0	0.0	5.4	5.9	75.5	10.3	64.4	0.2	0.0	0.0
1985	0.0	0.0	1.0	0.0	12.4	14.5	53.3	73.5	63.9	0.0	0.0	0.0
1986	0.0	0.0	0.0	0.0	0.0	27.8	94.3	129.7	122.3	1.5	0.0	0.0
1987	0.0	0.0	0.0	0.0	8.0	13.6	<b>29.0</b>	113.3	4.6	57.8	0.0	0.0
1988	0.0	0.0	0.0	0.0	9.8	62.7	43.9	<b>99.0</b>	129.3	1.3	0.0	0.0
1989	0.0	0.0	3.5	0.0	<b>11.0</b>	15.9	57.0	103.1	67.8	9.5	0.0	0.0

**Obaied Monthly Rainfall in mms for the Period (1970-2010)**


<b>YEAR</b>	JAN.	FEB.	MAR.	APR.	MAY.	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
1971	0.0	0.0	3.0	0.0	24.0	113.0	243.0	75.8	202.5	40.6	0.0	0.0
1972	0.0	0.0	0.0	15.0	147.5	66.0	78.3	124.7	76.7	67.2	0.0	0.0
1973	0.0	0.0	0.0	0.0	32.2	44.0	73.6	131.4	158.9	28.7	0.0	0.0
1974	0.0	0.0	0.0	46.8	27.3	164.3	168.7	143.3	179.2	89.7	5.2	0.0
1975	0.0	0.0	0.0	0.0	55.1	86.7	170.2	119.4	178.8	44.7	0.0	0.0
1976	0.0	0.0	1.1	15.8	71.2	25.3	136.3	155.4	94.2	94.1	0.0	0.0
1977	0.0	0.0	0.0	0.0	24.9	102.4	317.1	237.0	151.0	48.2	0.0	0.0
1978	0.0	0.0	16.6	30.0	114.6	83.6	127.5	84.8	153.2	130.6	0.0	0.0
1979	0.0	0.0	0.0	20.6	59.8	155.4	130.9	259.7	70.2	39.7	0.3	0.0
1980	0.0	0.0	0.0	9.1	24.7	84.6	95.1	120.4	141.6	47.5	0.0	0.0
1981	0.0	0.0	<b>19.0</b>	10.2	58.7	71.2	223.7	163.9	121.3	114.5	0.0	0.0
1982	0.0	0.0	0.0	28.0	55.1	117.6	89.5	112.2	124.9	34.3	0.0	0.0
1983	0.0	0.0	0.0	1.9	14.1	204.4	46.5	184.6	201.6	2.4	0.0	0.0
1984	0.0	0.0	0.0	0.0	53.3	92.7	86.7	143.5	64.8	28.8	0.0	0.0
1985	0.0	0.0	0.2	12.2	80.3	157.4	62.4	106.9	146.8	39.9	0.0	0.0
1986	0.0	0.0	0.0	0.0	0.0	89.3	281.4	67.8	165.1	62.7	0.0	0.0
1987	0.0	0.0	0.0	0.0	105.9	59.9	184.7	86.7	87.6	0.3	0.0	0.0
1988	0.0	0.0	14.5	0.0	73.7	78.6	195.5	102.2	123.1	23.7	0.0	0.0
1989	0.0	0.0	4.3	0.0	129.0	104.2	161.9	182.2	148.1	100.9	1.0	0.0
1990	0.0	0.0	0.0	0.0	56.7	48.5	106.5	151.6	147.8		0.0	0.0

**Kadugly Monthly Rainfall in mms for the Period (1971-2010)** 



<b>YEAR</b>	JAN.	FEB.	MAR.	APR.	MAY.	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
1970	0.0	0.0	0.0	0.0	0.0	19.0	65.6	113.0	96.6	12.1	0.0	0.0
1971	0.0	0.0	0.0	0.0	3.0	8.3	91.6	88.2	64.8	0.0	0.0	0.0
1972	0.0	0.0	0.0	0.0	1.6	4.4	46.3	50.0	<b>17.0</b>	0.1	0.0	0.0
1973	0.0	0.0	0.0	4.5	5.7	1.0	23.4	78.9	<b>31.0</b>	0.0	0.0	0.0
1974	0.0	0.0	0.0	0.0	2.5	3.5	110.9	175.2	36.9	0.0	0.0	0.0
1975	0.0	0.3	0.0	0.3	0.0	2.5	56.4	52.7	28.3	0.0	0.0	0.0
1976	0.0	0.0	0.0	1.0	0.0	2.0	54.9	27.0	58.8	33.0	0.0	0.0
1977	0.0	0.0	0.0	0.0	16.8	3.5	22.9	114.5	25.5	0.0	0.0	0.0
1978	0.0	0.0	0.0	0.0	1.2	18.2	11.6	75.3	73.4	28.2	0.0	0.0
1979	0.0	0.0	0.0	12.1	11.8	8.9	31.3	80.9	5.7	19.2	0.0	0.0
1980	0.0	0.0	0.0	0.0	6.8	7.7	87.7	50.9	50.8	15.1	0.0	0.0
1981	0.0	0.0	0.0	0.0	0.2	42.4	67.4	46.2	29.3	11.7	0.0	0.0
1982	0.0	0.0	0.0	6.0	0.0	0.8	29.7	42.6	31.3	0.0	0.0	0.0
1983	0.0	0.0	0.0	0.0	0.0	1.0	20.9	29.0	21.8	0.0	0.0	0.0
1984	0.0	0.0	0.0	0.0	1.3	0.2	34.6	31.2	40.2	0.0	0.0	0.0
1985	0.0	0.0	0.0	<b>16.0</b>	15.7	29.2	44.6	54.1	12.0	0.0	0.0	0.0
1986	0.0	0.0	0.0	0.0	0.0	0.3	80.6	95.4	<b>14.0</b>	9.8	0.0	0.0
1987	0.0	0.0	0.0	0.0	21.1	19.5	13.3	91.2	58.4	10.5	0.0	0.0
1988	0.0	0.0	0.0	0.0	11.4	4.0	34.3	147.3	53.3	0.0	0.0	0.0
1989	0.0	0.0	0.0	0.0	38.8	<b>15.0</b>	<b>10.8</b>	49.5	43.6	0.0	0.0	0.0

**Fasher Monthly Rainfall in mms for the Period (1970-2010)** 



<b>YEAR</b>	JAN.	FEB.	MAR.	APR.	MAY.	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
1970	0.0	0.0	0.0	0.0	13.4	5.6	165.6	135.6	122.4	<b>16.7</b>	0.0	0.0
1971	0.0	0.0	0.0	5.5	25.8	15.2	159.2	248.4	54.3	5.9	0.0	0.0
1972	0.0	0.0	0.0	0.2	10.8	49.9	64.1	163.7	<b>29.0</b>	24.8	0.0	0.0
1973	0.0	0.0	0.0	2.7	7.8	23.6	79.5	82.7	15.3	2.2	0.0	0.0
1974	0.0	0.0	0.0	0.0	12.6	35.3	143.2	179.2	<b>34.0</b>	0.0	0.0	0.0
1975	0.0	0.0	0.0	0.0	0.4	0.9	149.5	162.5	36.6	0.0	0.0	0.0
1976	0.0	0.0	0.0	31.6	1.4	18.9	135.3	86.7	137.8	4.8	0.0	0.0
1977	0.0	0.0	0.0	51.0	5.2	79.6	215.3	133.5	48.8	0.0	0.0	0.0
1978	0.0	0.0	0.0	0.0	0.0	34.7	138.7	152.2	29.5	28.5	0.0	0.0
1979	5.3	0.0	0.0	6.2	5.1	79.9	192.1	162.1	17.5	3.0	0.0	0.0
1980	0.0	0.0	0.0	0.0	29.2	59.4	173.7	206.4	17.9	0.0	0.0	0.0
1981	0.0	0.0	0.0	0.0	4.3	64.5	<b>132.0</b>	85.8	37.7	23.8	0.0	0.0
1982	0.0	0.0	0.0	0.0	11.2	0.0	25.8	158.6	112.7	2.3	0.0	0.0
1983	0.0	0.0	0.0	0.0	0.0	<b>39.0</b>	<b>99.8</b>	47.8	54.7	0.0	0.0	0.0
1984	0.0	0.0	0.0	0.0	0.5	7.9	22.8	<b>36.0</b>	49.5	7.7	0.0	0.0
1985	0.0	0.0	0.0	2.8	0.0	109.7	141.3	134.5	26.4	0.0	0.0	0.0
1986	0.0	0.0	0.0	0.0	0.0	34.8	87.4	108.3	98.9	0.0	0.0	0.0
1987	0.0	0.0	0.0	0.0	6.2	20.2	78.2	122.3	2.5	8.7	0.0	0.0
1988	0.0	0.0	0.0	0.0	<b>3.0</b>	92.1	183.8	199.8	31.7	0.0	0.0	0.0
1989	0.0	0.0	0.0	0.0	0.0	51.4	50.5	153.5	78.4	50.6	0.0	0.0

**Geneina Monthly Rainfall in mms for the Period (1970-2010)** 



<b>YEAR</b>	JAN.	FEB.	MAR.	APR.	MAY.	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
1970	0.0	0.0	0.0	0.0	0.0	<b>10.0</b>	143.0	<b>116.0</b>	199.0	41.0	0.0	0.0
1971	0.0	0.0	0.0	0.0	13.0	41.5	67.5	110.5	126.3	9.6	0.0	0.0
1972	0.0	0.0	0.0	0.0	56.4	64.8	86.4	32.6	95.8	11.5	0.0	0.0
1973	0.0	0.0	0.0	15.6	27.0	20.0	194.0	<b>38.0</b>	34.5	33.3	0.0	0.0
1974	0.0	0.0	0.0	0.0	30.0	29.5	175.0	171.0			0.0	0.0
1975	0.0	0.0	0.0	0.0	2.7	61.3	134.4	116.2	98.3	0.0	0.0	0.0
1976	0.0	0.0	0.0	1.6	0.5	40.2	100.0	46.6	75.4	46.4	0.0	0.0
1977	0.0	0.0	0.0	0.0	21.9	66.4	70.8	196.9	9.1	18.2	0.0	0.0
1978	0.0	0.0	0.0	0.0	27.4	50.3	74.6	217.9	33.1	76.3	0.0	0.0
1979	0.0	0.1	0.0	1.6	<b>19.1</b>	50.5	56.2	106.0	58.8	26.0	0.0	0.0
1980	0.0	0.0	0.0	0.0	31.5	106.5	217.0	81.3	97.1	0.0	0.0	0.0
1981	0.0	0.0	8.6	0.0	3.3	42.1	158.3	56.2	29.5	41.0	0.0	0.0
1982	0.0	0.0	0.0	0.0	0.0	45.6	45.5	82.9	89.6	8.8	0.0	0.0
1983	0.0	0.0	0.0	0.0	7.0	77.0	123.7	53.4	75.5	0.0	0.0	0.0
1984	0.0	0.0	0.0	0.0	20.9	0.8	86.4	49.1	38.7	1.4	0.0	0.0
1985	0.0	0.0	<b>11.0</b>	1.6	3.0	14.6	125.3	103.2	88.7	0.0	0.0	0.0
1986	0.0	0.0	0.0	0.0	0.0	16.8	116.1	18.7	46.2	<b>17.0</b>	0.0	0.0
1987	0.0	0.0	0.0	0.0	20.0	<b>15.0</b>	72.3	34.7	93.5	13.0	0.0	0.0
1988	0.0	0.0	0.0	0.0	22.7	49.3	117.0	234.8	69.6	0.0	0.0	0.0
1989	0.0	0.0	0.0	0.0	66.8	106.9	95.8	76.9	51.1	25.2	0.0	0.0

**Nyala Monthly Rainfall in mms for the Period (1970-2010)** 



<b>YEAR</b>	JAN.	FEB.	MAR.	APR.	MAY.	JUN.	JUL.	AUG.	SEP.	OCT.	NOV.	DEC.
1974	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1975	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1976	1.6	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1977	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0	0.0	0.0	0.0
1978	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1979	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.7	0.0	0.0
1980	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1981	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1982	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1983	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1984	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1985	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1986	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1987	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0
1988	0.0	0.0	0.2	0.0	0.0	0.0	0.0	2.5	0.0	0.0	0.0	0.0
1988	0.0	0.0	0.2	0.0	0.0	0.0	0.0	2.5	0.0	0.0	0.0	0.0
1989	0.0	0.0	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1989	0.0	0.0	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1990	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1990	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

**Wadi Halfa Monthly Rainfall in mms for the Period (1974-2010)** 



## **Appendix (2)**



## **Annual Rainfall Data Records (In mm) for 16 stations**



## **Appendix(3)**

**The SPI\_6 , SPI\_9, SPI\_12 and SPI\_24 time series , for Gadaref station** 

Year	<b>Month</b>	SPI-6	SPI-9	<b>SPI-12</b>	<b>SPI-24</b>
1971	7	0.18	-99	-99	-99
1971	8	$-0.15$	-99	-99	-99
1971	9	$-0.31$	-99	-99	-99
1971	10	$-0.47$	$-0.5$	$-99$	-99
1971	11	$-0.45$	$-0.51$	$-99$	-99
1971	12	$\boldsymbol{0}$	$-0.51$	-99	$-99$
1972	$\mathbf{1}$	$-0.69$	$-0.47$	$-0.51$	-99
1972	$\overline{2}$	$-0.7$	$-0.44$	$-0.51$	-99
1972	$\mathbf{3}$	$-0.56$	$\boldsymbol{0}$	$-0.51$	-99
1972	$\overline{\mathbf{4}}$	$-0.35$	$-0.75$	$-0.52$	-99
1972	5	$-0.13$	$-0.77$	$-0.54$	-99
1972	6	0.03	$-0.34$	$-0.07$	-99
1972	$\overline{7}$	$-0.06$	$-0.07$	$-0.67$	-99
1972	8	0.27	0.26	$-0.05$	-99
1972	9	0.29	0.27	0.09	-99
1972	10	0.13	0.09	0.06	-99
1972	11	0.15	0.07	0.06	-99
1972	12	0.15	0.07	0.06	$-99$
1973	$\mathbf{1}$	0.25	0.11	0.07	$-0.37$
1973	$\overline{2}$	$-0.3$	0.15	0.07	$-0.37$
1973	$\mathbf{3}$	$-0.87$	0.15	0.06	$-0.37$
1973	$\overline{\mathbf{4}}$	$-0.5$	0.19	0.06	$-0.39$
1973	5	0.69	$-0.02$	0.25	$-0.25$
1973	6	$-0.71$	$-1.15$	$-0.25$	$-0.27$
1973	$\overline{7}$	$-0.73$	$-0.73$	$-0.35$	$-0.92$
1973	8	$-1.45$	$-1.44$	$-1.45$	$-1.17$
1973	9	$-0.26$	$-0.27$	$-0.47$	$-0.3$
1973	10	$-0.02$	$-0.07$	$-0.1$	$-0.07$
1973	11	$-0.2$	$-0.09$	$-0.1$	$-0.07$
1973	12	0.32	$-0.08$	$-0.1$	$-0.07$
1974	$\mathbf{1}$	0.55	$-0.03$	$-0.09$	$-0.08$
1974	$\overline{2}$	2.29	$-0.2$	$-0.09$	$-0.08$
1974	$\mathbf{3}$	0.86	0.31	$-0.09$	$-0.09$























