TIME SERIES ANALYSIS OF EXTREME HYDROLOGICAL EVENTS FOR ADAPTATION TO CLIMATE VARIABILITY

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DECLARATION AND RECOMMENDATION

DECLARATION

I solemnly declare that, this Thesis is my original work and that it has not been submitted to any other institution known to me for award of any other degree.

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RECOMMENDATION

This thesis has been submitted to Graduate School with our approval as University supervisors.

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DEDICATION

To the victims of hydrological extremes

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ABSTRACT

Climate variability affects the distribution of water resources in many parts of the world. This has been characterized by a disproportionate increase in the intensity and frequency of extreme hydrological events. Climate variability has not only adversely affected water availability but also altered the hydrological regimes of many lake basins. This has led to changes in the temporal and spatial distribution of water resources thereby threatening water and food security. In this regard therefore, adaptation planning to extreme hydrological events due to changing hydrological processes requires critical attention in the water and related sectors. In this study, the trends of extreme hydrological events were investigated within the Lake Naivasha basin. This was to provide a better understanding of the changes in hydrological trends to advance the ability to predict extreme hydrological events. The impact of these hydrological trends will be felt primarily in terms of water supply, thus this study evaluated the critical length and severity of hydrological droughts for planning drought mitigation. In light of the changing trends, frequency models for predicting extreme precipitation and stream flow events were developed. The Mann–Kendall and Spearman's Rank Correlation nonparametric tests were used to detect trends of precipitation and stream flows over a 50-year period from 1959 to 2008. The probability theory-based approach was used to estimate drought parameters. The drought episodes were treated as runs of deficit, and so the theory of runs was a major tool for analysis. Frequency models were developed for each gauging station and design events predicted for 2, 5, 10, 50 and 100-year return periods. The results for precipitation indicated no significant statistical trends at annual scales. The largest number of significant trends in extreme precipitation was identified during the month of April. Stream flow trends indicated significant increases in annual maxima at all gauging stations. Results from the probability theory-based approach indicate that, in the Lake Naivasha basin, a 100, 50, 10, 5 and 2-year droughts may persist continuously for 6, 4, 3, 2 and 1 years respectively. The Extreme Value Type I and Log Pearson Type 3 distribution models prediction results revealed that the predicted design storms increased as the returns periods increased from 2-year to 100-year. The results obtained in this study are useful for climate variability adaptation planning and management in different sectors in this region especially water supply, hydropower generation and agriculture.

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ACRONYMS AND ABBREVIATIONS

AM	Annual Maxima
CEI	Climate Extreme Index
D.O	District Officer
EVT	Extreme Value Theory
F.S	Forest Station
FAO	Food and Agricultural Organization
GEV	Generalized Extreme Value
GPD	Generalized Pareto Distribution
IPCC	Inter governmental Panel on Climate Change
KARI	Kenya Agricultural Research Institute
KS	Kolmogorov–Smirnov
LP3	Log Pearson Type III Distribution
MH	Mission Hospital
MK	Man Kendall
Nvs	Naivasha
POT	Peaks Over Threshold
PPCC	Probability Plot Correlation Coefficient
QMED	Median Annual Maximum Flow
RGS	River Gauging Station
Sch.	Scheme
SRC	Spearman's Rank Correllation
TAR	Third Assessment Report
WHO	World Health Organization
FAO	Food Agricultural Organization
UN	United Nation
SCAQMD	South Coast Air Quality Management District
DEFRA	Department for Environmental, Food and Rural Affairs
NCCRS	National Climate Change Response Strategy

LIST OF SYMBOLS

μ	Mean
C_k	kurtosis
C_s	skewness
C_v	coefficient of variation
km^2	Square Kilometre
m^3	Cubic metre
q	Probability
T	Return period
Z	Test statistic
α	Confidence level
ρ	Serial Correlation
σ	Standard deviation
$E(D_T)$	Actual drought severity
$E(L_T)$	Drought length in years
$E(S_T)$	Drought severity
I	Drought Intensity

CHAPTER ONE
INTRODUCTION

1.1 Background

Variability of hydrological regimes has far reaching impacts especially in developing countries such as Kenya. It has been aggravated by climate change and has had implications on water resources and food security and therefore requires new management strategies. This variability has brought about uncertainties in water resources management due to changes in intensity, frequency and persistence of occurrence of extreme hydrological events. In this regard therefore, adaptation to extreme hydrological events due to climate variability requires critical attention in the water and related sectors.

Changes in quantity and quality of water due to hydrological variability have led to food insecurity and increased vulnerability of poor rural farmers, especially in the arid and semi-arid regions. Fluctuations of hydrological variables have affected the function and operation of existing water resources management practices. Adverse effects of hydrological variability have aggravated the impacts of other stresses, such as population growth, changing economic activities, land-use change and urbanization (Mogaka *et al.*, 2006). The current water management practices need to be made dynamic so as to cope with the changes in hydrological variability which has a direct impact on water resources and its reliability. Hence the characteristics of extreme hydrological events need to be studied so as to apply the appropriate adaptation and mitigation measures.

Kenya is below the international water scarcity threshold of 1000 m^3 per capita with only 635 m^3 available per person per year (FAO 2007). This is likely to have gone down because population growth is forecasted to reduce the per capita fresh water availability to 235 m^3 by the year 2025 (UN-Water 2006). These figures fall below the 1000 m^3 global bench mark as recommended by the World Health Organization (WHO). This makes Kenya a water scarce country and the falling trend in fresh water availability can be attributed to factors such as climate change and variability, population growth and environmental degradation (WHO, 2006). To minimize the adverse effect brought about by these factors, it is therefore important to put in place water resources management measures to circumvent the variability of extreme hydrological events.

Lake Naivasha basin is a closed basin experiencing diverse climatic conditions ranging from semi-arid to humid. The water resources in this basin are under intensive use. For instance, 75% of Kenya's horticultural exports come from the flower industries established around this lake (Sharmo, 2002). The flower industries consume an approximately 60 million cubic metres (MCM) of water annually (Becht and Harper, 2002).

Lake Naivasha is a wetland of national and international importance. However, it is under constant anthropogenic pressure. This includes the quest for socioeconomic development within the lake ecosystem as well as other activities within the lake basin (Becht and Harper, 2002). The lake is an important source of fresh water in an otherwise water-deficient zone. It supports fishery, an extensive flower-growing industry and geothermal power generation. The adjacent area is ideal for horticulture, which plays a crucial role in the development of both the local and national Kenyan economy, providing employment to more than 30,000 people (Otiang'a and Oswe, 2007). However, the lake and its surrounding areas are fragile ecosystems that are facing increasing threats from irrigated agriculture, water abstraction, the fast-growing Naivasha Township, and human population growth throughout the basin (Olaka *et al.*, 2010).

Adaptation planning to climate variability and change is the use of information about present and future climate variability to review the suitability of current and planned practices, policies, and infrastructure (Schepp, 2009). It addresses questions such as; how will future climatic and non-climatic conditions differ from those of the past and do the expected changes affect current systems. It also involves making recommendations about action to be undertaken to reduce the risks and capitalize on the opportunities associated with climate change. Adaptation planning for hydrological events variability depends on understanding of their intensity, frequency and persistence (Sharma, 1997b). For instance, extreme drought events require management practices which will retain adequate water in the catchment during the rainy season and thereafter (Onyando *et al.*, 2004). Hence, to be able to adapt to future changes of extreme hydrological events due to climate variability, the trend of their temporal and spatial variability needs to be determined.

1.2 Statement of the problem

It is still not conclusive about how hydro-meteorological events have changed in different regions over the world particularly in Africa and specifically in Kenya. Although a lot of studies have been undertaken in the Lake Naivasha basin, little research have been undertaken to evaluate the changes in extreme meteorological and hydrological events.

The major effect of hydrological variability on the Lake Naivasha basin has been through changes in rainfall and stream flow processes (Olaka *et al.*, 2010). These factors are the controlling parameters of the Lake Naivasha basin water availability, consumption and demand. The water consumption and demand in this basin have increased in the past years (Bercht and Harper, 2002). This is associated with increase in population and developments in irrigation and industrial processes (Otiang'a and Oswe, 2007). Changing trends of rainfall and stream flow regimes have further affected availability of water resources in this basin. Thus, an understanding of spatial and temporal trends of hydrological variables is fundamental to a wide range of adaptation mechanisms in coping with climate change and variability.

1.3 Main objective

The main objective of this study was to analyze hydrological extreme events trends with a view to providing information for planning local coping mechanisms to climate variability.

1.3.1 Specific objectives

i. To identify trends in intensity, frequency and persistence of extreme precipitation and stream flow events.
ii. To evaluate extreme drought severity based on drought duration and intensity.
iii. To predict extreme precipitation and stream flow events for adaptation planning.

1.3.2 Research questions

i. Have the intensity, frequency and persistence of extreme precipitation and flow events changed over the last 50 years within the Lake Naivasha basin?
ii. What is the extent in the severity of extreme hydrological drought based on duration and intensity?
iii. What are the predicted return periods of precipitation and stream flow extreme events under the changing trends?

1.4 Justification

Extreme hydrological events are among the most serious threats to sustainable development at all levels. Studies have shown that about 90% of all natural disasters afflicting the world are related to severe weather and extreme climatic events (NCCRS, 2009). The economy of Lake Naivasha basin, which is the study area in this research, depends heavily on the availability of water resources. Rain-fed and irrigated agriculture in the basin contributes to 75% of Kenya's horticultural export (Sharmo, 2002). Even though Lake Naivasha basin receives high average annual rainfall, highly seasonal and spatial variability of rainfall and stream flows create periodic shortages of water for agricultural, industrial and domestic use (Muthuwatta, 2004). Therefore, proper knowledge of variations in hydrological regimes and their future trends and scenarios is essential for proper water management practices. Thus, understanding the existence of reliable hydrological trends which can be used to predict extreme hydrological events in the study area is of importance in planning water resources.

CHAPTER TWO

LITERATURE REVIEW

2.1 Hydrological trend analysis

Trend analysis is the method used for evaluation of the characteristics of hydrological variables such as intensity, frequency and persistence. These variables are averaged out in statistical measures, either greater than or of a specific magnitude within a certain area, that will occur within a certain period (Helsel and Hirsh, 2002). In the design, planning and management of hydrology and water resources, it is important to estimate the hydrological characteristics through trend analysis. This helps to provide a scientific base for trends in hydrological regimes. Where hydrological data exists, a variety of trend analysis methods can be used to analyze hydrological characteristics and detect any trends in the data.

The existence of a trend in a hydrological time series can be detected using appropriate statistical tests. Statistical procedures are used for the detection of the gradual trends over time. The purpose of trend testing is to determine if the values of a random variable generally increase or decrease over some period of time in statistical terms. The power of a test is the probability that it will reject a null hypothesis when it is false. The trend analysis of hydrological time series is of practical importance especially when assessing the effects of global climate change.

With global warming, the occurrence of extreme meteorological and hydrological events has been changing. This is as a result of variations in temperatures influencing the speed of the water cycle process. This in turn has resulted to changes in precipitation amount and intensity in some parts of the globe. Many outputs from Global Climate Models (GCM's) indicate substantial increases in the frequency and magnitude of extreme daily precipitation (McGuffie *et al.,* 1999).

For instance, Karl *et al.* (1995) found that the contribution to total annual precipitation of 1- day precipitation events exceeding 50.8mm increased from 9% in the year 1910 to 11% in the year 1990 in the United States. In addition, Karl and Knight (1998) found that the 8% increase in precipitation across the United States since the year 1910 was reflected primarily in heavy and extreme precipitation events. The results by Kunkel *et al.* (1999) confirmed that the national trend in short duration (1- 7 day) extreme precipitation events for the United States was upward at a rate of 3% per decade for the period 1931 to 1996.

In Australia, much of the country has experienced increases in heavy precipitation events, except in Southwestern part where there has been a decrease in both the number of rainy days and heavy precipitation events (Haylock and Nicholls, 2000). In the United Kingdom, increase in heavy wintertime precipitation events and decreases in heavy summertime precipitation events have been experienced (Osborn *et al.*, 2000). The study by Moberg *et al.* (2006) showed that, winter precipitation totals, averaged over 121 European stations north of 40^0 N, have increased significantly by 12% per 100 years, and trends in 90^{th}, 95^{th} and 98^{th} percentiles of daily winter precipitation have been similar.

New *et al.* (2001) showed that, on the basis of gridded observed monthly data, global land precipitation has increased by about 9mm over the twentieth century. Data from a number of countries provide evidence of increased intensity of daily precipitation. This has generally been manifested by increased frequency of wet days as well as increased proportion of total precipitation occurring during the heaviest events. For instance, Roy and Balling (2004) found out that, in general, there has been an increase in the frequency of extreme precipitation events in India over the period 1910 to 2000.

According to the observed data over half of the land area of the globe, there has been a wide spread increase in the frequency of heavy precipitation in the mid-latitudes during the past 50 to 100 years (Groisman *et al.*, 2005). The results of Zhai *et al.* (2005) indicated that, while there is little trend in total precipitation for China as a whole, significant increases in extreme precipitation have been found in Western China, the mid-lower reaches of the Yangtze River, and parts of the Southwestern and Southern China coastal areas.

While increased intensity of heavy rainfall is observed in many areas, no significant increase is observed in quite a number of other areas. For instance, Nicholls *et al.* (2000) calculated various indices for monitoring variations in Australian climate extremes, and showed that, most of the trends in the various indices of climate extremes investigated were relatively weak and with no statistical significance. No clear trend has emerged in the percentage of Australia extreme rainfall conditions since 1910.

Zhang *et al.* (2001) showed that there has been no long term trend in the frequency or intensity of extreme precipitation events in Canada during the 20^{th} century. Likewise, Koning and Franses (2005) showed that no statistically significant shift is found in the annual largest values of daily rainfall in the Netherlands over the course of a century. Su *et al.* (2006) analyzed the observed extreme temperature and precipitation trends over Yangtze River basin in China from 1960 to 2002. On the basis of daily data from 108 meteorological stations, the authors found no statistically significant change in rainfall intensity from a basin-wide point of view.

New *et al.* (2006), in their study of trends in daily extremes over mainly Southern Africa for the period 1961 to 2000, concluded that there are few consistent and statistically significant trends in the precipitation indices that were calculated. While evidences of increasing trends are presented for many regions, statistically significant decreasing trends in extreme rainfall events have also been found in some areas, including the Sahel region of Nigeria (Tarhule and Woo, 1998). In this regard therefore, the spatial and temporal pattern of changes in precipitation is complex and varies over the world. As revealed from the literature review above, it is clear that extreme precipitation events trends vary from region to region and from season to season.

In the context of significant global changes, whether or not the stream flow processes are mainly driven by meteorological processes and possibly more extreme weather may result in higher flood and drought risks. Some results show increases in extreme stream flow events. For instance, when investigating the relationship between changes in the probability of heavy precipitation and high stream flows over the United States, Groisman *et al.* (2001) showed that the variations of high and very high stream flow and heavy and very heavy precipitation are similar. The results by Zhang *et al.* (2005b) after evaluating the relations between the temperature, the precipitation and the stream flow during 1950 to 2003 of the Yangtze River basin, suggested that the present global warming will intensify the flood hazards in the basin. At the same time, other studies show no significant change in extreme flood events. For instance, Mudelsee *et al.* (2003) found no upward trends in the occurrence of extreme floods in Central Europe. Without any clear trends in stream flow studies, it's necessary to determine extreme stream flow trends in different regions so as to cope with the resulting variability of these trends.

In Western Kenya, trend analysis of rainfall showed that, on average, the annual rainfall has increased by 2.3 mm/year between 1962 and 2001 (Githui, 2008). Out of a total of 14 stations, four have shown significant trends at 1% significance level. Of particular interest with respect to the above is that, out of ten rainfall stations that showed an increasing trend, eight were found in the highlands. It is not however clear whether or not the observed trends are attributed to climatic factors.

Although a lot of studies have been undertaken on detecting the changes in extreme meteorological and hydrological events, it is still not conclusive about how hydro-meteorological events have changed in different regions over the world. Particularly in Africa and specifically in Kenya, very little research has been undertaken to evaluate the changes in extreme hydrological events. This is because the changes in climate vary significantly over different regions, and the link between excessive precipitation and hydrological flooding is affected by several factors. These include antecedent precipitation amount and the intensity, duration and spatial pattern of precipitation events, human activities such as land use change and dam construction, basin characteristics such as the size, topography, control structures, and drainage network of the basin. These factors vary from event to event, from season to season, and from region to region. Hence, there is need to have more research on how hydrological extremes have changed over different regions so as to have a comprehensive view of changes in water cycle at local, regional and global levels.

2.2 Climate change and variability

Climate change refers to a change in the state of the climate that can be identified by changes in the mean and/or the variability of its properties and that persists for an extended period, typically a decade or more (IPCC, 2007). Climate Variability encompasses the natural variation in the climate that would occur even in the absence of any underlying long-term change (IPCC 2001b). Climate variations result from radioactive forcing, but also from internal interactions between components of the climate system (IPCC, 2001b). Some external influences, such as changes in solar radiation and volcanism occur naturally and contribute to the natural variability of the climate system. According to Shaka (2008), other external changes, such as the change in the composition of the atmosphere that began with the industrial revolution, are the result of human activities.

Climate is a key factor that determines different characteristics and distribution of water resources (IPCC, 2007). Changes in climate average through changes in frequency and intensity of hydrological events will have a major impact on water resources (Aerts and Droogers, 2004). Climate variability affects the quantity and quality of the water resources with respect to both mean states and variability. Water use is impacted by climate variability, and also by food demand which drives irrigated agriculture, which has become, globally as the largest water-use sector. Therefore any significant variations in climate affecting water use or the hydrological cycle requires adaptation in the management of the water resources.

There are several indicators of climate variability and change which include annual temperatures, sea level rise, precipitation changes, stream flows and run-off among others. Temperature is the most frequently used indicator of climate variability and change. It can be used to analyze any regions climate variability and change over the past with long term instrumental record of average temperature (Smith, *et al.*, 2003). Global surface temperature reflects the interaction of several aspects of Earth's climate system. These include the amount of incoming sunlight, volcanic eruptions, land use changes and the concentration of greenhouse gases and other pollutants (Vliet *et al.*, 2002). On regional scale, the average temperature is affected by the same global influences but also local aspects of the climate system. These include the location of weather station, storm tracks, topography and changing ocean currents and sea surface temperature. Mean temperature including daily maximum and minimum temperatures and the seasonal cycle in temperature over relatively large spatial areas indicate the clearest signals of change in the observed climate (IPCC, 2001b). However, in this study temperature was not considered due to lack of good quality data for use in the study area.

Mean sea level is the height of the sea with respect to a local land benchmark averaged over a period of time, long enough that fluctuations caused by waves or tides are largely removed. Many coastal regions are already experiencing the effects of relative sea level rise (Rosenweig *et al.*, 2007). From a study by Bindoff *et al.* (2007), sea level has been rising at a rate of about 1.7 to 1.8 mm/year over the last century, with an increase rate of about 3mm/year during the last decade. According to a study by Woodworth and Blackman (2004) rising sea level potentially affects coastal regions hence it could not have been applied in Lake Naivasha basin.

An increase in global surface temperature will lead to changes in precipitation and atmospheric moisture, due to changes in atmospheric circulation, a more active hydrologic cycle, and increase in the water holding capacity through out the atmosphere (Held *et al.*, 2002). Water vapour in the atmosphere is also a climatically critical greenhouse gas (IPCC 2001b). Thus rainfall can be used as an indicator of observed climate change. Over the past century there has been a 2% increase in global precipitation, but that change was not spatially or temporally uniform (IPCC 2001b). Rainfall exhibits notable spatial and temporal variability (Hulmet *et al.*, 2005). Inter-annual rainfall variability is large over most of Africa and, for some regions multi-decadal variability is also substantial. Schreck *et al.* (2004) in his study found that during recent decades, Eastern Africa has been experiencing an intensifying dipole rainfall pattern on the decadal time scale. This was attributed to climate variability and change thus signifying rainfall can be used as an indicator of climate variability and change hence its use in this study.

Many studies have examined potential trends in measures of stream flow to detect climate variability and change. Labat *et al.* (2004) detected significant trends in some indicators of flow and demonstrated statistically significant links with trends in temperature and precipitation. At global scale, there is evidence of a broadly coherent pattern of change in annual run-off (Milly *et al.*, 2005). Variations in flow from year to year are also influenced in many parts of the world by large scale climatic patterns (Labat *et al.*, 2004). However, the methodology used to search for trends can influence the results. For instance, different statistical tests can give different indications of significance, and different periods of records can suggest different rates of change. Another limitation of stream flow analysis is the availability of consistent, quality controlled data. Available stream flow gauge records cover only about two thirds of the global actively drained land area and often contain gaps and vary in records (Dai *et al.*, 2002). But due to the interest of the international community in Lake Naivasha, adequate stream flow data was available for analysis hence it was chosen as one of the variable for analysis.

In Kenya, impacts of hydrological regimes variations were well manifested in the 2000/2001 La-Nina related severe and prolonged drought. Extreme rainfall impacts were also well manifested in the 1997/1998 El-Nino related severe floods as well as those that occurred in April-May 2003. Kenya is vulnerable to hydrological variability, due to its dependence on rainfall for its socio-economic development (Mogaka *et al.*, 2006). For instance, during floods, crops are destroyed, land degradation with increased soil erosion occurs, dams are washed away or filled up with silt and people are displaced. The result is loss of property, human lives and livestock.

Kenya's per capita water availability is very low and the situation is likely to get worse due to climate change among other factors. It is predicted that aggregate water demand will rise by 2025 (WHO, 2006). Thus, there is need to invest adequately in water resources management, especially due to high hydrological variability and in light of the changing climate.

2.3 Adaptation to climate variability and change

Adaptation to climate change refers to adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities (Adger *et al.*, 2007). The array of potential adaptive responses available is large, ranging from purely technological, through behavioral, to managerial and policy. While most technologies and strategies are known and developed in Kenya, their capacity to fully reduce the risks has been ineffective, particularly due to higher levels of hydrological variability and related impacts.

Adaptation planning for hydrological regimes variability depends on their intensity, frequency and persistence (Sharma, 1997a). For instance, extreme drought events require management practices which will retain the little water into the catchment during the rain season and there after (Onyando *et al.*, 2004). Hence, to be able to adapt to future changes of extreme hydrological events due to climatic variability, the trend of their temporal and spatial variability needs to be determined.

The water sector has been designed bearing in mind the variability in hydrology (Mogaka *et al.*, 2006). Consequently, numerous examples of adaptation to hydrologic variability and extreme events exist in the water sector (IPCC, 2007). Implementing these good practices more widely (e.g., efficient irrigation technologies, water harvesting, increased sub-surface, etc) would go a long way in confronting the climate change challenge. Adapting to climate change needs to be built on convectional interventions and requires a major shift in planning and designing water investments. New approaches in technology, management, as well as the development of flexible systems that can anticipate and react to changing hydrological regimes must be identified. New design standards and criteria will also need to be developed for changed hydrologic regimes. In all countries, social and physical adaptive measures will need to be developed. These will protect the most vulnerable populations and ecosystems from the effects of extreme weather associated with climate change.

2.4 Extreme hydro-meteorological indices

Considerable efforts have been put on defining indices for evaluating changes in extreme hydrological events. For instance, Karl *et al.* (1995) proposed a Climate Extreme Index (CEI) based on an aggregate of conventional climate indicators which include the following types of data; Annual maximum and minimum of daily precipitation, Monthly maximum and minimum temperatures, Annual maximum and minimum daily stream flows, monthly Palmer Drought Severity Index (PDSI), Land falling tropical storm and hurricane wind velocity.

The analysis of extreme events can be conducted with the annual maximum (AM) approach, or the peaks-over-threshold (POT) approach, also called partial duration series approach (PDS) (Lang *et al.*, 1999). An AM sample is constructed by extracting from a series of records the maximum value of each year, i.e. only one event per year is retained. Both the AM and POT approaches are adopted in the present study for analyzing extreme precipitation and stream flow events. In the persistence analysis, the n-day maxima precipitation is used. The 3-day, 7-day and 10-day index was chosen because previous studies have shown that, 3-day maxima and above are less sensitive to measurement errors (Chen *et al.*, 2006).

2.5 Trend analysis methods

An important task in hydrologic modeling is to determine if any trend exists in a time series data. This is not only for the purpose of modeling but also for detecting possible links between hydrologic process and environmental changes (Burn and Elnur, 2002). Many methods are available for detecting trends. The Non-parametric trend detection methods, defined as methods which use the ranks of the data values rather than the actual data values are less sensitive to extremes than parametric methods which apply the actual data values of the variables (Kundzewicz *et al.*, 2005).

Hydrological extremes are not usually fitted well by a Gaussian model (DEFRA, 2001b) and often contain a number of outliers. In this case therefore, it is sensible to use a robust non-parametric method that does not assume normality. As the median and distribution tail-ends play a vital role in analyzing time series data, the use of non-parametric methods is largely justified for trend analysis (Sneyers, 1990). Therefore, before a trend detection test can be performed, the data in question need to be tested to assess population characteristics to ensure the correct methods are instigated. In addition, non-parametric tests can test for a trend in a time series without specifying whether the trend is linear or non linear. Hence, the adoption of non-parametric trend tests methods in this study. Some of the commonly used methods in trend analysis are reviewed below.

2.5.1 Simple linear regression

It is one of the simple parametric methods of trend detection and estimation (SCAQMD, 1991). In this method, the expected annual summary statistic is assumed to be linear for the year in question. This statistical model is usually fitted by least squares, which is defined as finding a straight line such that the squared errors about that line are minimized. However, this method has some limitations in that, the method is most appropriate when the annual summary statistic is normally distributed with a constant variance and the assumption of linearity.

2.5.2 General linear regression

This method uses the set of annual summary statistics from a single site and fits a linear trend using simple linear regression. To estimate polynomial or other trend curves at a single site, other terms are used in the linear regression model. For instance, instead of expressing the annual mean as a straight line function of the calendar year, higher powers of the calendar year can be added to the regression equation and hence a quadratic or higher order polynomial trend curve can be estimated. Since this method only uses the annual summary statistics, it is not a very powerful method for detecting the trend at a single site. This is because there is a high probability that the slope or trend curve will not be found to be significantly different from the case of no trend.

2.5.3 Kolmogorov–Smirnov Test

The Kolmogorov–Smirnov (KS) test is one of the most useful non-parametric methods for comparing two samples to determine whether they follow the same distribution. It is a distribution-free test, which is based on looking at the maximum vertical distance between the empirical distribution functions of the two samples. The KS test is designed to detect a shift in the whole distribution of the first sample relative to the distribution of the second sample. The KS test tends to be more sensitive near the center of the distribution than at the tails (Filliben and Heckert, 2006), whereas when detecting changes in hydrologic regimes, the interest is in the variance and the tails of the data, because the variance difference and tail size may indicate the difference of the occurrence of extreme events.

2.5.4 Quantile test

The quantile test is a several-block test to detect a change in a time series (Johnson *et al.*, 1987). In detecting the trends in hydrologic regimes, detecting the difference between several distributions where only a portion of the distribution of the first group is shifted relative to the distribution of the second group is of paramount importance. Under the null hypothesis, the distribution of the first group and the second group are the same. The alternative hypothesis is that the distribution of the first group is partially shifted to the right of the distribution of the second group. This test combines observations, ranks them and computes the number of observations from first group out of the largest observations. The test rejects the null hypothesis if the number of observations from the first group is too large.

2.5.5 Spearman's Rank Correlation method

It is a non-parametric trend test which is less affected by the presence of extremes and non-normalities in the series (Lopez *et al.*, 2009). In this method, both sets of data are converted to ranks before calculating the coefficient. The rank is 1 for the highest summary statistic, 2 for the second highest, and so on. If there is no trend and all observations are independent, then all rank orderings are equally likely. This fact is used to calculate the statistical significance of the Spearman's rho statistic. A value significantly different from zero implies a significant trend. If ties in the annual statistics are present, then the significance level has to be adjusted to account for the number of ties. This method was used in this study because it works for non-normalities involving seasonality, missing values, censoring or unusual data reports and it has a high asymptotic efficiency (Fu *et al.*, 2004).

2.5.6 Mann-Kendall's trend test method

This non-parametric trend test method is employed to detect trends of precipitation and stream flow over a period. The test is based on the fact that, under hypothesis of a stable climate, the succession of climatological values must be independent and the probability distribution must remain always the same. It was first adopted by Hirch *et al.* (1999) from the Mann-Kendall's test (Kendall, 1975). Likewise, Gan (2004) used this method to analyze the hydro climatic trends over West-central Brazil. The efficiency of this test has been demonstrated using a Monte Carlo technique by Goosens and Berger (1987).

This method was adopted in this study because it works for non-normalities involving seasonality, missing values, censoring or unusual data reports and because of its high asymptotic efficiency (Fu *et al.*, 2004). It can also be applied on both annual and monthly basis.

2.6 Droughts

Drought results from less than normal precipitation for an extended period of time. The effects of drought in many activities depend on the severity, duration and geographical extent of precipitation deficiency. It also depend on whether precipitation is used directly (for example, to maintain soil moisture), or whether water supplies are drawn from stream flows.

Five types of drought have been defined by the World Meteorological Organization (Subrahmanyan, 1967).

Meteorological drought defined is only in terms of precipitation deficiencies in absolute amount, for specific durations. Climatologic drought is defined in terms of precipitation deficiencies, not in specific quantities but as a ratio to mean or normal values. Atmospheric drought, involves not only precipitation deficiencies but also temperature, humidity or wind speed. Agricultural drought principally involves the soil moisture and plant behavior, perhaps for a specific crop. Hydrological drought is defined in terms of reduction of stream flows, reduction in lake or reservoir storage, and lowering of ground water levels below a predefined threshold level. Such a threshold level has been termed the truncation level in hydrological droughts. This truncation level reflects the demand level for water hence the reason for the study of this type of drought in this research work.

The choice of truncation level is largely governed by the purpose of investigation (Panu and Sharma, 2002). Several studies have considered it as long term mean flow (Dracup *et al.,* 1980; Sen, 1980; Sharma, 1997b), while others took it as a percentile level of the flow duration curve ranging from Q_{50} (flows exceeding 50% of the time) to Q_{95} (Hisdal *et al.,* 2001; Hisdal and Tallaksen, 2003). A flow duration curve could be constructed based on annual, monthly or daily flow sequences. For example, when the interest is in the design and planning of water resources systems, on a permanent or long-term basis, for ameliorating drought, then a truncation level corresponding to the mean level of flow could result in a conservative design to produce a desirable drought mitigation scenario. In contrast, in regional drought frequency analysis, a value of truncation level such as Q_{70} or Q_{80} would portray more tangible drought impacts over the region (Panu and Sharma, 2002). However, in short-term contingency planning for drought amelioration, when drought impacts are vividly tangible, drought investigation could even be carried out at a truncation level of Q_{90}, to allow mobilization of resources on a cost- effective basis.

There are two dominant approaches for predicting the duration and severity of droughts associated with return period. In the time series simulation approach, the simulated stream flow is truncated at the desired level. The drought episodes (runs of deficits) are analyzed empirically using the theory of runs or through counting technique (Frick *et al.,* 1990; Chung and Salas, 2000). Horn (1989) successfully used this approach to describe the behaviour of droughts in Idaho, USA. In the probability theory-based approach, the properties of a drought, i.e. length (duration) and depth (severity) are derived from basic axioms of probability which enable estimates of length of the longest run and associated greatest severity for a desired return period (Sen, 1980; Guven, 1983; Sharma, 1997, 2000). This approach requires information on the underlying probability distribution of the stream flow series. This method was adopted in this study because it can be computed using the drought probability (q) and return period (T).

2.7 Methods of predicting extreme events

There are several approaches to simulate the frequency of extreme events, namely (i) parametric, (ii) non-parametric (iii) stochastic methods (iv) Extreme Value theory.

The parametric method is based upon fitting some particular distribution to a set of observed or simulated returns. This method is well known in climatology as a percentile method or as a return period approach (Jones and Reid, 2001). However, the approach has some drawbacks. For instance, the return period data distributions derived using this approach is not representative for tail estimation. These distributions of extreme returns are far from being asymptotic.

An historical or non-parametric approach addresses evaluation of appropriate return period histograms. A quantile approach (Karl and Knight, 1998; Jones and Reid, 2001; Rusticucci and Vargas, 2002) could be an example of historical method in the climatological studies. Non-parametric approach does not take into consideration events beyond sample range nor does it indicate the tail form. Thus, it is very difficult to estimate extreme quantiles following this method.

Stochastic methods (Monte Carlo) generate repeated situations that simulate returns based on random traction from some stochastic projections. These approaches assume normality and thus do not accommodate observed fat tails in the return data. The Monte Carlo techniques could be successfully carried out for data that is already simulated from Extreme Value (EV) distribution (Palutikof at el., 1999). Stochastic simulations of some extreme variables give an indication of climate conditions to be changed to non-stationary (Burlando and Rosso, 2002) thus demanding consideration of the conditional return distribution.

The Extreme Value Theory (EVT) approach is designed specifically for tail estimation, for recognition and modeling distributions in addition to dealing with non-stationary distribution. The EVT can be used to estimate extreme quantiles for a short record of data. McNeil (1998) considers EVT to be the best approach to measure the uncertainty inherent to the problem. The IPCC Workshop on Changes in Extreme Weather and Climate

Events (IPCC, 2002) pointed out gaps in extreme weather and climate events investigations. It recommended an EVT like a tail modeling approach, which has many potential advantages over other existing approaches. For example, descriptive indices of the extremes such as percentiles, growing season length and wet/dry day duration were addressed at this workshop as measures that do not fully summarize all the important attributes of extremes. The EVT operates with all attributes of extremes including frequency, intensity and persistence. This led to adoption of this method in this study.

2.8 Types of extreme value theory

The Extreme Value Theory exists in conventional, modern and intermediate forms. The conventional form is produced as a result of scientific investigations based on the three type's theorem (Fisher and Tippett, 1928; Gumbel, 1958). These authors's stated and justified that under certain conditions, the distribution of the standardized maxima/minima converges to the three limiting distributions, namely; Gumbel, Frechet and Weibull as the size of the series increases. A standard combination of these three basic families is called the Generalized Extreme Value (GEV) distribution. This technique is often referred to as the method based on limit theorems for block maxima or as the annual maximum method of return time estimation or as the annual maxima.

The modern form of the EVT is known as threshold form, and is based on the Generalized Pareto Distribution (GPD) which is the analogue of the GEV distribution for annual maxima. The GPD has proven to be more flexible than annual maximum methods (Smith, 2001). It can deal with asymmetries in the tails (McNail and Frey, 2000). The intermediate form is based on the r-largest order statistics method. The appropriate joint distribution is fitted to the r largest values in each year (r equals 1 is classical GEV method).

The IPCC Workshop on Changes in Extreme Weather and Climate Events in 2002 stated that application of Peaks Over Threshold (POT) technique is more recommended than the annual maxima method. Katz *et al.* (2002) considered POT approaches to supply more accurate estimates of the parameters and quantiles of the extremes under the condition of obtaining additional information about the extreme tails. The POT method could be suggested for climate extreme scenarios construction attempting to model current and future meteorological extremes, to derive a natural model to estimate first and second order return distribution parameters (Danielsson *et al.*, 2001).

Annual Maxima method was applied in this study because of the challenge of choosing the threshold in the other two methods. Choice of the threshold is basically a compromise between choosing a sufficiently high threshold so that the asymptotic theorem can be considered to be essentially exact and choosing a sufficiently low threshold so that we have sufficient data for estimation of the parameters.

2.9 Methods of fitting extreme value distribution

There are several methods used to evaluate parameters of the applied distribution in order to estimate how well a model fits the data. The most often used techniques are: Maximum Likelihood (ML), Bayesian, L-moments and graphical. A choice of the parameter estimation technique depends on the EVT form applied for the investigation.

For instance, the application of the Poisson-GPD model demands the use of the ML or Bayesian methods for meteorological and hydrological studies (El-Jabi *et al.*, 1998; Smith, 2001). It supplies more information about the presence of a heavy tail than used with block maxima model (Katz *et al.*, 2002). Smith (2001) advocates ML and Bayessian methods for the series of data generated by GCMs and RCMs. The ML method is recommended for application to provide estimations of conditional volatility (McNeil, 2000) and could be used in the presence of covariates (Katz *et al.*, 2002).

Graphical techniques include examination of the quantile-quantile (Q-Q) plot or probability plot correlation coefficient (PPCC). Booij (2002) referred to PPCC method as a simple and powerful method. The Q-Q method is widely used to explore data and to carry on fitness tests.

The L-moment theory offers a parameter estimation tool used in recent environmental sciences and preferably applied when dealing with small sample sizes (Kharin and Zwiers, 2000). The L-moments technique is recommended for parameter estimation along with utilization of the block maxima method (Kysely, 2002). For instance, Clarke (1973) used this method to fit daily mean discharge for 28 year period to two-parameter gamma distribution from Brenig basin. This author found that, the L-moments method is more accurate than the maximum likelihood method in fitting the distribution. Hence the method of moments which is almost as good as the L-moment for Gumbel distribution was chosen for estimation of the parameters of EVI model.

2.10 Data quality analysis

Hydrology is highly data dependent and requires good spatial and temporal data of the basin. The data must portray a good representation of the entire basin. The quality of the observed data is a vital factor, although the requirements are dependent on the purpose of the data and the method of analysis employed. In order to analyze the data quality, a number of quality tests can be done. Some of these tests include the parametric and non parametric tests.

Trends in time series data can be identified using either parametric or non parametric tests. Parametric tests depend on fitting a model to the empirical distribution of a given variable. When the distribution is unknown, or is likely to be fitted best by a non-Gaussian model, non-parametric statistical methods are useful and in many cases advisable (Rodrigo *et al.*, 1999).

Hydrological extremes are not usually fitted well by a Gaussian model (DEFRA, 2001b) and often contain a number of outliers. In this case therefore, it is sensible to use a robust non-parametric method that does not assume normality. As the median and distribution tail-ends play a vital role in analyzing time series data, the use of non-parametric methods is largely justified for trend analysis (Sneyers, 1990). Therefore, before a trend detection test is performed, the data in question need to be tested to assess population characteristics to ensure the correct methods are instigated. The following are some of the data quality analysis which was carried in this study to assess population characteristics of the data.

2.10.1 Homogeneity and consistency tests

The quality and reliability of the data obtained from the meteorological stations depend on many factors. Precipitation and stream flow gauging stations are influenced by the location of the station, the tool and method used and the observation quality and the time series might gain inhomogeneous structure. For this reason, the reliability and quality of the data to be used in the modeling of hydrology and water resources processes should be tested statistically. It can be stated that the natural structure of the observation values is not deteriorated when the precipitation time series have a homogenous structure. The studies in literature show that many methods are proposed for testing homogeneity and applied for various places. The methods for testing the homogeneity of the time series may be classified in two groups as absolute method and relative method (Karabork *et al.*, 2007).

In the first method, the test is applied for each station individually. Alternatively, in the second method, neighboring (reference) stations are also used for the testing process (Wijngaard *et al.*, 2003). But it is very difficult to find reference stations with a high correlation and a homogeneous structure in the studies covering very wide regions (Tayanç *et al.*, 1998). For this reason, in this study in which the precipitation and stream flow gauging stations throughout the Lake Naivasha basin covering a broad area were used and with missing observation records, the first test was used for homogeneity test. In this study, Pettitt tests was used for the determination of the inhomogeneous precipitation and stream flow series for the annual mean values of the stations making observations.

Standard Normal Homogeneity Test (SNHT) was proposed by Alexanderson (1986) to determine the inhomogeneous structure in the time series. The SNHT detects the inhomogeneous structures at the beginning and/or towards the end of the series. Detailed knowledge about the mathematical structure of the SNHT method can be seen in the studies of Alexanderson (1986), Alexandersson and Moberg (1997) and Gonzalez-Rouco et al. (2001).

The Pettit test developed by Pettit (1979), which is a nonparametric test that detects one point of change in the observed time series, is more sensitive to detect the inhomogeneous structures in middle of the time series (Costa and Soares, 2009). This technique is the most reliable technique for testing homogeneity in hydrologic time series. It explores the variation of a series with respect to a central value, usually the media. The number of interrupted runs of values larger and smaller than the median is counted. The Pettit's test requires no assumption about the distribution of data. It is an adaptation of the rank-based Mann-Whitney test that allows identifying the time at which the shift occurs. The null hypothesis is formulated such that the variables follow the same distribution, and the alternative hypothesis as being that at a time, there is a change of distribution. Hence, this method was adopted in this study as opposed to Standard Normal Homogeneity Test (SNHT).

2.10.2 Testing for normality

Testing to determine if a Gaussian model provides a good fit to the distribution of a time series can be achieved using various methods. The Kolmogorov-Smirnov normality test compares the observed cumulative distribution function of the sample data with an expected normal distribution. If the difference is sufficiently large, the null hypothesis of normality is rejected at an appropriate confidence level and the alternative hypothesis of a non-Gaussian distribution is accepted.

Other test statistics which are useful in describing the data distributions are the coefficients of variation, kurtosis and skewness. The coefficient of variation determines the ratio of the standard deviation of the data to the mean. The kurtosis coefficient measures how peaked a distribution is and the skewness coefficient measures the asymmetry of a distribution. A Gaussian distribution has kurtosis and skewness coefficient values of zero.

2.10.3 Variability test between stations

Variability tests are aimed at establishing whether the data collected has any significant variation and might require special treatment (Chemelil and Smout, 2000). Consequently the coefficient of determination (R^2) is used to check whether the data has any significant variation. Coefficient of determination (R^2) in this case means the proportion of total sum of squares attributable to another source of variation or the degree of closeness of data of one station to another (Conover *et al.*, 1981). If the coefficient of determination is close to 1.0, then the two stations can be compared in terms of variability. This test was applied to both rainfall and stream flow data in checking their variability in different stations.

2.10.4 Correlation tests

To investigate whether annual hydrological data are significantly correlated or not, the Bivariate Model with two tailed test was used because there was no control of the measured variable (Steel and Torrie, 1981). Probability value (p-value) from the model is used to compare the results from the correlation analysis. If the p-values from the analysis are less than the model values, then the data has no relationship at all otherwise there is some relationship (Buishand, 1982). Correlation in this case implies association or relationship between two or more station data. This was carried out in both rainfall and stream flow data.

In summary, many tests for trend detection have been used in studies of long time series of hydrological data. Yet, every test requires a number of assumptions to be satisfied. When underlying test assumptions are not fulfilled, acceptance and rejection regions of the test statistic cannot be rigorously determined. Therefore, such tests should be treated as methods of exploratory data analysis rather than as rigorous testing techniques.

The assumption of normality, needed in the case of parametric tests, may be an unacceptably simplifying one in the context of strongly positively skewed hydrological data.

In the case of non-parametric, robust tests, one does not need to assume the distribution of the data. Hirsch *et al.* (1991) found that non-parametric trend tests methods offer large advantages when the data are strongly non-normal, and suffer only small disadvantages (in terms of efficiency of power) for normally distributed data. In addition, non parametric methods are not affected by factors such as seasonality, missing values and in some cases, censored data and problems arising from small sample sizes. Hence the adoption of Mann-Kendall and Spearman's Rank Correlation trend tests in this study.

Testing for trends in drought is non-trivial because it is often the duration, intensity and severity of the drought that is critical. Furthermore, droughts may span a number of years, which means that much longer data sets are required for trend detection to be useful. Hydrological drought typically refers to periods of below normal stream flow or depleted reservoir storage. Two important parameters of hydrological droughts are the longest duration and the greatest severity over a desired return period, referred to as critical drought. The long-term mean of the annual flow sequences has been used as the truncation level for defining hydrological drought. Two well-known approaches, time series simulation and a probability theory-based approach are used to estimate drought parameters. A main advantage of the probabilistic approach is its parsimony with only two parameters namely; drought probability at the truncation level and return period for normal independent annual flow sequences. Furthermore, estimates of the greatest standardized severity can be taken as equal to the longest duration, thus eliminating the need for severity analysis, hence the adoption of this method in this study.

The annual maxima rainfall values are infrequent events and are therefore located at extreme tail of the distribution of the parent population. Their distribution is therefore different from that of the parent population. Such an extreme value distribution is expressed by the General Extreme Value (GEV) distribution which can be simplified into EV type I, II and III. Among the three models, EV type I is commonly used to model extreme rainfall events. In addition to this, a plot of the reduced variate $y = \{(x-\mu)/\alpha\}$ against variate x for all the stations described a straight line as expected for EV type I. Therefore, Extreme Value Type I distribution was chosen for prediction of Annual Maximum daily rainfall events.

The log-Pearson Type III distribution differs from most of the other distributions in that three parameters (mean, standard deviation, and coefficient of skew) are necessary to describe the distribution. By careful selection of these three parameters, it is possible to fit just about any shape of distribution. It is widely used for flow analysis because the data quite frequently fit the assumed population. It is this flexibility that led this method to be used in this study.

All the chosen and justified methods and tools discussed above were applied in chapter three of methodology in deriving trends and predicting extreme hydrological events for adaptation to climate change and variability.

CHAPTER THREE
MATERIALS AND METHODS

3.1 Study Area

The Lake Naivasha basin is located in the Kenya Rift Valley as shown in Figure 3-1. It lies between 0^0 46’ to 0^0 52’ S Latitude and 36^0 15’ to 36^0 25’ N Longitude. The maximum altitude is about 3990m above mean sea level (a.m.s.l) on the Eastern side of the Aberdare Ranges to a minimum altitude of about 1900 m (a.m.s.l) on the shores of Lake Naivasha.

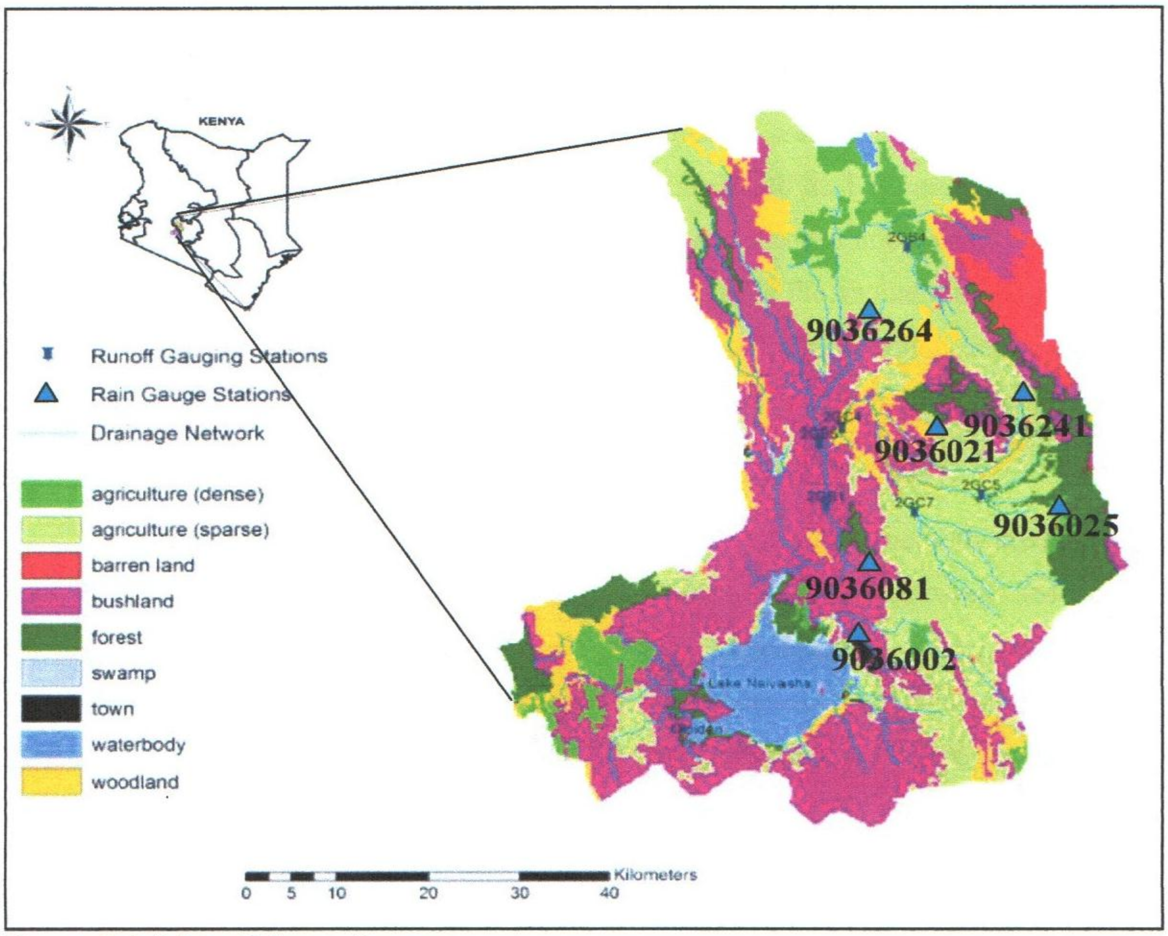


Figure 3-1: Map of the study area

The area of Lake Naivasha basin is approximately $3376km^2$. The rainfall and gauging stations which were considered for this study are also shown in Figure 3-1.

3.1.1 Drainage network for the Lake Naivasha basin

The two main perennial rivers flowing into Lake Naivasha are Malewa and Gilgil rivers. Of the two rivers, the Malewa River with a catchment area of $1600km^2$ is the major river that feeds this lake, with the river contributing about 90% of the discharge. Turasha, Nandarasi, Engare Mugutyu and Wanjohi are tributaries making the drainage of Malewa River. The Gilgil and Karati catchments are about $527km^2$ and $450km^2$ respectively contributing the remaining 10% of the discharge into Lake Naivasha (Lukman, 2003).

3.1.2 Climatic conditions for Lake Naivasha basin

Due to the difference in altitude, diverse climatic conditions exist within the Lake Naivasha basin. The rainfall regime within this basin is influenced by local relief with most of the basin area being in the rain shadow of the Aberdare ranges to the East and the Mau Escarpment to the West. There are two rainy seasons experienced in this basin. The long rains and short rains occur in the months of March to May and October to November respectively. The Lake Naivasha basin receives an average annual rainfall of 610mm, with the wettest slopes of the Aberdare ranges receiving as much as 1525mm per annum. The annual temperature ranges from 8^0 C to 30^0 C which is experienced in the months of July and March respectively. The potential evaporation is about twice the annual rainfall in the semi arid areas which lie in the lower catchment. In the humid zones, which lie on the upper catchment, the rainfall exceeds potential evaporation in most parts of the year (Farah, 2001).

3.1.3 Geology and soils

The major soils in the study area are of volcanic origin. The soils found on the mountain and major escarpments of the basin are developed from olivine basalts and ashes of major older volcanoes. They are generally well drained, very deep (1.2-1.8 m) and vary from dark reddish brown to dark brown, clay loam to loamy soils with thick acid humic topsoil in shallow to moderately deep and rocky places. They are generally classified as humic andosols (Sombroek *et al.*, 1980).

3.1.4 Vegetation and land use

The land cover of the Lake Naivasha basin can be broadly categorized into four main groups namely; agriculture, grassland, bush land and forest. In the upper Abardare Ranges region, the predominant land cover classes are forest and crops. In the semi arid region, there are extensive areas of grassland and bush land which are used for grazing. Intensive horticultural farming under irrigation is very common around the lake.

3.2 Data acquisition and selection

Six rainfall gauging stations (9036002, 9036025, 9036081, 9036264, 9036021 and 9036241) and four stream flow gauging stations (2GB1, 2GB4, 2GB5 and 2GC4) were selected for analyses for time series trends for the period 1959 to 2008. These gauges were selected based on availability of adequate length of records and also on the completeness of data i.e. those with less than 10% missing data (Table 3-1 and Table 3-2). The selection was done using the method by Haylock and Goodess (2004).

Table 3-1: Rainfall gauging stations details

Station Number	Station Name	Elevation (m)	Latitude (m)	Longitude (m)	Missing (%)	Data Period
9036002	Nvs. D.O.	1900	214315	9920714	0.0	1959-2008
9036025	Kinagop F.S	2629	238582	9935474	0.5	1959-2008
9036081	Nvs. KARI	1925	212459	9966799	4.8	1959-2008
9036264	Mawigo Sch.	2484	223586	9944688	6.1	1959-2008
9036021	N. Kinagop MH	2458	229029	9940556	4.1	1959-2008
9036241	Geta F.S.	2591	207148	9948369	3.7	1959-2008

Trend analysis requires river flows where artificial disturbances are minimal. In addition, there has to be an adequately long time series record of sufficient quality data. Bower *et al.* (2004) stated that long term records equate to a minimum of 25 years. The chosen station records in the Lake Naivasha basin met this minimum requirement, having records of over 50 years. The gauge records used in this study started on 1st of January 1959 and ended on 31st of December 2008. In this study, the data was obtained from the Water Resources Management Authority (WRMA) regional offices at Naivasha at a daily temporal resolution. Gauging stations locations are mapped in Figure 3-1 with attributes detailed in Table 3-1 and 3-2.

Table 3-2: Stream Flow gauging stations details

Station Number	Station Name	Elevation (m)	Latitude (m)	Longitude (m)	Missing (%)	Data Period
2GB01	Malewa	1950	209181	9926382	0.0	1959-2008
2GB05	Malewa	2323	212101	9964638	2.9	1959-2008
2GB04	Wanjohi	2438	220260	9969946	5.5	1959-2008
2GC04	Turasha	2005	210747	9945470	4.8	1959-2008

3.3 Data quality analysis and estimation methods

The data quality tests applied prior to trend analysis included; Homogeneity and correlation tests. These tests are discussed in the following section.

3.3.1 Homogeneity and consistency test

In this study, homogeneity tests were applied to six precipitation gauging stations and four stream flow gauging stations. For both rainfall and stream flow gauging stations, monthly and annual mean records of stations covering the years between 1959 and 2008 were considered. In each of the stations, each month was analyzed separately. In consequence of the analysis, annual total mean data were obtained by using the monthly values. For this reason, homogeneity test was applied for the annual mean records and Pettitt Test was applied to ensure that the data were statistically reliable to be used in this study.

The null hypothesis was formulated such that the variables follow the same distribution, and the alternative hypothesis as being that at a time, there was a change of distribution. This was accomplished in XLSTAT, a statistical analysis add-in offering a wide variety of functions to enhance the analytical capabilities of Excel. In XLSTAT, the probability-value and an interval around the probability-value were evaluated using a Monte Carlo re-sampling method.

3.3.2 Correlation tests

To investigate whether annual hydrological data are significantly correlated, Pearson correlation coefficient was applied to all datasets in XLSTAT. Precipitation data for each gauging stations was paired with all other gauging stations' records and the Pearson correlation coefficient (R) calculated in XLSTAT at 0.05 significance level. The method indicated whether precipitation gauging stations were either positively or negatively correlated and the results presented in a matrix form. The same process was then repeated for stream flow gauging stations.

3.3.3 Estimating missing rainfall data

The weighting factor method was used to fill up missing data based on the assumption that, gauges that are spatially close to each other tend to depict similar rainfall characteristics. The steps involved were; identification of neighbouring stations, correlation and linear regression analysis, identification of the base station and computation of missing data by regression.

By means of statistical correlation coefficient, mean values and linear regression curves, the rainfall gauging stations that yielded similar characteristics were compared with rainfall gauging stations with missing data. These statistical parameters were calculated for each neighbouring rainfall station and the station for which the data needed to be filled. The Pearson linear correlation coefficient (R) was calculated to check the relationship between the stations data.

3.3.4 Estimating missing stream flow data

The missing records in stream flow data was estimated based on the premise of correlations between the gauging stations displaying hydrological homogeneity in terms of coefficient of variation (C_v), skewness (C_s) and serial correlation (ρ) (Panu *et al.*, 2003). The missing data was traced in the daily flow sequences, and infilling was accomplished in daily flows. In this procedure, the stations with missing data were paired with similar stations which had observed data for that period. The pairing process explicitly considered values of the C_v, C_s and ρ as being closely equal. Only those stations whose values of C_v, C_s and ρ were closely equal were paired together. The infilling was then done using a linear regression equation between the data sets. At every stage of data infilling, it was ensured that the data so obtained yielded the statistic within the regional expectations.

3.4 Trends in hydrological extremes

Three variables were investigated to cover a range of possible changes in extreme hydrological events using both the Mann-Kendall Test and Spearman's Rank Correlation method. These variables are; (i) maximum values which represented the extreme intensity of various temporal data series (ii) the number of events falling above long term percentile values which represented extreme frequency, (iii) the n-day maxima which looks at maximum totals for extreme persistence. Both precipitation and flow time series were analyzed for extremes in intensity and frequency. Only the precipitation time series were tested for trends in extreme persistence.

For the MK test, the time series were defined as $X_1, X_2, \ldots, X_n$ where the values of X were treated as a random sample of n independent, identically distributed variables and F_i is the continuous cumulative distribution function of X_i , where $i=1,2,\ldots,n$. The Mann-Kendall test statistic, Z, is defined as:

$$Z = \sum_{k=1}^{n-1}\left[\sum_{j=k+1}^{n}\operatorname{sgn}(x_j - x_k)\right] \qquad 3\text{-}1$$

Where, x_j and x_k are sequential data values for the dataset record of length n. The test statistic represents the number of positive differences minus the number of negative differences between the adjacent points in the time series and equates to the sum of *Sgn* series, which is defined as: $sgn(x_j - x_k) = \begin{cases} 1 \; if \; x_j - x_k > 0 \\ 0 \; if \; x_j - x_k = 0 \\ -1 \; if \; x_j - x_k < 0 \end{cases}$ 3-2

Kendall (1975) stated the mean and the variance of Z, $E(Z)$ and $V(Z)$, respectively, under the null hypothesis H_o of randomness, given the possibility that there may be ties in the x values, as:

$$E(Z) = 0$$

$$V(Z) = n(n-1)(2n+5) - \sum_t \frac{t(t-1)(2t+5)}{18} \qquad 3\text{-}3$$

Where, t is the extent of any given tie. $\sum t_i$ denotes the summation over all ties and is only used if the data series contain tied values. The standard normal variate Z is calculated as:

$$Z \begin{cases} \frac{s-1}{\sqrt{[Var(S)]}} & if \; S > 0 \\ 0 & if \; S = 0 \\ \frac{s+1}{\sqrt{[Var(S)]}} & if \; S < 0 \end{cases} \qquad 3\text{-}4$$

Positive values of Z indicate an upward trend and negative values indicate a downward trend, and the test statistic Z is deemed significant at $\alpha < 0.05$ confidence level.

For the Spearman's Test, both sets of data *Xi* (year *i*) and *Yi* (value of the record for *Xi)* were converted to ranks x_i and y_i before calculating the Z statistic which is given by:

$$Z = \frac{6\sum d_i^2}{n(n^2-1)} \qquad 3\text{-}5$$

Where $d_i = x_i - y_i$ (the difference between the ranks of corresponding values of x_i and y_i), and n is the number of values in the data set. Statistically, significant trends were defined as those below the threshold $\alpha < 0.05$.

3.4.1 Trends in intensity of hydrological extremes

The daily maxima time series records were analyzed for trends in extreme precipitation and flows. An annual maxima (AM) sample was constructed by extracting from a series of both precipitation and flows records, the maximum value of each year and month. The yearly maxima of daily maximum precipitation and flow records were then used to define the AM series, which corresponds to the largest record per year. In addition to trend analysis of the AM time series, exceedence of the discharge median threshold was considered for the flow records.

The median annual maximum flow (QMED) is the middle-ranking value in an ordered AM series. It is commonly used as a flood index estimate that represents a discharge threshold exceeded on average once every two years (Reed and Robson, 1999). Annual extreme event counts were calculated as the number of times the QMED was exceeded by the daily flow series. This gave an indication of the temporal frequency of extreme events and whether the 2-year flood threshold was exceeded throughout the time series record above the average rate. Statistical trend analysis was performed on monthly and annual maximum values of precipitation and flow time series.

3.4.2 Trends in frequency of hydrological extremes

Daily precipitation and maximum flow magnitudes were categorized into several classes. The time series records were divided into frequency percentiles with the largest percentiles indicative of infrequent extreme hydrological events. As extreme hydrological events were of interest, only the extreme upper tail of the distributions was analyzed. Above the 90^{th} percentile is usually taken to signify very wet periods or periods of high flows, and above the 95^{th} percentile is generally allocated as a threshold for extreme hydrological frequencies (Haylock and Nicholls, 2000). Therefore, the data were analyzed for counts of days that exceeded the long term 90^{th}, 95^{th}, and 97^{th} percentiles (top 10%, 5% and 3% respectively).

3.4.3 Trends in persistence of precipitation extremes

In addition to individual hydrological extreme values exceeding a certain threshold, maximum 3-day, 7-day and 10-day rainfall totals were calculated to determine whether periods of prolonged rainfall indicate increased rainfall persistence. The *N*-day totals were assigned to the central date of the *N*-day period. The maximum of the *N*-day totals were then calculated for monthly and annual time periods.

3.5 Evaluation of extreme drought severity based on drought duration and intensity

The length of a drought spell and associated severity for a given return period was calculated using the probability based analytical relationships. The theorem of extremes of random variables using probability (q) and r provided a basis for derivation $E(L_T)$ and $E(S_T)$ relationships. Any uninterrupted sequence of deficits below the mean flow was regarded as drought length equal to the number of deficits in the sequence. This was carried out at the gauging station 2GB1 on River Malewa which is the main river draining the basin and feeding Lake Naivasha.

3.5.1 Critical drought duration, $E(L_T)$ and severity $E(S_T)$

In order to identify the underlying probability of the annual stream flow and their dependence structure, natural flow sequences were used in the analysis. The values of μ, γ, ρ, σ and cv were computed using the standard procedure as documented in Chow et al. (1988). For a time series x_i truncated at a level x_0, the truncation level μ_0 is equal to $\frac{(x_0-\mu)}{\sigma}$, Further, if x is normally distributed, so would be u. Therefore for a normally distributed sequence, u will be written as a standard normal deviate (z) and the probability;

$q = P(x \leq x_0) = P(u \leq u_0) = P(z \leq z_0)$ *is evaluated as*:

$$q = P(u \leq u_0) = P(z \leq z_0) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z_0} exp(-0.5z^2)\, dz = F(z_0) \qquad 3\text{-}6$$

For instance, the value of q at a truncation level equivalent to the mean level for a normal probability distribution of flow sequence is 0.5, which can be the integration of the above standard normal probability function from -∞ to 0 ($u_0 = z_0 = 0$). For a flow sequence with a coefficient of variation of cv and the truncation level at T_l of the mean flow, the value of u_0=z_0=$(T_l\mu - \mu)/\sigma = T_l - 100/cv$.

In this study, the value of q was obtained by using standard probability tables.

The probabilistic relationship for $E(L_T)$ and $E(S_T)$ was obtained by applying the theorem of extremes of random variables as applied by Sharma (2000) and Biamah *et al.* (2005) as expressed in equations 3-7 and 3-8.

$$E(L_T) = \sum_{j=1}^{\infty} jP(L_T = j) \qquad 3-7$$

$$P(L_T = j) = exp\left[-Tq(1-r)r^{j-1}\right]\left[exp\{Tq(1-r)^2 r^{j-1}\} - 1\right] \qquad \text{3-8}$$

Where j stands for the length of the drought duration and takes on values 1, 2, 3..., up to infinity. In this study j was considered at a maximum of 25, as probabilities beyond j >25 are extremely small and can be regarded negligible. Equation (3-7) thus was expressed as;

$$E(L_T) = 1P(L_T = 1) + 2P(L_T = 2) + 3P(L_T = 3) + \cdots + 25P(L_T = 25) \qquad \text{3-9}$$

The value of r, representing an extended continuance of drought years, was related to q, as shown by Sen (1977):

$$r = q + \frac{1}{2\pi q}\int_0^p exp[-0.5z_0^2/1 + v] \times (1 - v^2)^{-0.5} dv \qquad \text{3-10}$$

Where, v is a dummy variable for integration. The integral in equation (3-10) was evaluated by excel spreadsheet and values of r for a given q and z_0 were computed. For an independent or random stream flow series $r = q$ and a value of drought intensity (I) was estimated using a formula by Sharma (2000):

$$I = \left[exp(-0.5z_0^2)/(q\sqrt{2\pi})\right] - z_0 \qquad \text{3-11}$$

The value of I in the above calculations turned out to be negative (since drought epochs are below the truncation level and hence negative in terms of sign); therefore absolute value were used in the calculation of the severity defined as;

$$E(S_T) = IE(L_T) \qquad \text{3-12}$$

It is noted that, when the analysis is implemented in the standard domain, $L_{T,}$ I and S_T are all dimensionless and without units. Thus the actual drought severity $E(D_T)$ was computed using the relationship $D_T = \sigma S_{T,}$ which results in:

$$E(D_T) = \sigma IE(L_T) \qquad \text{3-13}$$

Where S_T, I, L_T, D_T and σ is Drought Severity, Intensity, Length, Actual drought severity (m^3) and standard deviation respectively.

3.6 Prediction of extreme events for adaptation planning

3.6.1 Prediction of extreme precipitation events

Statistical analyses were carried out to derive frequency model parameters and their probability distribution for the collected data. It involved determination of statistical parameters (mean and standard deviation) and model parameters as shown in equation 3-18. The extreme Value distribution has three asymptotic forms and to select which form fitted the data, plotting was done. A plot of the reduced variate $y = \{(x-\mu)/\alpha\}$ against variate x for all the stations described a straight line as expected for EVI. Therefore, Annual Maximum daily rainfall events were then predicted using the Extreme Value Type I distribution as described by Chow *et al.* (1988).

In this case, the probability distribution function is given by the following equation.

$$F(x) = exp\left[-exp\left(-\frac{x-\mu}{\alpha}\right)\right] \quad -\infty \leq x \leq \infty \qquad 3\text{-}14$$

The parameters α *and* μ were estimated by equation 3-15,

$$\alpha = \frac{\sqrt{6}s}{\pi} \quad , \mu = \bar{x} - 0.5772\alpha \qquad 3\text{-}15$$

Where μ was the mode of distribution or point of maximum probability density and Z is the reduced variate defined by the equation,

$$Z = \frac{x-\mu}{\alpha} \qquad 3\text{-}16$$

Substituting the reduced variate into equation 3-14 and solving for Z it yields

$$Z = -ln\left[ln\left(\frac{1}{F(x)}\right)\right] \qquad 3\text{-}17$$

Since $F(x) = \frac{T-1}{T}$, then equation 3-17 can be rewritten as:

$$Z_T = -ln\left[ln\left(\frac{T}{T-1}\right)\right] \qquad 3\text{-}18$$

For the EVI distribution X_T is related to Z_T by the following equation

$$X_T = \mu + \alpha Z_T \quad 3\text{-}19$$

Where X_T is the maximum annual daily rainfall event of return period (T). Thus this equation yields the maximum annual rainfall event of a specific return period (T).

3.6.2 Prediction of extreme stream flow events

The Annual Maximum stream flow events prediction was carried out based on Log Pearson Type III distribution from the gauging stations. This procedure involved converting the discharges into logarithmic values and deriving the statistical parameters namely; the means, standard deviation and coefficient of skewness. The parameters were then used to derive probability models for the Lake Naivasha basin. The distribution was expressed as in equation 3-20:

$$f(x) = \frac{\lambda^{B}(y-\epsilon)^{B-1}e^{-\lambda(x-\epsilon)}}{x\Gamma(B)} \quad 3\text{-}20$$

The parameters of Log Pearson Type III distribution were determined as in equations 3-21, 3-22 and 3-23:

$$\lambda = \frac{S_y}{\sqrt{B}} \quad 3\text{-}21$$

$$B = \left[\frac{2}{C_s(y)}\right]^2 \quad 3\text{-}22$$

$$\epsilon = \bar{y} - S_y\sqrt{B} \quad 3\text{-}23$$

Where, y = logarithm of maximum annual daily stream flow events, S_y= standard deviation of maximum annual daily stream flow events. Maximum annual daily stream flow events for specified return periods were derived using equation 3-24.

$$\log x = \overline{\log x} + K\sigma_{\log x} \quad 3\text{-}24$$

Where $\overline{\log x}$ is the logarithmic mean, $\sigma_{\log x}$is the logarithmic variance of the maximum annual daily stream flow events and K is the frequency factor obtained from Tables of K values for Log Pearson Type III distribution (Haan 1977). This was done through interpolation between coefficient of skewness and return period.

3.6.3 Comparison of derived and observed maximum annual hydrological events

To compare the derived and observed values, the data from each gauging station were divided into two portions of twenty five (25) years each. Probability models were then established for the first portion for each gauging station. Using the derived models, extreme annual daily events were derived and compared with observed data in the second portion of the data period.

The resulting predicted maximum precipitation and stream flow events of the first portion of the data were compared to the observed values of the second portion of the data for each gauging station. The accuracy for each model was determined using the coefficient of determination (R^2). The coefficient of determination (R^2) calculates the proportion of variability in a dataset that is accounted for by a statistical model as in equation 3-25:

$$R^2 = 1 - \left\{ \sum_{i=1}^{n} (y_i - x_i)^2 \div \sum_{i=1}^{n} (y_i - \bar{y})^2 \right\} \qquad 3-25$$

Where n is the number of observations, x_i is the predicted values, y_i is the observed value and $\bar{y}$ is the sample mean of the dataset. A correlation of 1 indicates a perfect positive linear relationship between variables and a correlation of -1 indicates a perfect negative linear correlation.

CHAPTER FOUR

RESULTS AND DISCUSSION

The methodology discussed in chapter three was applied to the Lake Naivasha basin using data from the following rainfall and river gauging stations. The rainfall gauging stations were Naivasha D.O. rainfall station (9036002), North Kinangop mission hospital (9036021), Kinangop forest rainfall station (9036025), Mawingo scheme rainfall station (9036264), Geta forest station (9036241), and Naivasha KARI rainfall station (9036081). The river gauging stations were Malewa (2GB1), Malewa (2GB5), Wanjohi (2GB4) and Turasha (2GC4). The results and discussions are presented in this Chapter.

4.1 Data quality analysis and estimation method

In data quality analysis, the Pettit's test was applied in homogeneity and consistency analysis. To investigate whether annual hydrological data are significantly correlated, the Pearson correlation co-efficient method was applied in all datasets.

4.1.1 Homogeneity and consistency test

The non-parametric Pettit test was applied to check homogeneity of the time series records. The test explored variation of the time series with respect to central median values, and if the test statistic $|Z| < 2.58$, then the null hypothesis was accepted at $\alpha = 0.05$ confidence level. The Pettit test Z-values along with descriptive statistics identifying standard deviation (σ), coefficient of variation (C_v), skewness (C_s) and kurtosis (C_k) for the precipitation and flow time series were presented in Table 4-1a and b. Pettit test Z-values indicated that all variables were homogeneous at $\alpha = 0.05$ for the annual data series.

Table 4-1a: Precipitation descriptive statistics

Station	X_{min}	X_{max}	X_{med}	μ	σ	C_v	C_s	C_k	KS	Z
9036002	21.6	70.7	42.9	43.9	7.02	0.22	2.26	7.23	0.18	0.37
9036021	28.0	71.3	49.2	48.3	9.57	0.24	2.31	8.03	0.19	-1.20
9036025	24.0	78.0	40.0	42.9	11.15	0.29	2.54	9.63	0.19	0.59
9036264	23.4	91.5	42.0	44.4	5.32	0.26	2.74	11.95	0.20	-0.98
9036241	23.4	78.0	43.7	43.9	6.47	0.28	2.61	12.69	0.19	-0.20
9036081	21.5	90.3	44.2	48.2	7.99	0.39	2.11	6.60	0.18	0.01

This homogeneity and consistency tests confirmed that the data was of good quality and suitable for use. Test statistic used to describe the distribution of time series data were the coefficient of variation, kurtosis and skewness. Daily variance in the time series was large for all variables as indicated by coefficient of variation, C_v, given as a percentage. The distribution also indicated large positive skewness, C_s, and large kurtosis, C_k, values. The Kolmogorov-Smirnov test statistic (KS), which is an indicator used to compare the observed cumulative distribution function of the sample data with an expected normal distribution, led to the rejection of normality for all datasets at a confidence level of $\sigma < 0.01$. With variables found to be homogeneous, but not fitted well by a normal distribution, the Mann-Kendall (MK) non-parametric test was adopted as a suitable trend analysis method and the Spearman's Rank Correlation (SRC) method adopted to confirm the results of the Mann-Kendal trend test.

Table 4-1b: Stream flow descriptive statistics

Station	X_{min}	X_{max}	X_{med}	μ	σ	C_v	C_s	C_k	KS	Z
2GB1	1.30	46.37	7.49	9.44	8.15	0.86	2.20	6.71	0.25	0.48
2GB4	0.37	9.41	2.10	2.33	1.60	0.68	1.79	5.67	0.24	0.02
2GB5	0.69	23.15	4.41	5.84	4.88	0.83	1.55	2.31	0.21	0.74
2GC4	0.05	15.43	1.87	3.11	2.91	0.93	2.10	5.15	0.26	0.37

4.1.2 Correlation test

To investigate whether annual hydrological data were significantly correlated, Pearson correlation coefficient was applied to all datasets in XLSTAT. The results were as shown in Appendix A. The test analyzed whether rainfall gauging stations were either positively or negatively or not correlated at all by setting Pearson Correlation coefficient (R). Significant level given by p-value indicated percentage value beyond which the variables could not be related to each other.

The correlation test tells which data need to be grouped together in quality analysis. The correlation was significant at 0.05 confidence level as shown in Table A-1 (Appendix A) of rainfall multiple correlations which meant that, p-value above 0.05 indicated rainfall events were different in terms of kind and frequency.

From the analysis, Naivasha D.O. and Naivasha KARI rainfalls were positively correlated (0.999) but there was no significance difference since p-value of 0 was less than the set level of 0.01. Naivasha D.O. and North Kinangop mission hospital rainfall stations were positively correlated (0.293) but significantly different since the p-value of 0.223 was higher than set value of 0.01. North Kinangop mission hospital and Kinagop North forest station rainfall stations were positively correlated (0.999) but there was no significance difference since the p-value of 0.00 was less than 0.01, as presented in Table A-1

Correlation analyses for the stream flows were conducted and the results are as shown in Table A-2 (Appendix A). The stream flow correlation analysis was carried out with null hypothesis that all stream flows were significantly different since they belong to different sub catchments.

4.1.3 Estimation of missing rainfall data

In order to choose the appropriate method for filling the missing rainfall data, multiple correlation and regression analysis was done to find out whether rainfall scenarios were of the same kind and frequency. The estimated values of KARI Naivasha were computed by weighting method, with Naivasha D.O. rainfall station taken as the base station. These two stations were grouped together as they had similar characteristics as per the correlation analysis in Table A-1 (Appendix A)

All the other stations were positively correlated and were grouped together for estimation of missing data. Kinangop North forest station was chosen as the base station and the weighting factor method was applied to fill all the missing daily values of precipitation.

4.1.4 Estimation of missing stream flow data

Stream flow data estimation was done using a procedure based on the premise of correlations between the gauging stations displaying hydrological homogeneity in terms of coefficient of variation (C_v), skewness (C_s) and serial correlation (ρ) (Panu *et al.*, 2003). The missing data was traced in the daily flow sequences, and infilling was accomplished in daily flows.

From Table A-2 (Appendix A), 2GB1 was paired with 2GB5 since they portrayed hydrological homogeneity. Regression analysis was applied to daily flows for periods with complete data for the two stations. Infilling was then done to daily flow records by applying the developed regression equation developed. Similarly, 2GB4 and 2GC4 gauging stations were paired together since they depicted hydrological homogeneity as shown in Table A-2 (Appendix A).

4.2 Trends in hydrological extremes

The Mann-Kendall and Spearman rank correlation techniques were used to test for the presence of trends. Positive values of the test statistic Z indicate increasing trends and negative values of Z values indicate decreasing trends. Z was deemed significant at a confidence level $\alpha < 0.05$. The Mann-Kendall rank statistic is a non parametric test, which was used to test for existence of a linear trend while the Spearman's Rank Correlation test confirmed the results of the Mann-Kendall test.

4.2.1 Trends in intensity of hydrological extremes

Precipitation maxima

From Table 4-2, both methods indicated that no significant trends existed in the annual maxima precipitation records. The MK test showed that monthly maxima trends increased significantly in the month of April at gauging stations 9036025, 9036264 and 9036021 while the SRC test indicated significant increases in station Nos. 9036021 and 9036025. In addition, the MK test indicated that monthly maxima trends decreased at gauging stations 9036002 and 9036081 which the SRC test did not detect. Both tests indicated a significant decrease of trends in monthly maxima precipitation in the month of November at the gauging stations 9036025 and 9036241. As highlighted in Table 4-2, the monthly maxima analysis revealed some general increasing trends with an increase in April rainfall occurring concurrently at gauging stations 9036021, 9036264 and 9036025.

Two factors which may be influencing changes in extreme precipitations were identified by Frei et al. (2000). The first one being a change in the general circulation of the atmosphere affecting the preferred track of storms and the second that global warming is inducing a global moistening of the atmosphere. Over many high latitude land areas, including the upper catchment of the Lake Naivasha basin, more intense precipitation events have been observed. The trend in changing precipitation and associated trends in stream flows can strongly be linked to large-scale atmospheric circulation changes.

Climate studies show an increase in the global mean near surface temperature (IPPC, 2001b). This is likely to have led to more evaporation from the lake and evapo-transpiration rates which may lead to a more vigorous hydrological cycle in the basin. Increases in greenhouse gases in the atmosphere produce global warming. This occurs through increases in down-welling infrared radiation and, thus, not only increases surface temperatures but also enhances the hydrological cycle, as much of the heating at the surface goes into evaporating surface moisture. This rise in global water vapour concentration may have resulted in an increase in the intensity of extreme precipitation events and the changes in worldwide precipitation regimes.

Table 4-2: Analysis of annual and monthly maxima precipitation

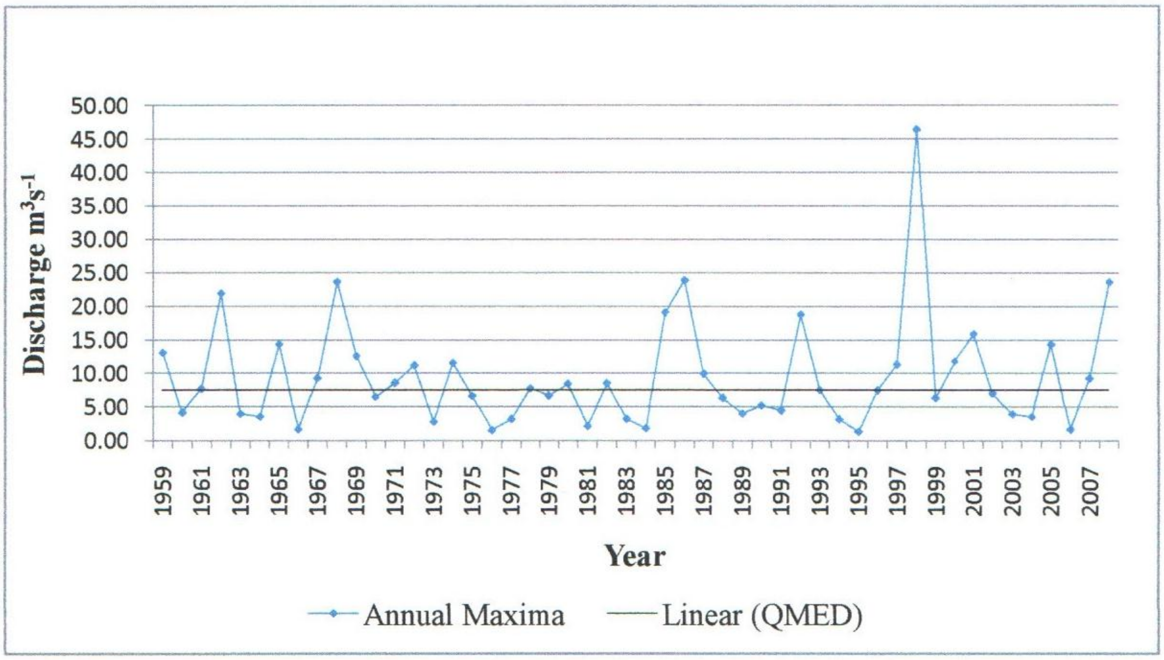
Station	9036002		9036021		9036025		9036264		9036241		9036081	
	Z	α	Z	α	Z	α	Z	α	Z	α	Z	α
Annual												
Ann- MK	-1.28	0.11	0.23	0.40	0.02	0.49	-0.45	0.32	0.56	0.28	0.25	0.39
SRC	-1.81	1.97	-6.04	1.45	0.66	1.36	-3.21	1.53	-1.34	1.57	-1.00	1.46
Monthly												
Jan - MK	0.49	0.06	-0.34	0.36	-0.32	0.37	-1.58	0.05	-0.32	0.71	0.00	0.50
SRC	0.36	1.77	-1.38	1.46	-0.33	0.56	-2.51	1.77	-1.32	1.15	-o.22	1.33
Feb - MK	-0.6	0.25	-1.18	0.12	0.00	0.50	-2.65	0.39	0.74	0.22	-0.14	0.44
SRC	-0.21	1.54	-0.99	1.69	0.56	1.26	-1.80	1.40	0.35	1.59	-2.44	1.58
Mar -MK	0.90	0.18	0.58	0.29	1.11	0.13	-0.18	0.42	0.86	0.19	0.95	0.16
SRC	2.68	1.41	0.86	1.25	0.91	0.61	-0.56	1.17	0.59	0.15	0.87	0.38
Apr - MK	**-1.78**	**0.03**	**1.78**	**0.04**	**1.79**	**0.03**	**1.75**	**0.04**	-1.40	0.08	**-1.76**	**0.03**
SRC	-1.58	1.46	**1.37**	**0.03**	**2.59**	**0.04**	0.52	1.72	-2.39	1.38	-2.72	1.28
May -MK	0.00	0.50	0.52	0.29	1.14	0.12	0.73	0.23	1.12	0.13	0.57	0.48
SRC	0.13	1.27	0.79	1.17	2.71	1.34	1.37	1.39	2.61	1.48	0.92	1.21
Jun - MK	0.96	0.16	0.18	0.42	1.16	0.12	-0.04	0.48	0.49	0.31	0.96	0.16
SRC	1.74	1.15	0.42	0.36	0.69	0.34	-1.48	0.67	0.87	1.28	1.68	0.82
Jul - MK	-1.04	0.14	0.39	0.31	-0.85	0.19	-0.62	0.26	-0.54	0.30	-0.27	0.39
SRC	-2.87	0.87	0.78	0.72	-2.67	1.28	-0.92	0.38	-2.78	0.83	-0.89	0.52
Aug - MK	0.82	0.20	0.23	0.40	0.30	0.37	0.37	0.35	0.46	0.32	0.57	0.28
SRC	0.98	0.82	0.78	0.87	0.81	1.27	0.54	1.45	0.87	0.32	0.39	0.83
Sept -MK	-0.55	0.28	0.13	0.44	-1.61	0.05	-0.15	0.43	0.25	0.39	1.58	0.05
SRC	-1.67	1.34	0.97	0.91	-2.67	0.28	-1.57	0.90	0.87	1.28	2.91	0.18
Oct - MK	0.30	0.10	0.71	-0.30	0.27	0.10	0.51	0.06	0.09	0.16	0.32	0.22
SRC	0.87	1.32	0.22	-2.34	0.27	0.20	1.56	0.87	0.18	1.27	1.37	0.37
Nov -MK	0.97	0.16	0.39	0.34	**-2.59**	**0.01**	1.03	0.15	**-1.96**	**0.02**	0.52	0.30
SRC	2.17	0.87	0.98	0.82	**-1.68**	**0.04**	2.01	0.89	**-2.81**	**0.01**	0.87	0.71
Dec -MK	0.55	0.28	-0.97	0.16	-1.14	0.12	-0.77	0.22	-0.43	0.33	-0.49	0.31
SRC	1.23	1.29	-2.67	0.13	-1.51	0.43	-0.91	0.88	-2.67	0.47	-1.16	0.91

Note: Boldface indicates significance at α <0.05

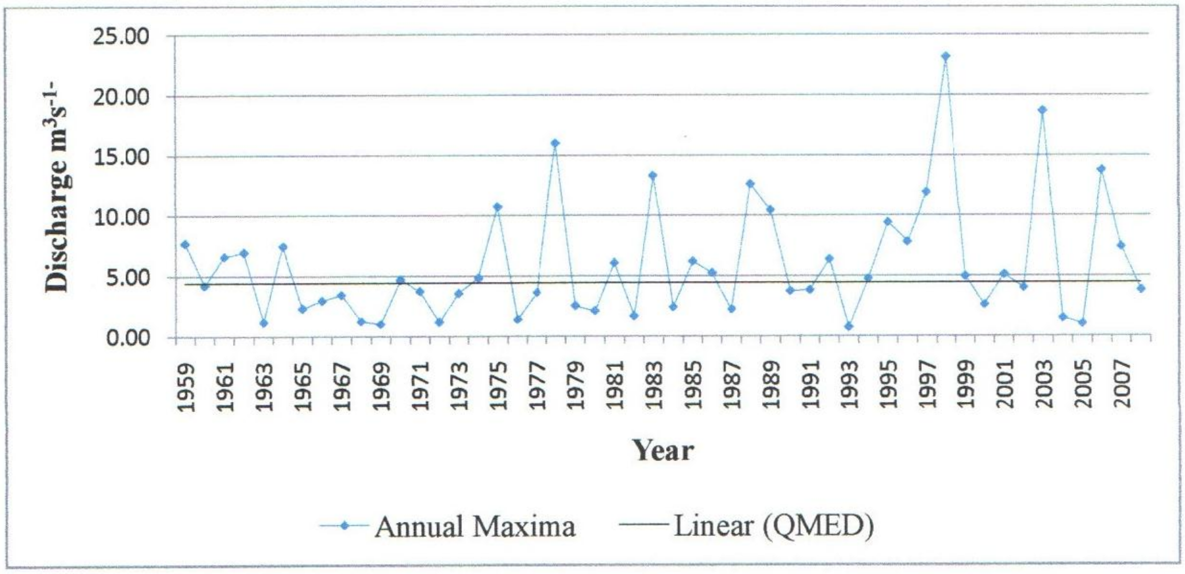
Precipitation trends, however, show mixed signals with some locations indicating increasing trends, while the majority do not show any significant trends. The annual precipitation shows no significant trends due to a general decline in the long rain season. The November precipitation trends show a decreasing trend due to, among others, an extension of precipitation into January and February over some locations in recent years (NCCRS, 2009).

QMED exceedence

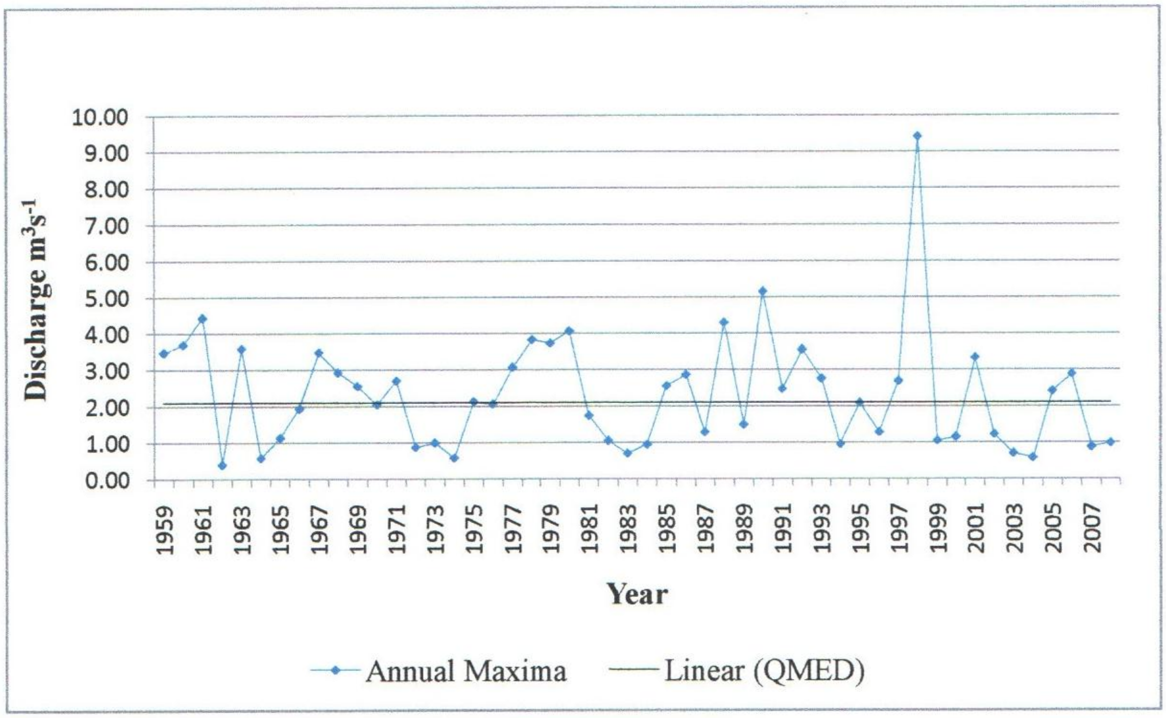
Figures 4-1a, b, c and d, indicate daily discharge values which exceeded the QMED threshold at individual gauging stations. The long term threshold has evidently been exceeded more, both in frequency and magnitude in the latter part of the time series for all sites. Intensity changes were greatest at gauging station 2GB5 with flows indicating a steady linear increase over time. The gauging station 2GC4 also exhibited a slight increase in QMED exceedence over the study period but there was a decrease in gauging station 2GB4 over the same period. The gauging station 2GC4 is located on the upper catchment of the Lake Naivasha basin meaning that land cover/use change which is evident in this sub-catchment may be affecting runoff. The values for the annual frequency were high at all stations for 1998, reflecting the occurrence of the 1998 El-Nino floods.



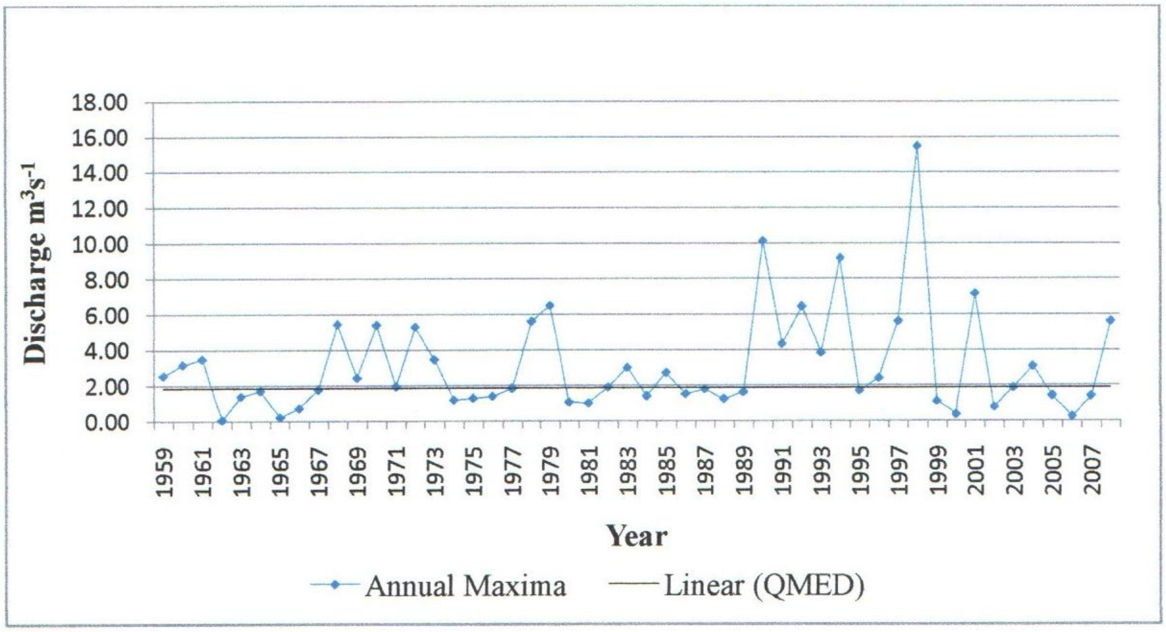
(a) 2GB1 (Malewa) Annual Maxima with QMED at 7.49m^3s^{-1}



(b) 2GB5 (Malewa) Annual Maxima with QMED at 4.41m^3s^{-1}



(c) 2GB4 (Wanjohi) Annual Maxima with QMED at 2.10m^3s^{-1}



(d) 2GC4 (Turasha) Annual Maxima with QMED at 1.87m^{3}s^{-1}

Figure 4-1: Daily maximum flows showing exceedence of the long-term QMED threshold

Adaptation to climate change and variability requires the determination of how hydrological processes have been altered over recent years. Prolonged flow over the Lake Naivasha basin from the year 1990 to 2008 as shown in gauging stations 2GB1 (Figure 4-1a) may be due to the effects of precipitation changes on stream flow regimes. The exceedence of QMED in the last 10 years has intensified in gauging stations 2GB1. This may have been caused by the dependence on the extent of change in climatic variables influencing the catchment, as well as basin morphology and the configuration of the drainage network and stream channel.

Precipitation and evaporation are the most important drivers of the hydrological system. Changes in these primary processes due to climate variability may be significantly influencing the timing and volume of stream flows. This may be occurring through changes in soil water storage, groundwater-surface water interactions and the variability of hydrological processes in the Lake Naivasha basin.

Flow maxima

Both test results indicate significant trends in annual maxima (AM) at all gauging stations as shown in Table 4-3. There are significant trends indicated by both methods in the month of April at gauging station 2BG1. This is even significant at $\alpha < 0.01$ which re-emphasizes the substantial increase in magnitude above the QMED threshold. The trends in the month of November increased significantly at gauging stations 2GB4 and 2GC4 with no other trends apparent noted at other gauging stations. The maximum flow trends for the month of April increased significantly over the last 50 years at all gauging stations. No other monthly trends were detected.

The characteristics of flow magnitudes and frequencies are highly sensitive to climatic variations, in particular to changes in precipitation regimes (Lamb, 1972), as well as changes in physical catchment properties. The influence of precipitation on river flow regimes is complex with intricate interactions between evaporation losses, soil moisture conditions, catchment geology, land use and artificial changes to watercourses.

Precipitation is important for predicting changes in flow regimes, but a simple increase in precipitation does not necessarily result in increased river flows, as evident from the Mann-Kendal and Spearman's Rank Correlation trend analysis results in the Lake Naivasha basin. Significant increases in the month of April and November flows coincided with trends in precipitation record. The April and November maxima rainfall *Z*-values indicated an increase but not at a significant level. On average, stream flow was seen to increase with increase in rainfall. However, increase in stream flow may occur over short periods of time that may not be suitable for any meaningful economic activities, unless measures are put in place to harvest the excess stream flow. In other words, increase in stream flow during the rainfall seasons will not always alleviate the problem of water shortage in the dry season, but will cause flooding rather than reduce water shortage.

Table 4-3: Analysis of annual and monthly maxima Stream flow

	2GB1		2GB5		2GB4		2GC4	
	Z	α	Z	α	Z	α	Z	α
Annual								
Ann-MK	**1.639**	**0.047**	**2.984**	**0.007**	**1.137**	**0.034**	**1.137**	**0.034**
SRC	**2.210**	**0.028**	**3.728**	**0.032**	**1.831**	**0.045**	**1.539**	**0.042**
Monthly								
Jan- MK	0.719	0.361	0.160	0.138	0.365	0.629	0.071	0.472
SRC	0.678	1.294	0.349	1.391	0.284	1.190	0.183	0.732
Feb- MK	0.913	0.112	0.000	0.500	0.573	0.208	0.500	0.390
SRC	0.520	1.218	0.257	1.167	0.521	1.171	0.261	1.138
Mar-MK	0.633	0.472	0.206	0.418	0.216	0.481	0.268	0.377
SRC	0.851	0.561	0.661	0.361	0.265	0.417	0.437	0.524
Apr- MK	**1.820**	**0.034**	**0.169**	**0.033**	1.499	0.607	1.230	0.093
SRC	**2.183**	**0.015**	1.211	1.981	1.671	1.291	1.823	1.381
May-MK	0.670	0.413	1.519	0.064	1.231	0.131	0.856	0.196
SRC	0.851	1.131	1.961	1.270	1.952	1.191	0.927	1.178
Jun- MK	1.000	0.061	0.657	0.226	-1.106	0.143	1.214	0.113
SRC	2.179	0.371	1.893	0.682	-2.294	0.372	0.482	0.483
Jul- MK	0.315	0.099	0.430	0.074	-0.171	0.473	0.143	0.443
SRC	0.736	0.851	0.824	0.562	-0.879	0.816	0.429	0.871
Aug- MK	0.731	0.332	0.657	0.256	-0.607	0.272	0.928	0.177
SRC	1.168	0.872	1.034	0.723	-1.389	0.710	1.592	0.567
Sept-MK	0.547	0.060	0.582	0.280	-0.428	0.334	1.213	0.113
SRC	0.931	1.230	1.109	0.934	-2.389	0.149	1.730	0.872
Oct- MK	1.000	0.301	0.807	0.210	1.477	0.142	1.089	0.138
SRC	1.831	0.923	1.872	0.991	2.176	0.720	2.193	0.710
Nov- MK	0.828	0.202	0.582	0.280	**1.713**	**0.043**	**1.891**	**0.029**
SRC	1.781	0.871	1.820	0.923	**2.131**	**0.022**	**2.389**	**0.047**
Dec- MK	1.000	0.101	0.094	0.463	0.431	0.333	0.821	0.206
SRC	1.831	0.834	1.570	1.294	1.672	0.921	2.178	0.901

Note: Boldface indicates significance at $\alpha < 0.05$

Changes in land cover and land use may also have direct implications on stream flow trends in the Lake Naivasha basin. The land cover change in the Lake Naivasha basin has been fairly high in recent years. Deforestation may have led to decreased precipitation interception, transpiration and soil moisture deficits. This may lead to alterations in evapo-transpiration, soil stability and the timing and quantity of surface runoff.

Land cover/use changes are likely to have affected soil characteristics and subsequent susceptibility to climate induced changes. Intense agricultural practices in the Lake Naivasha basin may be causing a reduction in soil water storage capacity and infiltration rate leading to overland flow and rapid surface runoff into rivers. Over the past years, there has been an increase in agricultural intensification due to economic pressures. These have affected the soil physical properties and enhance runoff generation at the local level.

4.2.2 Trends in frequency of hydrological extremes

Precipitation percentiles

Analysis of precipitation percentile exceedence by both tests indicated significant negative trends in the number of days exceeding the annual 97th percentile at gauging stations 9036002 and 9036081 as shown in Table 4-4. Significant precipitation trends were detected both by the MK and SRC test at gauging stations 9036025 where the annual 95th percentile exceedence values all increased throughout the time series records.

The changes in the frequency of precipitation extremes may be one of the most significant consequences of climate change. The significant increases in the gauges at the upper catchment of the Lake Naivasha basin of precipitation events may be attributed to changes in mean state of the overall precipitation determining the potential frequency with which extremes are exceeded. Changes in climate variability from day to day and year to year may also be influencing changes in the frequency of extremes.

Table 4-4: Analysis of annual precipitation percentiles

	9036002		9036021		9036025		9036264		9036241		9036081	
	Z	**α**	**Z**	**α**	**Z**	**α**	**Z**	**α**	**Z**	**α**	**Z**	**α**
Ann												
90th-MK	0.15	0.36	1.54	0.07	0.52	0.40	-0.25	0.40	0.48	0.19	-0.14	0.44
SRC	0.67	1.12	2.56	0.87	0.67	0.97	-0.87	0.92	0.90	0.72	-0.71	0.97
95th-MK	0.58	0.29	0.21	0.47	**1.99**	**0.03**	-0.54	0.29	0.57	0.28	-0.75	0.22
SRC	1.67	1.05	0.93	1.42	**2.23**	**0.03**	-1.67	0.45	0.98	1.26	-1.44	0.45
97th-MK	**-1.66**	**0.04**	1.76	0.23	0.39	0.36	0.00	0.50	0.08	0.46	**-1.76**	**0.03**
SCR	**-2.45**	**0.02**	2.87	0.84	0.53	0.87	1.98	1.01	0.47	1.89	**-2.78**	**0.02**

Note: Boldface indicate significance at $\alpha < 0.05$

Flow percentiles

Fitting of trends by both the MK and SRC tests to the flow percentile exceedence data revealed that the annual 95th percentile exceedence had significant trends at gauging stations 2GB1 and 2GB5 as shown in Table 4-5. The annual 90th and 97th percentiles exceedence at gauging stations 2GB4 and 2GC4 decreased significantly. Overall, trends in the standard normal variate (*Z*-values) showed a general decrease in annual percentile exceedence for all gauging stations.

The increase of the wet season rainfall may result in a higher high flow index value. During periods of excessive rainfall, high flow discharges increase when rainwater is not stored through infiltration and percolation processes in the unsaturated zone and this may have led to increase of wet periods at gauging stations 2GB1 and 2GB5. Increases in flow discharges are expected in areas where agricultural land has largely increased by deforestation and in case of land degradation (Mati *et al.*, 2008). This may be attributed to trends in gauging stations 2GB1 and 2GB5 which are in the lower parts of the Lake Naivasha basin.

Table 4-5: Analysis of annual Stream flow percentiles

	2GB1		2GB5		2GB4		2GC4	
	Z	α	Z	α	Z	α	Z	α
Annual								
90th-MK	-0.492	0.334	-0.732	0.322	**-0.172**	**0.016**	**-0.198**	**0.023**
SRC	-1.651	1.267	-2.201	0.972	**-2.28**	**0.037**	**-2.228**	**0.049**
95th-MK	**1.827**	**0.034**	**1.789**	**0.043**	1.312	0.095	-0.769	0.221
SRC	**1.772**	**0.015**	**1.981**	**0.017**	3.261	0.948	-1.389	1.289
97th-MK	-0.521	0.301	-0.789	0.190	**-1.896**	**0.015**	**-1.842**	**0.033**
SRC	-1.841	0.662	-1.842	1.981	**-3.462**	**0.032**	**-3.267**	**0.011**

Note: Boldface indicate significance at $\alpha < 0.05$

4.2.3 Trends in persistence of precipitation extremes

The gauging station No. 9036241 exhibited significant trends in the *N*-day maxima as shown in Tables 4-6 a, b and c. Although there are no significant trends in the *3*-day maxima in the annual trends, there is significant decreasing trends in the *3*-day maxima trends in gauging stations No 9036002 and 9036081 in the month of April as indicated in Table 4-6 a. Monthly *3*-day maxima show increasing trends in April and November at the gauging stations No. 9036025 and 9036241.

The changes in precipitation persistence at the gauging stations No. 9036241 show increases in *7*-day annual maxima in addition to persistence increase in precipitation at the gauging stations No. 9036025 and 9035241 for the *10*-day annual maxima as shown in Table 4-6c. For gauging stations No. 9036025 and 9036241 both *7*-day and *10*-day maxima increased in the months of April and November as revealed in Tables 4-6b and c. A reduction in both *7*-day and *10*-day monthly maxima at gauging station 9036002 is exhibited in Tables 4-6b and c.

Table 4-6a: Analysis of annual and monthly *3*-day precipitation

Station	9036002		9036021		9036025		9036264		9036241		9036081	
	Z	α	Z	α	Z	α	Z	α	Z	α	Z	α
Ann-MK	0.18	0.24	0.47	0.38	1.45	0.06	-0.71	0.20	1.84	0.07	-0.06	0.49
SRC	1.23	0.93	1.87	0.97	2.23	0.75	-1.84	0.67	2.89	0.73	-0.68	0.93
Monthly												
Jan-MK	0.34	0.36	-0.74	0.265	-0.42	0.37	0.78	0.26	-0.32	0.71	0.30	0.35
SRC	1.28	0.89	-1.37	0.97	-6.13	0.72	0.27	1.26	-0.69	1.28	1.38	0.78
Feb-MK	-0.44	0.66	-1.45	0.21	0.40	0.22	-1.15	0.36	0.38	0.22	-0.46	0.641
SRC	-1.55	0.89	-2.44	0.57	1.28	0.59	-2.51	1.12	0.97	0.59	-1.65	0.88
Mar-MK	1.80	0.06	0.52	0.30	1.16	0.54	-1.18	0.06	1.18	0.53	1.958	0.06
SRC	2.44	0.92	1.11	1.42	2.14	1.28	-2.44	0.92	2.44	1.25	2.67	0.92
Apr-MK	**-1.56**	**0.04**	1.788	0.07	**1.72**	**0.036**	1.755	0.07	**1.96**	**0.02**	**-1.76**	**0.04**
SRC	**-2.51**	**0.03**	2.36	0.98	**2.31**	**0.002**	2.21	0.98	**2.68**	**0.04**	**-2.24**	**0.07**
May-MK	0.80	0.19	-1.31	0.09	1.17	0.16	0.70	0.23	1.13	0.11	0.57	0.20
SRC	0.34	1.28	-2.01	0.72	2.13	1.87	0.31	1.62	2.01	0.96	0.17	1.29
Jun-MK	0.89	0.16	0.16	0.46	1.18	0.11	-0.42	0.43	0.42	0.31	0.98	0.16
SRC	0.37	1.18	1.93	0.17	2.18	0.96	-1.56	0.14	1.56	0.28	0.56	1.93
Jul- MK	-1.34	0.18	0.32	0.37	-0.81	0.16	-0.60	0.25	-0.83	0.14	-1.27	0.19
SRC	-1.42	1.69	0.27	1.57	-0.35	1.62	-3.31	0.14	-0.39	1.57	-1.21	1.70
Aug-MK	0.81	0.26	0.28	0.46	0.39	0.39	0.35	0.34	0.68	0.20	0.71	0.89
SRC	0.34	0.59	0.62	1.89	1.37	0.76	1.23	0.72	0.26	0.11	0.24	0.06
Sept-MK	-0.51	0.89	0.32	0.47	-1.18	0.06	-0.56	0.39	0.57	0.99	1.88	0.56
SRC	-1.98	0.06	0.72	1.88	-2.62	3.31	-2.32	0.78	2.12	0.07	2.62	2.31
Oct-MK	0.30	0.10	0.70	0.30	0.27	0.10	0.51	0.06	**0.79**	**0.03**	0.32	0.22
SRC	1.02	1.54	1.37	1.02	0.93	1.54	1.98	3.31	1.67	2.90	1.12	0.87
Nov-MK	0.98	0.14	0.37	0.36	**2.47**	**0.014**	1.09	0.12	**1.24**	**0.002**	0.51	0.31
SRC	0.46	1.62	0.72	0.70	**1.32**	**0.031**	2.01	1.01	**2.62**	**0.011**	1.98	1.04
Dec-MK	0.76	0.39	-0.91	0.14	-1.12	0.16	-0.76	0.20	-0.47	0.33	-0.42	0.30
SRC	1.47	0.73	-0.07	1.62	-2.43	1.54	-1.47	0.86	-1.88	0.64	-1.86	1.02

Note: Boldface indicates significance at α <0.05

Table 4-6b: Analysis of annual and monthly 7-day precipitation

Station	9036002		9036021		9036025		9036264		9036241		9036081	
	Z	α	Z	α	Z	α	Z	α	Z	α	Z	α
Ann-MK	0.54	0.31	0.54	0.31	1.55	0.07	0.71	0.22	**2.14**	**0.018**	0.56	0.39
SRC	2.12	1.02	2.12	1.02	2.04	0.73	2.56	0.93	3.19	0.56	2.17	1.67
Monthly												
Jan-MK	0.00	0.50	-1.15	0.12	0.42	0.33	0.47	0.31	1.04	0.15	0.01	0.53
SRC	0.13	1.22	-2.51	1.01	1.86	1.21	1.97	1.02	1.88	1.16	0.18	1.25
Feb-MK	-0.04	0.46	0.55	0.28	1.47	0.07	0.95	0.16	1.38	0.08	0.46	0.48
SRC	-0.58	1.94	2.10	0.97	2.24	0.73	0.45	1.18	2.67	0.76	1.93	1.99
Mar-MK	1.58	0.06	0.62	0.25	-0.11	0.44	0.23	0.41	-0.18	0.43	-1.44	0.07
SRC	2.75	0.62	2.58	0.98	-2.43	1.96	0.94	1.92	-1.98	1.85	-2.15	0.73
Apr-MK	-1.16	0.17	**-2.10**	**0.01**	**1.74**	**0.04**	-1.45	0.07	**2.40**	**0.008**	-1.43	0.07
SRC	-2.53	1.23	**-3.02**	**0.04**	**1.36**	**0.03**	-2.21	0.73	**4.34**	**0.03**	-2.15	0.73
May-MK	1.75	0.15	-1.25	0.36	1.87	0.19	1.70	0.13	1.83	0.17	1.57	0.18
SRC	1.38	1.16	-0.16	1.37	2.57	1.27	1.35	1.60	2.52	1.23	2.72	1.25
Jun-MK	0.76	0.13	0.86	0.16	1.81	0.21	-0.72	0.34	1.42	0.23	0.78	0.15
SRC	2.62	1.60	0.35	1.18	2.49	0.91	-2.58	1.35	2.20	0.94	2.67	1.16
Jul-MK	-1.41	0.21	0.23	0.37	-0.18	0.61	-0.06	0.52	-0.08	0.54	-1.72	0.19
SRC	-2.21	0.91	0.94	1.39	-1.98	1.46	-0.78	2.10	-0.91	2.12	-1.41	1.38
Aug-MK	0.18	0.62	0.82	0.26	1.39	0.39	0.21	0.64	1.68	0.32	0.71	0.69
SRC	1.98	1.58	2.73	0.99	1.91	1.67	0.91	1.61	1.32	1.04	2.56	1.77
Sept-MK	0.61	0.19	0.23	0.38	-1.81	0.16	0.56	0.17	-1.57	0.17	0.88	0.16
SRC	2.55	1.38	0.94	1.40	-2.49	1.18	2.17	1.23	-2.36	1.23	0.39	1.18
Oct-MK	0.60	0.14	0.80	0.35	0.87	0.18	0.58	0.16	0.79	0.30	0.62	0.12
SRC	2.54	1.63	0.30	1.37	0.32	1.98	2.11	1.18	0.28	1.02	2.51	1.06
Nov-MK	0.89	0.17	0.73	0.63	**1.76**	**0.03**	0.91	0.15	**1.74**	**0.05**	0.51	0.31
SRC	0.38	1.23	2.61	1.60	**1.38**	**0.01**	0.41	1.16	**1.36**	**0.004**	1.22	1.02
Dec-MK	0.67	0.18	-0.85	0.40	1.21	0.61	0.77	0.27	0.57	0.37	0.32	0.37
SRC	2.42	1.98	-0.38	1.78	1.76	2.50	2.83	2.89	1.41	1.13	1.37	1.13

Note: Boldface indicates significance at α <0.05

Table 4-6c: Analysis of annual and monthly *10*-day precipitation

Station	9036002		9036021		9036025		9036264		9036241		9036081	
	Z	α	Z	α	Z	α	Z	α	Z	α	Z	α
Ann-MK	0.74	0.43	0.29	0.38	**1.95**	**0.02**	1.19	0.11	**2.24**	**0.01**	0.26	0.40
SRC	2.60	1.85	0.96	1.40	**1.76**	**0.04**	2.19	2.43	**3.81**	**0.03**	0.99	1.78
Monthly												
Jan-MK	0.31	0.35	-1.45	0.07	0.39	0.34	0.49	0.31	0.60	0.27	0.71	0.23
SRC	1.02	1.37	-2.22	0.73	1.16	1.36	1.91	1.02	1.54	0.99	2.52	0.94
Feb-MK	-0.24	0.40	0.05	0.48	1.27	0.10	0.75	0.22	1.28	0.88	0.26	0.41
SRC	-1.63	1.78	0.56	1.99	1.21	2.41	2.61	0.93	1.22	0.37	0.99	1.82
Mar-MK	1.48	0.07	0.68	0.24	-0.81	0.20	-0.23	0.42	-0.78	0.23	1.44	0.08
SRC	2.29	0.73	1.57	0.94	-0.32	0.90	-0.91	1.82	-2.65	0.94	2.20	0.79
Apr-MK	1.16	0.13	-1.60	0.06	0.74	0.48	-0.74	0.27	**1.84**	**0.02**	-0.41	0.37
SRC	2.53	1.62	-2.56	0.70	2.60	1.90	-2.60	0.99	**1.74**	**0.04**	-1.79	1.39
May-MK	0.17	0.45	0.31	0.37	1.47	0.09	1.16	0.43	1.83	0.17	0.87	0.20
SRC	2.76	1.87	1.02	1.51	2.28	0.93	2.53	1.85	1.70	2.76	0.36	0.90
Jun-MK	0.46	0.33	-0.66	0.26	-0.14	0.44	0.47	0.32	1.52	0.05	1.14	0.12
SRC	1.98	1.35	-1.59	0.97	-2.51	1.93	1.90	1.33	2.32	0.38	2.12	2.45
Jul-MK	-0.64	0.25	0.14	0.47	0.99	0.16	0.18	0.42	1.98	0.06	-1.17	0.43
SRC	-2.54	0.93	2.01	1.98	1.44	2.78	2.92	1.80	3.36	0.07	-1.56	1.85
Aug-MK	0.52	0.32	-0.08	0.46	-1.09	0.13	-1.09	0.13	0.96	0.16	0.56	0.09
SRC	1.94	1.39	-0.09	1.89	-2.08	2.47	-2.08	2.47	1.41	2.78	1.51	0.93
Sept-MK	-1.56	0.09	-0.43	0.32	-0.58	0.26	-1.61	0.06	-0.57	0.17	-0.09	0.17
SRC	-2.87	0.93	-1.95	1.00	-1.45	0.98	-2.93	0.70	-1.98	1.56	-0.10	1.56
Oct-MK	0.65	0.08	0.50	0.37	0.37	0.28	1.58	0.66	1.79	0.20	0.72	0.18
SRC	1.55	0.79	2.01	1.39	1.15	1.11	2.41	1.57	1.73	0.90	2.54	0.59
Nov-MK	0.89	0.17	0.73	0.63	**1.76**	**0.03**	0.91	0.15	**1.74**	**0.05**	0.51	0.31
SRC	0.40	1.56	2.57	1.52	**1.71**	**0.04**	1.07	2.48	**1.68**	**0.02**	1.92	1.02
Dec-MK	**-2.07**	**0.02**	0.85	0.12	1.24	0.21	0.75	0.17	1.57	0.38	1.82	0.47
SRC	-3.56	1.07	0.34	2.45	1.84	0.90	2.59	1.56	2.51	1.47	1.69	2.01

Note: Boldface indicates significance at α <0.05

Generally, time series analysis results indicate changes in both magnitude and frequency of precipitation records, yet the largest number of significant trends is found in the *N*-day maxima persistence analyses. In the Lake Naivasha basin, the seeder-feeder mechanisms is of influence, where moist low level air from the lake is forced to rise over the Aberdare escarpment and is cooled to its saturation point as it rises. This is reflected in the trend observations as the gauging stations with the largest number of significant persistence trends are located on the upper parts of the Lake Naivasha basin where they receive the highest annual rainfalls.

It is important to note that even without climate change, climate variability still exists and is an important factor that affects a wide range of human activities. Due to climate change and variability, the trends of extreme climate events have been changing. Therefore, there is need for planning for these changing trends. The situation is complicated further as a result of population growth and changes in land and water use. It cannot be taken lightly that there may be water stress even with increased amounts of water yields in this region. Therefore, it is imperative to put in place measures to harness any excess water for use during periods of little or no rainfall.

4.3 Evaluation of extremal drought severity based on duration and intensity

The probabilistic approach was used to estimate the duration and severity of a T-year hydrological drought on historical data of annual flows. The truncation was at the mean level of the gauging station 2GB1 in the Lake Naivasha basin. For the probabilistic approach, the assumption that annual flow sequences are normal and independent was a reasonable choice for analysis, since ρ and γ happen to be insignificantly small. This is because, this assumptions yields marginally conservative values of severity which is a desirable feature for design aspects of water resources systems for ameliorating drought conditions.

The value of z_o is 0.0 for the truncation level equal to the mean flow, and the corresponding value of q was computed to be 0.5 from equation 3-13 and results presented in Table D-6 (Appendix D). For a flow time series, the value of $r = q = 0.5$ indicates that flows are random and, consequently, the drought episodes are also random. By using the values of z_o, q, r and T (=2, 5, 10, 50 and 100 years) in equations 3-6 to 3-12, the values of L_T, I and S_T were calculated and the results presented in Table 4-7.

The value of D_T was calculated from equation 3-13 and the results are also presented in Table 4-7. All these computations were accomplished using a MS Excel spreadsheet and the results are shown in Tables D-1, D-2, D-4 and D-5 (Appendix D)

Table 4-7: Values of L_T, I, S_T and D_T at various Return Periods in years

Return Period	2-year	5-year	10-year	50-year	100-year
L_T	0.85	1.74	2.66	3.97	5.98
I	0.80	0.80	0.80	0.80	0.80
S_T	0.68	1.39	2.13	3.99	4.78
$D_T(m^3)$	4.3×10^7	8.5×10^7	1.3×10^8	1.7×10^8	2.6×10^8

The important elements of a hydrological drought phenomenon are the longest duration and the largest severity for desired return period. These elements form the basis for designing water storage systems to cope with droughts for adaptation planning to climate change. Based on the results given in Table 4-7, on average the 100-year drought in the Lake Naivasha basin is expected to last for 6 years in a row and, thus, the corresponding severity is equal to 4.78. Similarly, the 2, 5, 10, and 50-year droughts are expected to last for 1, 2, 3 and 4 years respectively with the drought lengths rounded off to a whole year.

It is evident from the probabilistic approach for a normal probability distribution that high values of *cv* result in high values of D_T. Based on this, hydrological drought severity is expected to be high in parts of the basin experiencing high inter-annual variability in annual flow sequences. Such occurrences will be common in the semi-arid regions of the Lake Naivasha basin which routinely experience variable precipitation patterns.

The values of drought duration for normal independent flows were predicted using two independent variables, T and q. Therefore, from this perception, the critical hydrological droughts will persist for the same number of years in the entire Lake Naivasha basin. Likewise, standardized severity is also expected to be the same in the entire basin. However, each river will undergo a different level of actual severity D_T (m^3), because of different values of mean flows and associated co-efficient of variation.

These results have a significant implications pertaining to future water resources planning in the Lake Naivasha basin, especially against the backdrop of a higher likelihood of multi-year droughts due to climate variability. This risk must be considered in planning, design, operation and selection of water resources development scenarios in the Lake Naivasha basin. In particular, when attention is being focused on developing the lower parts of the basin, planners have to appreciate the fact that this region is very drought-prone, unlike the abundantly water-rich upper parts of the basin around the aberdare forest.

4.4 Prediction of extreme events for adaptation planning

4.4.1 Prediction of extreme precipitation events

The Extreme Value Type I distribution parameters were computed from the data in Table B-1 (Appendix B) of maximum annual daily rainfall events. These parameters were then fitted in the EVI models and used to predict rainfall events for specified return periods. The means and standard deviations of maximum annual daily rainfall as presented in Table B-1 (Appendix B) were used to derive Extreme Value Type I models presented in Table 4-8.

Table 4-8: Extreme Value Type I derived probability models

Station Id.	Probability Frequency Model	Coefficient of Determination	Data Period (Years)
9036002	$F(x) = exp\left[-exp\left(-\frac{x-39.4844}{7.6558}\right)\right]$	0.98	50
9036021	$F(x) = exp\left[-exp\left(-\frac{x-43.1119}{8.9883}\right)\right]$	0.99	50
9036025	$F(x) = exp\left[-exp\left(-\frac{x-37.2665}{9.9333}\right)\right]$	0.99	50
9036264	$F(x) = exp\left[-exp\left(-\frac{x-39.0490}{9.2706}\right)\right]$	0.97	50
9036241	$F(x) = exp\left[-exp\left(-\frac{x-38.3829}{9.5583}\right)\right]$	0.99	50
9036081	$F(x) = exp\left[-exp\left(-\frac{x-39.8875}{14.7479}\right)\right]$	0.98	50

The derived Extreme Value Type I (EVI) distributions in Table 4-8 were then used to predict extreme rainfall events. The model parameters, significance level (α) and point of maximum density (μ) were calculated using equation 3-18 and substituted in probability models in Table 4-8 directly.

The results of the derived probability frequency models are presented in Table 4-9 for extreme events (in millimeters) for desired return periods.

Table 4-9: Extreme events in mm estimated using derived frequency probability models based on EVI

Station Number	2-year	5-year	10-year	50-year	100-year
9036002	42.29	50.97	56.71	69.36	74.70
9036021	46.40	56.59	63.34	78.18	84.46
9036025	40.91	52.17	59.62	76.03	82.96
9036264	42.45	52.95	59.91	75.22	81.69
9036241	41.89	52.72	59.89	75.68	82.35
9036081	44.29	61.01	72.08	96.43	106.73

As indicated in Table 4-9, the predicted design events for gauging stations 9036021 and 9036081 are higher. This is because these stations lie in the semi arid areas where rainfall is erratic but with infrequent isolated storms. The deviations from rainfall stations chosen for the same return periods were not significantly different. For instance, for 2-year return period, the maximum annual daily rainfall derived were between 41.89 mm and 46.40mm. This implies that, for gauging stations which are in the upper catchment, their frequency models can be used for prediction in any other sub-catchment in the upper basin since the predicted events were almost similar.

The return periods of 2, 5, 10, 50 and 100 years as shown in Table 4-9 were selected for prediction of extreme events because they are normally used in catchment and water resources management practices. For instance, the five-year and ten-year storms are used for cut off drains, gully control structures, artificial waterways and culverts which are all means of collecting surface run-off. Fifty-year and hundred-year ones are used in reservoir design (Onyando *et al.*, 2004).

These results are important for planning catchment management activities. This is because they influence the kind of structures to be designed. For instance, for adaptation purposes structures should be designed to retain water in the catchment for agriculture, domestic and livestock watering among others.

Developing adaptation strategies for fresh water resources affected by global climate variability is complicated by the fact that water resources could either increase or decrease based on inter-annual precipitation pattern and extreme hydrological events. Therefore, planners will need to develop adaptation strategies for both drought and flooding conditions. One way to manage the impacts of climate variability on water resources is through capturing and controlling river flows as a result of increased run-off from these extreme rainfall events. Storage dams will be required to be built to retain and store surface run-off that is in excess of the user requirements and to release the run-off during the periods when low flows are not sufficient to meet the user needs, a practice that can also serve to maintain aquatic ecosystems.

4.4.2 Prediction of extreme stream flow events

The parameters of Log Pearson Type III distribution models were derived from the data in Tables C-1, C-2, C-3, C-4 and C-5 (Appendix C) of maximum annual daily stream flow events. These parameters were then fitted in Log Pearson Type III distribution models and used to predict stream flow events for specified return periods. The statistical parameters calculated from the stream flow data were; logarithmic sum, mean, variance and coefficient of skewness.

Table 4-12 presents the derived Log Pearson Type III distribution models for predicting stream flows in the Lake Naivasha basin and co-efficient of determination confirms their fitness.

Table 4-11: Derived Log Pearson Type III Distribution models

Station Number	Derived LP3	Coefficient of determination	Data Period
2GB1	Log x=0.84 + 0.13k	0.97	50
2GB5	Log x=0.62 + 0.14k	0.96	50
2GB4	Log x=0.27 + 0.09k	0.97	50
2GC4	Log x=0.31 + 0.20k	0.96	50

Where x is the measured stream flow and k is frequency factor selected from Table C-6 (Appendix C) for the computed value of coefficient of skewness and desired return periods. The coefficient of determination defined as the portion of the data that fits Log Pearson Type III were used to justify LP3 fitness.

The derived Log Pearson Type III distribution models were used to simulate stream flow data for the specific return periods. The estimated stream flows from the derived LP3 distribution models were derived and the results are presented in Table 4-13 for some of the selected return periods of interest in water resources and basin management practices.

Table 4-12: Derived stream flow (m^3/s) using derived LP3 distribution models

Station Number	2-year	5-year	10-year	50-year
2GB1	6.85	13.98	20.80	45.32
2GB5	4.50	9.05	12.30	20.75
2GB4	2.05	3.15	4.02	8.73
2GC4	1.16	4.88	6.15	12.88

From the results of Table 4-12, it can be seen that the return period increases as the estimated value by the derived LP3 models also increases in all stream flow gauging stations. This implies that, the peak discharges for longer periods of time are erratic and variable hence their prediction may not be reasonable. This phenomenon can be controlled by using mean annual daily discharges that minimizes the effect of peak daily discharge variability though if an extreme stream flow event happens rapidly for instance a high flow peak, then the annual maxima series will ideally be derived from daily data flows because the extreme stream flow event could be missed with mean annual daily discharge hence the use of daily extreme flows.

4.4.3 Comparison of derived and observed maximum annual hydrological events

To confirm whether the derived maximum annual daily rainfall values using the established frequency probability models were within acceptable range for corresponding return periods, the data for each rainfall station was divided into two portions. Derived extreme hydrological events from frequency models of the first portion of the data were compared with observed values from the second portion of the data. The results of the comparison are presented in Table 4-10.

Table 4-10: Comparison of derived and observed maximum annual rainfall events (mm)

	2-year		5-year		10-year		
Station Number	**Derived**	**Observed**	**Derived**	**Observed**	**derived**	**observed**	**Mean Deviation (%)**
9036002	43.01	40.8	51.97	50.8	57.22	53.5	5.5
9036021	49.66	58.5	60.28	68.2	65.43	69.7	11.0
9036025	41.41	40.0	56.49	61.3	59.62	61.6	4.9
9036264	45.36	44.7	47.65	44.7	57.78	54.4	4.8
9036241	39.06	36.2	53.27	51.2	55.76	53.0	5.7
9036081	47.29	50.0	60.01	58.0	62.08	56.6	6.2

The results show that the mean percentage deviation range is 4.8 % to 11.0% for all gauging station for return periods of 2-year, 5-year and 10-year. In gauging station 9036021, the observed events are larger than the derived events with the highest percentage deviation of 11.0%. However, in most of the other rainfall gauging stations the derived events are higher than the observed events. This means that, derived values are nearly the same as the observed ones and the resulting slight variation could be adequately covered by a factor of safety when applying derived rainfall events for design purposes (FAO, 1986).

CHAPTER FIVE
CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The severity of extreme hydrological events such as stream flows, precipitation and hydrological drought has intensified due to global warming and other environmental factors. Changes in the hydrological cycle have in turn affected water and run-off processes. Consequently, this has affected the discharge regime of rivers. The water resources in the study area are already under intense pressure from increased human population. This region has been vulnerable to drought, due to its dependence on rainfall for economic and social development. Water for domestic and other uses is derived from rivers and boreholes whose recharge depends on rainfall. This study was important because it has enhanced the understanding of trends in extreme hydrological regimes and improved the ability to predict precipitation and stream flow events, which can be used for better management and development of water resources in this region.

The overall objective of the study was to analyze hydrological extremes trends with a view to providing information for planning local coping mechanisms to climate change and variability. Trends in intensity, frequency and persistence of hydrological extremes were identified. This was achieved by the non-parametric Mann-Kendall and Spearman's Rank Correlation trend test which were used to detect trends in six rainfall gauges and four stream flow gauges across the basin. The critical drought parameter, namely the longest drought duration and the greatest severity were predicted using the probabilistic approach. Finally the frequency analysis of extreme annual daily precipitation and stream flows based on EVI and LP3 were satisfactorily used to develop models for predicting maximum annual daily hydrological events for adaptation planning to climate variability.

The application of the two trend detection tests identified some significant trends in extremes of precipitation and flow time series data in the Lake Naivasha basin. There were no significant trends in annual precipitation with significant trends in the months of April and November. Trends in stream flows were significant at annually scales but also revealed significant trends in the months of April and November. Overall, trends are not particularly strong as there is little temporal consistency across the trends in hydrological extremes for intensity, frequency and persistence. Nonetheless, the trend test statistics show some significant results which may be explained by a shift in climate variability of the Lake Naivasha basin. Given the impending challenges posed by changes in the trends of extreme hydrological events as shown by results in this study, it is important for policy makers to recognize the role of water resources as a primary medium through which climate variability will have an impact on development and to incorporate these considerations in overall development planning and management. These results will also assist policy makers, planners, water managers and water users in adaptation planning to the unfolding changes in trends of extreme hydrological events. This will help in managing and using water resources, in a manner that reflects water's variability, uncertainty, scarcity and abundance

The drought analysis revealed that the annual stream flow sequences can be construed as samples from the normal independent flow sequences. The probabilistic analysis of drought revealed that, in the prevailing trends of hydrological extremes, 100-year, 50-year, 10-year, 5-year and 2-year droughts will persist for 6, 4, 3, 2 and 1 years respectively. The longest drought duration and severity have uniform values for the entire study area in view of the normal and random probability structure of annual flows. However, actual severity will display variability in proportion to the coefficient of variation or standard deviation. These results have a significant implications pertaining to future water resources planning in the Lake Naivasha basin, especially against the backdrop of a higher likelihood of multi-year droughts due to climate variability. This risk must be considered in planning, design, operation and selection of water resources development scenarios in the Lake Naivasha basin. In particular, when attention is being focused on developing the lower parts of the basin, planners have to appreciate the fact that this region is very drought-prone, unlike the abundantly water-rich upper parts of the basin around the aberdare forest.

Based on the developed models, prediction of design precipitation and stream flows was carried out for every gauging station. The return periods used in this process were 2, 5, 10, 25 and 100 years. The study revealed that as the return period increased, the predicted extreme hydrological events also increased. A comparison of design precipitation events generated by the developed frequency models and those from observed values revealed a mean deviation ranging from 4.8% to 11.0% as the returns periods increased from 2-year to 10-year. This shows that, derived values are nearly the same as the observed ones and the resulting slight variation could be adequately covered by a factor of safety when applying derived rainfall events for adaptation planning purposes. These results are useful for adaptation against climate variability and change in that, they can be used in the design of water resources systems and other basin management structures. The structures requiring design include dams, spillways, culverts and drainage ditches among others. The design of these structures is necessary in order to ensure their efficient functioning and also to improve their life of operation. Appropriate design will ensure that the right size of the structures to withstand the extreme hydrological events is determined.

Adaptation measures can be a criterion for decision-making. A measure that contribute to solving existing water management problems and enhance adaptive capacity in the future should be prioritized. Beyond direct water management, institutional instruments such as land use planning can substantially reduce the vulnerability of communities to extreme precipitation events based on natural disasters if they are informed by reliable predicted data. Thus resilience against extreme precipitation storms can be achieved by building protective infrastructure or through planning which restricts settlement in vulnerable areas.

5.2 Recommendations

The results from this study provide a baseline for planning and management of water resources in different sectors in the Lake Naivasha basin especially in agriculture and water supply. Developing knowledge of hydrological trends and their prediction aids the ability to make informed decisions about how the society should respond under future climate systems. Understanding and management of hydrological changes comes with successful mitigation and the ability to adapt to changing hydrological extreme events trends. However, the following recommendations are made for further research on hydrological extremes trends and adaptation planning to climate variability and change.

The trend test should be carried out seasonally, covering long and short rainy seasons in the basin to identify the seasonal shifts of hydrological extremes. Also, there is need to evaluate the magnitude of these trends under different land use/cover change scenarios in order to determine which of the two changes, namely; climate variability and land use/cover change, produce more distinct changes in stream flow and how they affect each other.

There is need for further study on predictions of drought onset and development of objective quantification of drought and associated economic impacts to accurately quantify the monetary benefits of improved drought prediction and adaptation. A study should be also undertaken on to what extent is changes in the statistics of extreme hydrological events are predictable.

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APPENDICES

APPENDIX A
CORRELATION TEST

Table A-1: Rainfall Multiple Correlation at 0.05 significance level

Station	Statistic	9036002	9036021	9036025	9036264	9036241	9036081
9036002	R	1	0.293	0.297	-0.019	0.293	0.999
	Sig(2-tailed)		0.223	0.217	0.954	0.223	0
	N	50	50	50	50	50	50
9036021	R	0.293	1	0.999	0.992	0.995	0.297
	Sig(2-tailed)	0.223		0	0	0	0.217
	N	50	50	50	50	50	50
9036025	R	0.297	0.999	1	0.992	0.999	0.297
	Sig(2-tailed)	0.217	0		0	0	0.217
	N	50	50	50	50	50	50
9036264	R	-0.019	0.992	0.992	1	0.992	-0.019
	Sig(2-tailed)	0.954	0	0		0	0.954
	N	50	50	50	50	50	50
9036241	R	0.293	0.995	0.999	0.992	1	0.293
	Sig(2-tailed)	0.223	0	0	0		0.223
	N	0	50	50	50	50	50
9036081	R	0.999	0.297	0.297	-0.019	0.293	1
	Sig(2-tailed)	0	0.217	0.217	0.954	0.223	
	N	50	50	50	50	50	50

Table A-2: Stream Flow Multiple Correlation at 0.05 significance level

Station	Statistic	2GB1	2GB5	2GB4	2GC4
2GB1	R	1	0.999	0.993	0.996
	Sig(2-tailed)		0	0	0
	N	50	50	50	50
2GB5	R	0.999	1	0.900	0.912
	Sig(2-tailed)	0		0	0
	N	50	50	50	50
2GB4	R	0.993	0.900	1	0.992
	Sig(2-tailed)	0	0		0
	N	50	50	50	50
2GC4	R	0.996	0.912	0.992	1
	Sig(2-tailed)	0	0	0	
	N	50	50	50	50

APPENDIX B

DAILY MAXIMA ANNUAL RAINFALL AND TRENDS

Table B-1: Daily maxima annual rainfall at each rainfall gauging station

Year	9036002	9036021	9036025	9036081	9036241	9036264
1959	21.6	47.2	24.6	44.2	25.9	29.7
1960	50.8	47.0	28.4	27.2	41.9	23.4
1961	50.0	53.8	39.4	35.6	39.9	61.2
1962	29.2	57.2	48.0	53.8	36.8	49.5
1963	51.1	56.4	50.8	61.5	78.0	63.8
1964	40.1	60.2	53.3	43.4	55.9	49.8
1965	32.0	38.1	34.3	34.3	29.5	36.1
1966	47.0	30.7	39.4	30.5	43.2	45.7
1967	34.3	30.0	43.2	59.9	29.2	41.4
1968	44.7	50.2	43.2	38.1	35.0	43.9
1969	45.5	39.4	45.7	33.0	30.1	37.6
1970	47.0	35.3	50.0	50.8	41.9	46.0
1971	70.7	36.3	30.2	21.5	29.3	91.5
1972	55.8	47.5	33.3	81.3	31.1	43.2
1973	41.9	43.1	34.4	25.2	30.1	30.3
1974	39.5	53.3	27.9	28.5	28.5	39.5
1975	52.0	50.2	35.0	32.3	61.0	44.6
1976	28.9	32.3	78.0	39.4	40.5	37.0
1977	51.3	63.7	70.8	63.0	46.5	66.3
1978	38.7	70.8	35.0	44.2	50.7	43.4
1979	38.7	57.4	30.0	48.9	44.5	74.4
1980	42.3	31.7	62.5	26.5	41.9	46.0
1981	33.8	47.2	55.4	30.1	56.3	37.4
1982	55.3	38.5	47.0	51.0	37.5	35.1
1983	43.6	48.2	60.0	88.5	50.0	30.0
1984	47.4	36.0	34.5	29.2	54.4	40.1
1985	40.8	58.5	40.0	88.0	36.2	44.7
1986	61.7	64.0	38.0	50.0	44.4	38.6
1987	62.5	54.0	61.3	62.0	51.2	44.4
1988	50.8	68.2	36.9	58.0	47.2	48.5
1989	37.8	52.2	70.1	82.0	37.4	47.0
1990	37.1	56.2	33.2	80.0	53.0	41.4
1991	36.3	28.0	71.0	32.0	39.4	36.1
1992	44.9	32.0	47.4	90.3	53.0	31.8
1993	53.5	69.7	61.6	56.6	39.1	54.4
1994	36.2	29.0	40.1	86.2	46.7	34.3
1995	42.3	39.0	54.4	67.4	34.5	47.0

1996	61.8	56.4	26.3	43.2	77.0	43.9
1997	52.0	60.9	30.3	55.4	73.5	48.9
1998	48.0	46.2	49.6	41.0	42.0	53.3
1999	31.9	51.3	41.3	48.0	32.5	39.9
2000	37.0	36.8	37.5	22.5	50.0	39.9
2001	56.0	40.2	42.0	51.8	50.3	55.1
2002	37.0	52.5	40.1	37.9	50.9	50.3
2003	48.8	63.9	39.0	48.7	60.0	43.2
2004	41.2	59.0	37.1	46.7	35.6	44.1
2005	45.6	53.2	40.9	30.8	42.1	32.1
2006	32.4	51.8	37.0	29.5	42.7	30.4
2007	30.1	45.6	45.8	43.2	43.5	45.7
2008	45.3	71.3	26.7	39.0	23.4	37.8

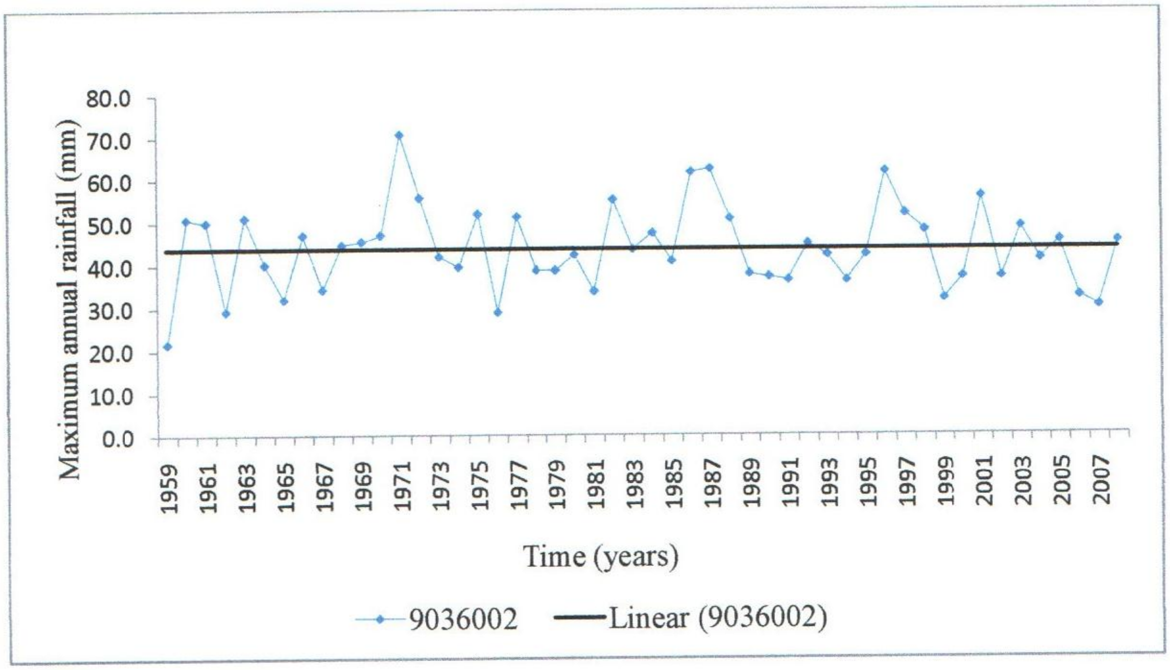

Figure B-1: Station No 9036002 maximum annual daily rainfall trend

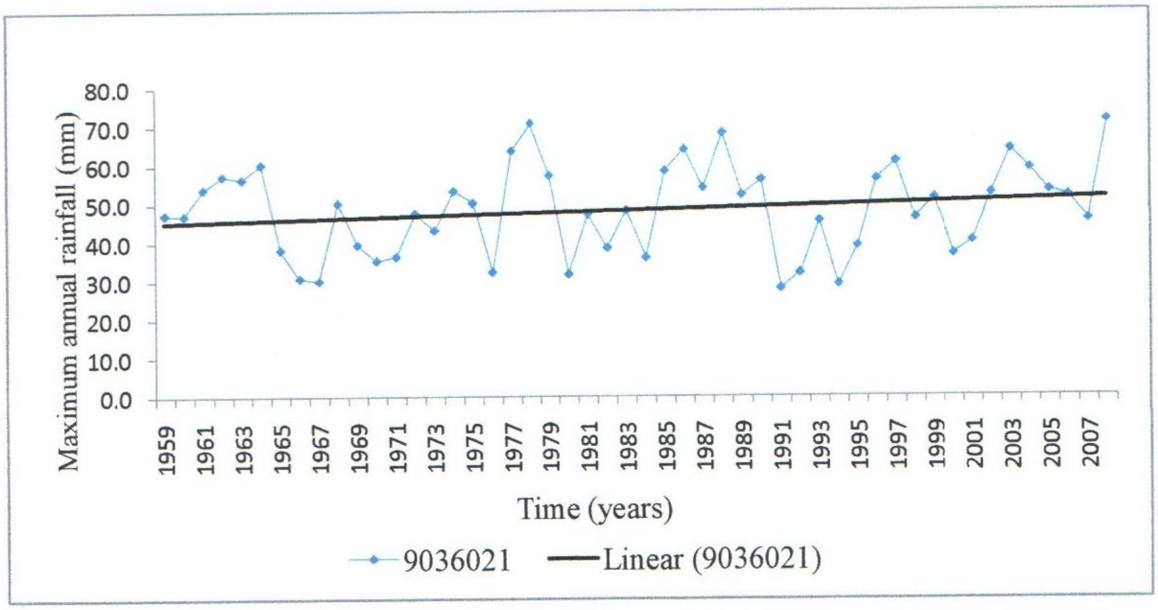

Figure B-2: Station No 9036021 maximum annual daily rainfall trend

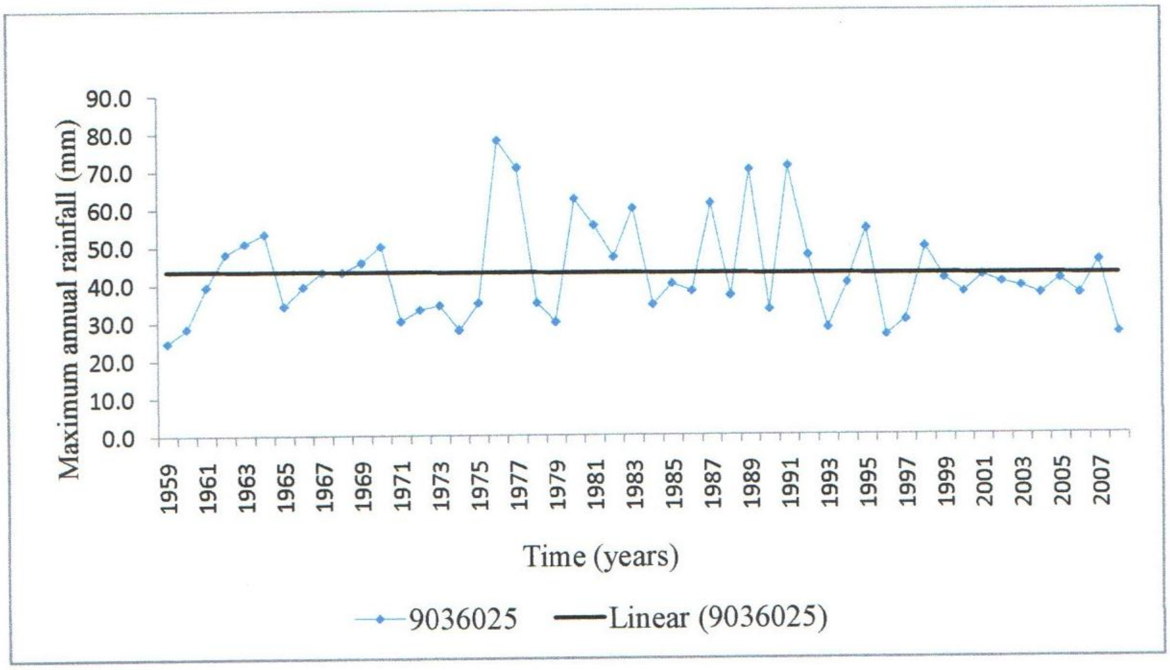

Figure B-3: Station No 9036025 maximum annual daily rainfall trend

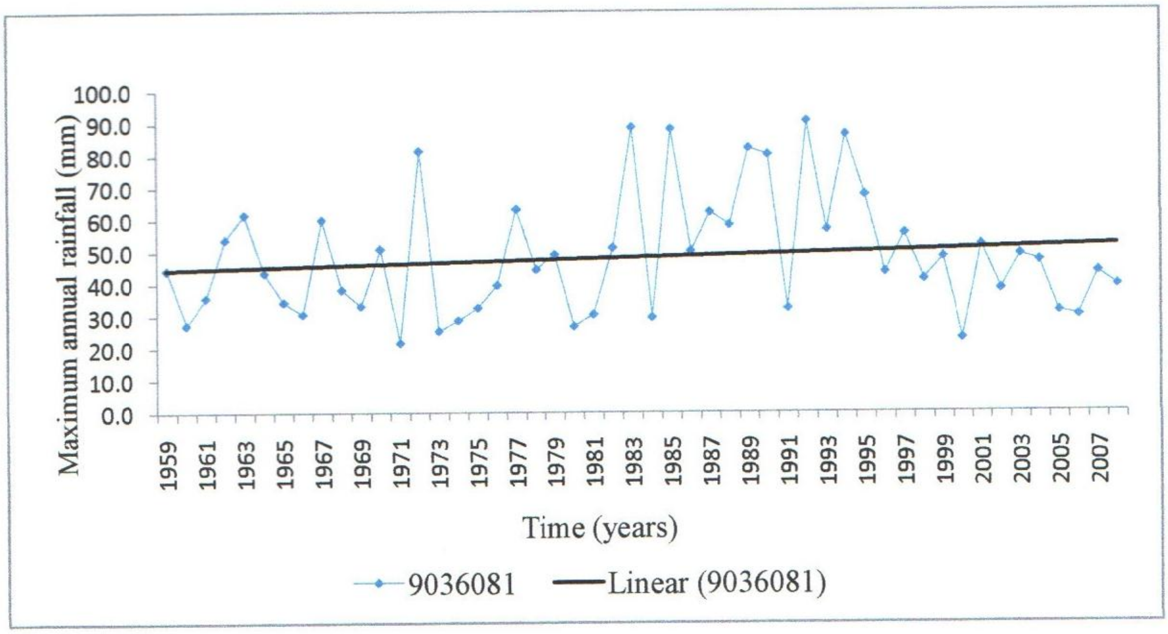

Figure B-4: Station No 9036081 maximum annual daily rainfall trend

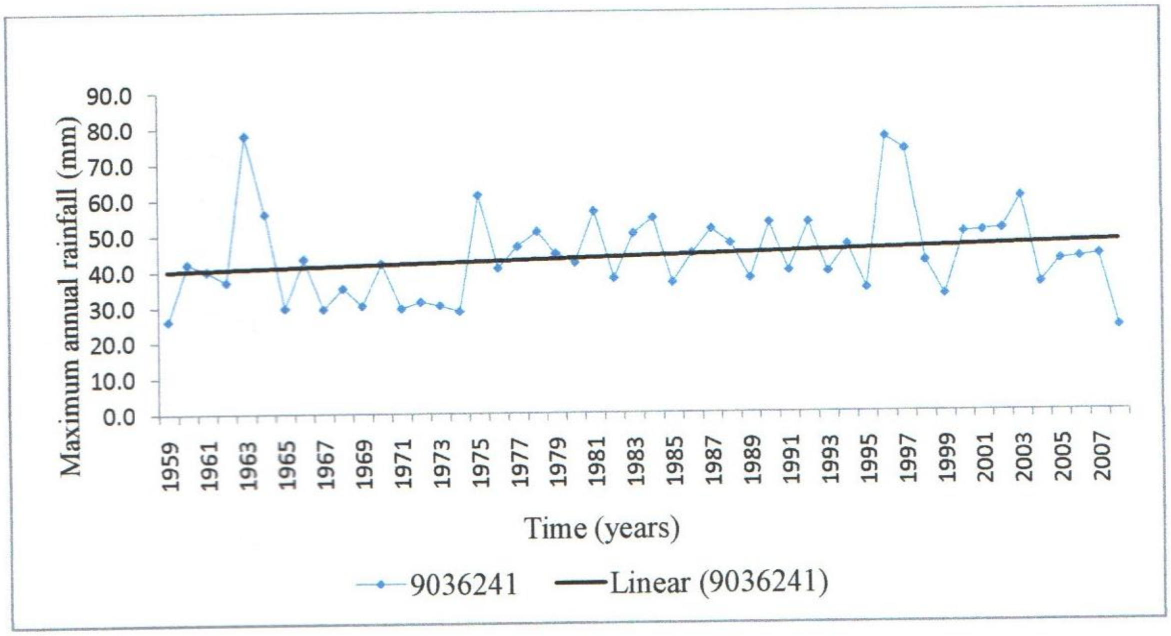

Figure B-5: Station No 9036241 maximum annual daily rainfall trend

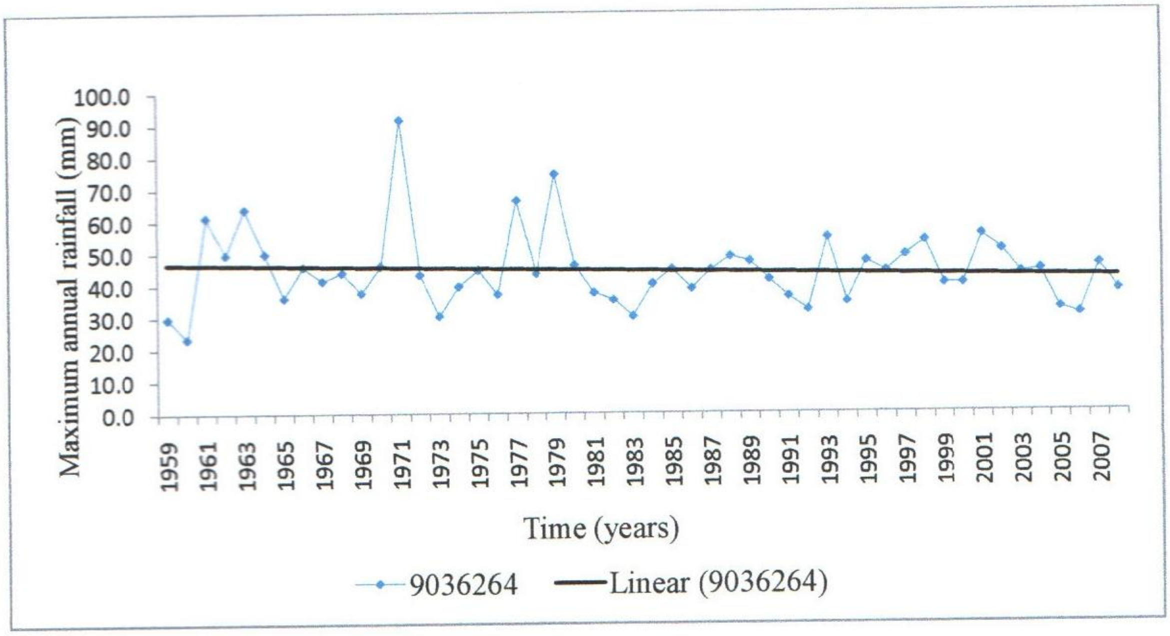

Figure B-6: Station No 9036264 maximum annual daily rainfall trend

APPENDIX C

STREAM FLOW ANALYSIS

Table C-1: Rating equations applied in each gauging station

RGS	DATES USED	Rating Equation: $Q = c(H - H_o)^n$				
		C	**n**	**Ho**	**Hmin**	**Hmax**
2GB1	23/06/1931	21.7477	1.5081	0	0	2.77m
		23.2108	1.5629	0	0.3	
		26.4055	2.0372	0	0.76	
		31.8373	1.5933	0	1.5	
	18/04/1951	25.96	1.821	0.03	0	3m
2GB5	15/05/1959	4.9017	1.7418	0	0	3.05m
	01/09/1974	2.7914	3.6779	0	0	3.05m
2GB4	09/03/1961	5.890887	1.506156	0	0	0.8m
2GC4	26/07/1950	8.129249	1.687367	0	0	1.83m

Table C-2: Annual peak flows (m^3/s) for gauging station No. 2GB1

Year	Discharge(X)	m	T	Log X	Prob-%
1998	46.37	1.00	51.00	1.67	1.96
1986	23.84	2.00	25.50	1.38	3.92
1968	23.60	3.00	17.00	1.37	5.88
2008	23.60	4.00	12.75	1.37	7.84
1962	21.89	5.00	10.20	1.34	9.80
1985	19.06	6.00	8.50	1.28	11.76
1992	18.78	7.00	7.29	1.27	13.73
2001	15.89	8.00	6.38	1.20	15.69
1965	14.34	9.00	5.67	1.16	17.65
2005	14.34	10.00	5.10	1.16	19.61
1959	13.08	11.00	4.64	1.12	21.57
1969	12.55	12.00	4.25	1.10	23.53
2000	11.81	13.00	3.92	1.07	25.49
1974	11.55	14.00	3.64	1.06	27.45
1997	11.35	15.00	3.40	1.05	29.41
1972	11.19	16.00	3.19	1.05	31.37
1987	9.93	17.00	3.00	1.00	33.33
1967	9.29	18.00	2.83	0.97	35.29
2007	9.29	19.00	2.68	0.97	37.25
1971	8.57	20.00	2.55	0.93	39.22
1982	8.51	21.00	2.43	0.93	41.18
1980	8.41	22.00	2.32	0.92	43.14
1978	7.76	23.00	2.22	0.89	45.10
1961	7.70	24.00	2.13	0.89	47.06
1993	7.52	25.00	2.04	0.88	49.02
1996	7.47	26.00	1.96	0.87	50.98
2002	7.03	27.00	1.89	0.85	52.94
1979	6.68	28.00	1.82	0.82	54.90
1975	6.64	29.00	1.76	0.82	56.86
1970	6.46	30.00	1.70	0.81	58.82
1988	6.33	31.00	1.65	0.80	60.78
1999	6.33	32.00	1.59	0.80	62.75
1990	5.20	33.00	1.55	0.72	64.71
1991	4.45	34.00	1.50	0.65	66.67
1960	4.13	35.00	1.46	0.62	68.63
1989	4.02	36.00	1.42	0.60	70.59
1963	3.93	37.00	1.38	0.59	72.55
2003	3.93	38.00	1.34	0.59	74.51
1964	3.54	39.00	1.31	0.55	76.47
2004	3.54	40.00	1.28	0.55	78.43
1983	3.17	41.00	1.24	0.50	80.39
1977	3.16	42.00	1.21	0.50	82.35

1994	3.16	43.00	1.19	0.50	84.31
1973	2.76	44.00	1.16	0.44	86.27
1981	2.12	45.00	1.13	0.33	88.24
1984	1.80	46.00	1.11	0.26	90.20
1966	1.66	47.00	1.09	0.22	92.16
2006	1.66	48.00	1.06	0.22	94.12
1976	1.51	49.00	1.04	0.18	96.08
1995	1.30	50.00	1.02	0.11	98.04
Sum				41.93	
Mean				0.84	
Variance				0.13	
Skewness				-0.11	

Table C-3: Annual peak flows (m^3/s) for gauging station No. 2GB4

Year	Discharge(X)	m	T	Log X	Prob-%
1998	9.41	1.00	51.00	0.97	1.96
1990	5.15	2.00	25.50	0.71	3.92
1961	4.43	3.00	17.00	0.65	5.88
1988	4.29	4.00	12.75	0.63	7.84
1980	4.06	5.00	10.20	0.61	9.80
1978	3.83	6.00	8.50	0.58	11.76
1979	3.73	7.00	7.29	0.57	13.73
1960	3.69	8.00	6.38	0.57	15.69
1963	3.58	9.00	5.67	0.55	17.65
1992	3.55	10.00	5.10	0.55	19.61
1959	3.47	11.00	4.64	0.54	21.57
1967	3.47	12.00	4.25	0.54	23.53
2001	3.33	13.00	3.92	0.52	25.49
1977	3.07	14.00	3.64	0.49	27.45
1968	2.92	15.00	3.40	0.47	29.41
2006	2.87	16.00	3.19	0.46	31.37
1986	2.86	17.00	3.00	0.46	33.33
1993	2.75	18.00	2.83	0.44	35.29
1971	2.70	19.00	2.68	0.43	37.25
1997	2.68	20.00	2.55	0.43	39.22
1969	2.55	21.00	2.43	0.41	41.18
1985	2.55	22.00	2.32	0.41	43.14
1991	2.46	23.00	2.22	0.39	45.10
2005	2.41	24.00	2.13	0.38	47.06
1975	2.12	25.00	2.04	0.33	49.02
1995	2.09	26.00	1.96	0.32	50.98
1976	2.06	27.00	1.89	0.31	52.94
1970	2.04	28.00	1.82	0.31	54.90
1966	1.93	29.00	1.76	0.29	56.86
1981	1.73	30.00	1.70	0.24	58.82
1989	1.48	31.00	1.65	0.17	60.78
1987	1.27	32.00	1.59	0.10	62.75
1996	1.27	33.00	1.55	0.10	64.71
2002	1.21	34.00	1.50	0.08	66.67
2000	1.15	35.00	1.46	0.06	68.63
1965	1.12	36.00	1.42	0.05	70.59
1982	1.04	37.00	1.38	0.02	72.55
1999	1.04	38.00	1.34	0.02	74.51
1973	0.99	39.00	1.31	0.00	76.47
2008	0.97	40.00	1.28	-0.01	78.43

1984	0.94	41.00	1.24	-0.03	80.39
1994	0.94	42.00	1.21	-0.03	82.35
1972	0.86	43.00	1.19	-0.07	84.31
2007	0.86	44.00	1.16	-0.07	86.27
1983	0.69	45.00	1.13	-0.16	88.24
2003	0.69	46.00	1.11	-0.16	90.20
1964	0.57	47.00	1.09	-0.24	92.16
1974	0.57	48.00	1.06	-0.24	94.12
2004	0.57	49.00	1.04	-0.24	96.08
1962	0.39	50.00	1.02	-0.41	98.04
Sum				13.49	
Mean				0.27	
Variance				0.09	
Skewness				-0.23	

Table C-4: Annual peak flows (m^3/s) for gauging station No. 2GB5

Year	Discharge(X)	m	T	Log X	Prob-%
1998	23.15	1.00	51.00	1.36	1.96
2003	18.68	2.00	25.50	1.27	3.92
1978	16.00	3.00	17.00	1.20	5.88
2006	13.74	4.00	12.75	1.14	7.84
1983	13.27	5.00	10.20	1.12	9.80
1988	12.56	6.00	8.50	1.10	11.76
1997	11.91	7.00	7.29	1.08	13.73
1975	10.71	8.00	6.38	1.03	15.69
1989	10.44	9.00	5.67	1.02	17.65
1995	9.41	10.00	5.10	0.97	19.61
1996	7.78	11.00	4.64	0.89	21.57
1959	7.68	12.00	4.25	0.89	23.53
1964	7.44	13.00	3.92	0.87	25.49
2007	7.37	14.00	3.64	0.87	27.45
1962	6.93	15.00	3.40	0.84	29.41
1961	6.57	16.00	3.19	0.82	31.37
1992	6.34	17.00	3.00	0.80	33.33
1985	6.16	18.00	2.83	0.79	35.29
1981	6.04	19.00	2.68	0.78	37.25
1986	5.19	20.00	2.55	0.72	39.22
2001	5.06	21.00	2.43	0.70	41.18
1999	4.92	22.00	2.32	0.69	43.14
1974	4.77	23.00	2.22	0.68	45.10
1994	4.69	24.00	2.13	0.67	47.06
1970	4.64	25.00	2.04	0.67	49.02
1960	4.17	26.00	1.96	0.62	50.98
2002	3.97	27.00	1.89	0.60	52.94
1991	3.77	28.00	1.82	0.58	54.90
2008	3.76	29.00	1.76	0.58	56.86
1971	3.69	30.00	1.70	0.57	58.82
1990	3.69	31.00	1.65	0.57	60.78
1977	3.59	32.00	1.59	0.56	62.75
1973	3.52	33.00	1.55	0.55	64.71
1967	3.40	34.00	1.50	0.53	66.67
1966	2.91	35.00	1.46	0.46	68.63
2000	2.53	36.00	1.42	0.40	70.59
1979	2.46	37.00	1.38	0.39	72.55
1984	2.35	38.00	1.34	0.37	74.51
1965	2.29	39.00	1.31	0.36	76.47
1987	2.17	40.00	1.28	0.34	78.43

1980	2.05	41.00	1.24	0.31	80.39
1982	1.61	42.00	1.21	0.21	82.35
2004	1.41	43.00	1.19	0.15	84.31
1976	1.33	44.00	1.16	0.12	86.27
1968	1.21	45.00	1.13	0.08	88.24
1963	1.15	46.00	1.11	0.06	90.20
1972	1.13	47.00	1.09	0.05	92.16
1969	0.97	48.00	1.06	-0.01	94.12
2005	0.93	49.00	1.04	-0.03	96.08
1993	0.69	50.00	1.02	-0.16	98.04
Sum				31.22	
Mean				0.62	
Variance				0.14	
Skewness				-0.16	

Table C-5: Annual peak flows (m^3/s) for gauging station No. 2GC4

Year	Discharge(X)	m	T	Log X	Prob-%
1998	15.43	1.00	51.00	1.19	1.96
1990	10.10	2.00	25.50	1.00	3.92
1994	9.13	3.00	17.00	0.96	5.88
2001	7.13	4.00	12.75	0.85	7.84
1979	6.47	5.00	10.20	0.81	9.80
1992	6.42	6.00	8.50	0.81	11.76
1978	5.59	7.00	7.29	0.75	13.73
1997	5.59	8.00	6.38	0.75	15.69
2008	5.59	9.00	5.67	0.75	17.65
1968	5.43	10.00	5.10	0.73	19.61
1970	5.38	11.00	4.64	0.73	21.57
1972	5.27	12.00	4.25	0.72	23.53
1991	4.33	13.00	3.92	0.64	25.49
1993	3.82	14.00	3.64	0.58	27.45
1961	3.47	15.00	3.40	0.54	29.41
1973	3.43	16.00	3.19	0.54	31.37
1960	3.16	17.00	3.00	0.50	33.33
2004	3.05	18.00	2.83	0.48	35.29
1983	2.98	19.00	2.68	0.47	37.25
1985	2.70	20.00	2.55	0.43	39.22
1959	2.55	21.00	2.43	0.41	41.18
1969	2.43	22.00	2.32	0.39	43.14
1996	2.40	23.00	2.22	0.38	45.10
1971	1.94	24.00	2.13	0.29	47.06
1982	1.89	25.00	2.04	0.28	49.02
2003	1.85	26.00	1.96	0.27	50.98
1977	1.84	27.00	1.89	0.26	52.94
1987	1.77	28.00	1.82	0.25	54.90
1967	1.76	29.00	1.76	0.25	56.86
1964	1.70	30.00	1.70	0.23	58.82
1995	1.68	31.00	1.65	0.23	60.78
1989	1.61	32.00	1.59	0.21	62.75
1986	1.50	33.00	1.55	0.18	64.71
2005	1.40	34.00	1.50	0.15	66.67
1976	1.39	35.00	1.46	0.14	68.63
1984	1.39	36.00	1.42	0.14	70.59
1963	1.38	37.00	1.38	0.14	72.55
2007	1.37	38.00	1.34	0.14	74.51
1975	1.27	39.00	1.31	0.10	76.47
1988	1.22	40.00	1.28	0.09	78.43

1974	1.18	41.00	1.24	0.07	80.39
1999	1.09	42.00	1.21	0.04	82.35
1980	1.05	43.00	1.19	0.02	84.31
1981	0.99	44.00	1.16	0.00	86.27
2002	0.75	45.00	1.13	-0.12	88.24
1966	0.72	46.00	1.11	-0.14	90.20
2000	0.37	47.00	1.09	-0.43	92.16
2006	0.23	48.00	1.06	-0.64	94.12
1965	0.21	49.00	1.04	-0.68	96.08
1962	0.05	50.00	1.02	-1.30	98.04
Sum				15.55	
Mean				0.31	
Variance				0.20	
Skewness				-1.03	

Table C-6: Values of *K* for use with the Log Pearson Type III Distribution

	Recurrence Interval in Years					
	2	10	25	50	100	200
Skew Coeff	Chance %					
g	50	10	4	2	1	0.5
2.0	-0.31	1.30	2.22	2.91	3.61	4.29
1.8	-0.28	1.32	2.19	2.85	3.50	4.15
1.6	-0.25	1.33	2.16	2.78	3.39	3.99
1.4	-0.23	1.34	2.13	2.71	3.27	3.83
1.2	-0.19	1.34	2.09	2.63	3.15	3.66
1.0	-0.16	1.34	2.04	2.54	3.02	3.49
0.9	-0.15	1.34	2.02	2.49	2.96	3.40
0.8	-0.13	1.34	1.99	2.45	2.89	3.31
0.7	-0.12	1.33	1.97	2.41	2.82	3.22
0.6	-0.09	1.33	1.94	3.36	2.75	3.13
0.5	-0.08	1.32	1.91	2.31	2.69	3.04
0.4	-0.07	1.32	1.88	2.26	2.62	2.95
0.3	-0.05	1.31	1.85	2.21	2.54	2.86
0.2	-0.03	1.30	1.82	2.16	2.47	2.76
0.1	-0.02	1.29	1.79	2.11	2.40	2.67
0	0	1.282	1.751	2.054	2.326	2.576
-0.1	0.017	1.270	1.716	2.000	2.252	2.482
-0.2	0.033	1.258	1.680	1.945	2.178	2.388
-0.3	0.050	1.245	1.643	1.890	2.104	2.294
-0.4	0.066	1.231	1.606	1.834	2.029	2.201
-0.5	0.083	1.216	1.567	1.777	1.955	2.108
-0.6	0.099	1.200	1.528	1.720	1.880	2.016
-0.7	0.116	1.183	1.488	1.663	1.806	1.926
-0.8	0.132	1.166	1.448	1.606	1.733	1.837
-0.9	0.148	1.147	1.407	1.549	1.660	1.749

Source: Haan 1977

APPENDIX D

DROUGHT ANALYSIS

Table D-1: Summary of computation for $E(L_T)$, I and $E(S_T)$ for 2-year drought

Statistics of annual flow sequences	J	$P(L_T = j)$	$P(L_T = j) \times j$
Mean = 3.35 m^3/s	1	0.172270123	0.172270123
Std deviation = 1.69 m^3/s	2	0.10369612	0.207392239
Skewness = 0.15 (≈ 0)	3	0.05691616	0.170748481
$\rho = 0.19$ (≈ 0)	4	0.029820172	0.119280687
$T = 2$-years	5	0.015263203	0.076316013
$\mu_o = 0$	6	0.007721501	0.046329008
$cv = 0.193$	7	0.003883431	0.027184018
$z_o = 0$	8	0.001947412	0.015579293
$q = r = 0.5$	9	0.000975133	0.008776198
	10	0.000487924	0.004879238
	11	0.000244051	0.002684564
	12	0.000122048	0.001464576
	13	6.10296×10^{-5}	0.000793384
	14	3.05162×10^{-5}	0.000427227
	15	1.52584×10^{-5}	0.000228877
	16	7.62931×10^{-6}	0.000122069
	17	3.81468×10^{-6}	6.48495×10^{-5}
	18	1.90734×10^{-6}	3.43322×10^{-5}
	19	9.53673×10^{-7}	1.81198×10^{-5}
	20	4.76837×10^{-7}	9.53674×10^{-6}
	21	2.38418×10^{-7}	5.00679×10^{-6}
	22	1.19209×10^{-7}	2.62260×10^{-6}
	23	5.96046×10^{-8}	1.37091×10^{-6}
	24	2.98023×10^{-8}	7.15256×10^{-7}
	25	1.49012×10^{-8}	$3.72529- \times 10^{-7}$
		$E(L_T)$	0.854612919
		I	0.8
		$E(S_T)$	0.683690335

Table D-2 Summary of computation for $E(L_T)$, I and $E(S_T)$ for 5-year drought

Statistics of annual flow sequences	J	$P(L_T = j)$	$P(L_T = j)$ x j
Mean = 3.35 m^3/s	1	0.248756632	0.248757
Std deviation = 1.69 m^3/s	2	0.1963542	0.392708
Skewness = 0.15 ($\approx$ 0)	3	0.123729698	0.371189
ρ = 0.19 ($\approx$ 0)	4	0.069503486	0.278014
T = 5-years	5	0.036841788	0.184209
$\mu_o = 0$	6	0.018967648	0.113806
$cv = 0.193$	7	0.009623655	0.067366
$z_o = 0$	8	0.004847185	0.038777
$q = r = 0.5$	9	0.002432483	0.021892
	10	0.00121847	0.012185
	11	0.000609793	0.006708
	12	0.000305036	0.00366
	13	0.000152553	0.001983
	14	7.62852×10^{-5}	0.001068
	15	3.81448×10^{-5}	0.000572
	16	1.90729×10^{-5}	0.000305
	17	9.53661×10^{-6}	0.000162
	18	4.76834×10^{-6}	8.58×10^{-5}
	19	2.38418×10^{-6}	4.53×10^{-5}
	20	1.19209×10^{-6}	2.38×10^{-5}
	21	5.96046×10^{-7}	1.25×10^{-5}
	22	2.98023×10^{-7}	6.56×10^{-6}
	23	1.49012×10^{-7}	3.43×10^{-6}
	24	7.45058×10^{-8}	1.79×10^{-6}
	25	3.72529×10^{-8}	9.31×10^{-7}
		$E(L_T)$	1.743542
		I	0.8
		$E(S_T)$	1.394834

Table D-3 Summary of computation for $E(L_T)$, I and $E(S_T)$ for 10-year drought

Statistics of annual flow sequences	J	$P(L_T = j)$	$P(L_T = j) \times j$
Mean = 3.35 m^3/s	1	0.204419798	0.20442
Std deviation = 1.69 m^3/s	2	0.248756632	0.497513
	3	0.1963542	0.589063
Skewness = 0.15 (≈ 0)	4	0.123729698	0.494919
$\rho = 0.19$ (≈ 0)	5	0.069503486	0.347517
T = 10-years	6	0.036841788	0.221051
	7	0.018967648	0.132774
$\mu_o = 0$	8	0.009623655	0.076989
$cv = 0.193$	9	0.004847185	0.043625
$z_o = 0$	10	0.002432483	0.024325
	11	0.00121847	0.013403
$q = r = 0.5$	12	0.000609793	0.007318
	13	0.000305036	0.003965
	14	0.000152553	0.002136
	15	7.63085×10^{-5}	0.001145
	16	3.81448×10^{-5}	0.00061
	17	1.90729×10^{-5}	0.000324
	18	9.53661×10^{-6}	0.000172
	19	4.76834×10^{-6}	9.06×10^{-5}
	20	2.38418×10^{-6}	4.77×10^{-5}
	21	1.19209×10^{-6}	2.50×10^{-5}
	22	5.96046×10^{-7}	1.31×10^{-5}
	23	2.98023×10^{-7}	6.85×10^{-6}
	24	1.49012×10^{-7}	3.58×10^{-6}
	25	7.45058×10^{-8}	1.86×10^{-6}
		$E(L_T)$	2.661456
		I	0.8
		$E(S_T)$	2.129165

Table D-4 Summary of computation for $E(L_T)$, I and $E(S_T)$ for 50-year drought

Statistics of annual flow sequences	J	$P(L_T = j)$	$P(L_T = j) \times j$
Mean = 3.35 m^3/s	1	0.001926727	0.001927
Std deviation = 1.69 m^3/s	2	0.042006479	0.084013
Skewness = 0.15 (≈ 0)	3	0.165674454	0.497023
$\rho = 0.19$ (≈ 0)	4	0.248221975	0.992888
T = 50-years	5	0.218800484	1.094002
$\mu_o = 0$	6	0.145943716	0.875662
$cv = 0.193$	7	0.084383055	0.590681
$z_o = 0$	8	0.045384182	0.363073
$q = r = 0.5$	9	0.02353675	0.211831
	10	0.011985622	0.119856
	11	0.006047901	0.066527
	12	0.003037821	0.036454
	13	0.001522391	0.019791
	14	0.000762067	0.010669
	15	0.00011436	0.001715
	16	0.00019068	0.003051
	17	9.53538×10^{-5}	0.001621
	18	4.76803×10^{-5}	0.000858
	19	2.38410×10^{-5}	0.000453
	20	1.19207×10^{-5}	0.000238
	21	5.96041×10^{-6}	0.000125
	22	2.98022×10^{-6}	6.56×10^{-5}
	23	1.49011×10^{-6}	3.43×10^{-5}
	24	7.45057×10^{-7}	1.79×10^{-5}
	25	3.72529×10^{-7}	9.31×10^{-6}
		$E(L_T)$	4.972587
		I	0.8
		$E(S_T)$	3.97807

Table D-5 Summary of computation for $E(L_T)$, I and $E(S_T)$ for 100-year drought

Statistics of annual flow sequences	J	$P(L_T = j)$	$P(L_T = j) \times j$
Mean = 3.35 m^3/s	1	3.72664×10^{-6}	3.73×10^{-6}
Std deviation = 1.69 m^3/s	2	0.001926727	0.003853
	3	0.042006479	0.126019
Skewness = 0.15 (≈ 0)	4	0.165674454	0.662698
$\rho = 0.19$ (≈ 0)	5	0.248221975	1.24111
T = 100-years	6	0.218800484	1.312803
	7	0.145943716	1.021606
$\mu_o = 0$	8	0.084383055	0.675064
$cv = 0.193$	9	0.045384182	0.408458
$z_o = 0$	10	0.02353675	0.235368
	11	0.011985622	0.131842
$q = r = 0.5$	12	0.006047901	0.072575
	13	0.003037821	0.039492
	14	0.001522391	0.021313
	15	0.000764396	0.011466
	16	0.000381252	0.0061
	17	0.00019068	0.003242
	18	9.53538×10^{-5}	0.001716
	19	4.76803×10^{-5}	0.000906
	20	2.38410×10^{-5}	0.000477
	21	1.19207×10^{-5}	0.00025
	22	5.96041×10^{-6}	0.000131
	23	2.98022×10^{-6}	6.85×10^{-5}
	24	1.49011×10^{-6}	3.58×10^{-5}
	25	7.45057×10^{-7}	1.86×10^{-5}
		$E(L_T)$	5.976616
		I	0.8
		$E(S_T)$	4.781293

Table D-6: Values of z_o, q and drought density I at the mean level of truncation for various cv values

Value of cv	Normal pdf			Lognormal pdf			Gamma pdf		
	z_m	q	I	z_{mg}	Q	I	z_{ml}	q	I
0.2	0.5	0.5	0.8	0.099	0.54	0.83	0.069	0.53	0.82
0.4	0.5	0.5	0.8	0.19	0.58	0.87	0.13	0.55	0.85
0.6	0.5	0.5	0.8	0.28	0.61	0.91	0.21	0.58	0.88
0.8	0.5	0.5	0.8	0.35	0.64	0.94	0.27	0.611	0.90
1.0	0.5	0.5	0.8	0.42	0.84	0.97	0.33	0.63	0.93

Table D-7: Values of q and values of r at various ρ values at the mean level of truncation for various probability distributions

	All cvs	cv= 0.2		cv = 0.4		cv = 0.6		cv = 0.8		cv = 1.0	
	N	G	LN	G	LN	G	LN	G	LN	G	LN
q	0.50	0.53	0.54	0.56	0.58	0.58	0.61	0.61	0.64	0.64	0.66
ρ=0.1	0.53	0.56	0.57	0.58	0.61	0.61	0.64	0.63	0.67	0.66	0.71
ρ=0.3	0.60	0.62	0.63	0.64	0.67	0.67	0.70	0.69	0.74	0.71	0.78
ρ=0.5	0.67	0.69	0.70	0.71	0.73	0.73	0.76	0.75	0.80	0.77	0.84
ρ=0.7	0.75	0.77	0.77	0.78	0.80	0.80	0.82	0.81	0.86	0.83	0.89

Key: N = Normal, G = Gamma, LN = Lognormal