ANALYSIS OF LONG TERM DEPENDENCE IN HYDROCLIMATIC PROCESSES

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MATRIC NO. 2006/24072EA

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FEDERAL UNIVERSITY OF TECHNOLOGY, MINNA

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BEING A FINAL YEAR PROJECT SUBMITED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF BACHELOR OF ENGINEERING (B. ENG) DEGREE IN AGRICULTURAL AND BIORESOURCES ENGINEERING, FEDERALUNIVERSITY OF TECHNOLOGY, MINNA.

FEBRUARY, 2012

Declaration

I hereby declare that this project work is a record of a research work that was undertaken and written by me. It has not been presented before, for any degree and diploma or certificate at any university or institution. Information derived from personal communications, internet, published and unpublished work were duly referenced in the text.

29-02-2012

Osunnaiye Gbenga .O.

Date

CERTIFICATION

This is to certify that the project entitled "Analysis of long term dependence in hydroclimatic processes" by Osunnaiye, Gbenga Oluwatosin. meets the regulations governing the award of the degree of Bachelor of Engineering (B. Eng) of the Federal University of Technology, Minna and it is approved for its contribution to scientific knowledge and literary presentation.

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Dedication

This project work is dedicated to the Almighty God, who, in His infinite mercy, saw me through the moments of disappointment and joy throughout this period. I praise His holy name for His favor and goodness toward me. He alone is worthy to be praised.

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Energy and resources have gone into the completion of this project work. There were times of disappointment, times of sorrow and times of joy. There were also periods I thought I know it all and also periods I know noting. I give glory to Almighty God, for sparing my life and making it possible for me to successfully complete this work. I wish to express my profound gratitude to my supervisor, Dr. M. Y. Otache for his patience, assistance and concern towards this project work; I wish him the very best in all his endeavors in life.

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Abstract

The phenomenon of long-term dependence provides an elegant explanation and interpretation of an empirical law, commonly referred to as the "Hurst effect". To this end , in this study, this phenomenon which characterizes hydrological and other geophysical time series was studied. The long-term memory was analysed for some selected hydroclimatic processes (rainfall, streamflow, temperature, and evaporation) at characteristic time scales, by using heuristic procedures indicated that there may be the presence of long-term component in mean daily flow series but there is no discernible reason to suspect the presence of same in the others; i.e., monthly data series of the rainfall, evaporation and temperature. This may connote the exhibition of short memory. However, considering the short length of data used and the implication of pre-processing strategy employed for asymptotic properties to hold, the results are inconclusive. Therefore it is recommended that robust heuristic methods, long length of data and deeper preprocessing strategy be employed.

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CHAPTER ONE

1.0 INTRODUCTION

1.1 Background to the study.

Hydroclimatic process encompasses processes as evaporation and transpiration (E), Precipitation (P), Run-off (R), Stream flow and Temperature. Hydroclimatology provides a systematic structure for analyzing how the climate system causes time and space variations (both global and local) in the hydrologic cycle. Changes in the relationship between the climate system and the hydrologic cycle underlie floods, drought and possible future influences of global warming on water resources. Land-based data, satellite data, and computer models contribute to our understanding of the complex time and space variations of physical processes shared by the climate system and the hydrologic cycle.

Hydroclimatic processes has some unique characteristics such as, seasonal (i.e monthly or multiples of a month), autocorrelation, cross correlation, intermittency and stationarity. The stochastic analysis, modelling and simulation of climatic and hydrologic processes such as precipitation, stream flow and sea surface temperature usually assume stationarity or randomness of the process under consideration. On the annual timescale, the analysis of climatic and hydrologic processes is generally based on assumed stationarity under a time series framework or randomness under a probabilistic framework. While this assumption may be reasonable within a short time frame (a few decades depending on the particular case), empirical evidences shows that most hydroclimatic processes deviate from stationarity in the long term. To some extent., the assumption of stationarity has persisted because most historical records have been too short to accurately detect nonstationarity, and because of lack of mathematical frameworks for analyzing and modelling the dynamics of non stationary processes. However, as record lengths have increased, trends, oscillatory behavior, and sudden shifts have been observed in sample records.

Climate is not constant but rather varying in time and expressed by the long – term (e.g 30 years) time average of a natural process, defined on a fine scale. The evolution of climate is represented as a stochastic process. Hydroclimatic process exhibits a scaling behavior also known as long – range dependence or the Hurst phenomenon and because of this dependence, the uncerntainty limits of the future are affected by the available observations of the past. Storage-related stochastic properties such as the range of cumulative departures R_n^{**}, the rescaled range R_n^*, and the Hurst slope. K have been widely used in the literature as measures of long-term dependence and for comparing alternative models of hydrologic series (Hurst, 1951; Wallis and O'Connell, 1973; Hipel and McLeod, 1994).

1.2 Statement of problem

The presence of long-term memory can be done or assessed by applying different heuristic methods; though in many cases, they cannot provide any additional information about the spectral density of the hydroclimatic processes. If long-range dependence is present, it connotes a significant serial correlation between observations which are far apart in time. However, it is noted that reliable long-term memory can be performed only when the sample size of the available data is large enough for asymptotic properties to hold. It is strongly suggested that the dearth of continuous data or availability of limited sample creates indeterminacy problem. But the Question is : what size of sample is adjudged large enough or appropriate for any meaningful analysis? Thus the fact that no appropriate length of sample size is advocated in Literature constitute a situation that is dire since any arbitrary choice of data length might introduce subjectivity in the conclusions that may be drawn.

1.3 Objectives of study

To assess the presence or otherwise of long – range dependence in hydro climatic process so as to determine appropriate modelling schemes.

1.4 Justification

1. Long-range dependent processes provide an elegant explanation and interpretation of the popular "Hurst effect".

2. The phenomenon of long-range dependence has a long history; it remain a topic of active research in the study of economic and financial time series, and has been extensively documented in hydrology, meteorology and geophysics.

3. Recent results have led to a re-awakening of the need by hydrologists to further analyse long-term or range dependence in temporal series of hydroclimatic data.

4. This Quest is aimed at developing suitable methods for estimating and modelling the intensity of long-term dependence in time series, as well as provides insight to what might be the reasons for the Hurst Phenomenon.

1.5 Scope of study

The scope of this study is limited to the determination of the presence or otherwise of long term memory in hydro climatic processes and analysis of its intensity.

CHAPTER TWO

2.0 REVIEW OF RELATED LITERATURE

Anning Wei and Raymond M. Leuthod pointed out that there are three main methods existing to estimate H (Hurst exponent) : the Classical rescaled range (R/S) analysis, Modified R/S analysis, and the ARAMA model. The first two methods are mostly concerned with establishing whether long-range dependence exists in the process being examined . An AFIMA model is the extension of an ARFIMA model, and is able to measure the strength of long-range dependence. Beside all these, there is also the Aggregated Variance Method (AVM).Long term persistence (LTP) which was studied first by Hurst (1951), is also a phenomenon known as scaling behaviour, is a tendency of hydroclimatic variables to exhibit clustering behaviour in certain periods of time (i.e. droughts). The presence of LTP is usually investigated by estimating the Hurst exponent H, which ranges between 0 and 1. The range $0.5 < H < 1$ corresponds to a persistent process and the range $0 < H < 0.5$ corresponds to an independent process, and the value $H = 0.5$ corresponds to a purely random process. The scaling behaviour has been identified in several hydrological time series by a number of investigators including (to mention a few of the more recent studies) Koutsoyianis (2002), Koutsoyiannis (2003a), Cohn and Lins (2005), Koutsoyiannis and Montanari (2007), Khaliq *et al.*, (2008), and Hamed (2008). It is hypothesized that LTP may reflect the long-term variability of several factors such as solar forcing, volcanic activity and so on. It is well known that the presence of LTP has significant impact on the interpretation of trends identified under the independence or short-term persistence (STP) assumptions.

Long memory refers to the ability of a hydrological system to "remember" past states over long term (decades).Dependence over non periodic cycles is defined as the presence of extended periods of similar behavior which are of unequal duration (Booth, Kaen and Koveos (1982). Mandelbrot (1972) argued that rescaled range (R/S) analysis can detect non periodic cycles even when the cycles have lengths greater than or equal to the sample period. The importance of Mandelbrot's (1972) argument is that it raises the question of whether R/S analysis can be used to detect long term dependence. Long term dependence to Mandelbrot (1972) means the "Joseph effect", named after the Old Testament prophet who foretold seven years of prosperity followed by seven years of famine [Mandelbrot and Wallis (1968)]. The "Joseph effect" implies that a time series has infinite memory, that is, an event occurring today will still have an effect on events occurring into perpetuity. In studies of geophysical records, Mandelbrot and Wallis (1969) found a number of series with infinite memory. However, the type of time series found in this field very possibly has finite memory cycles that are longer than their time samples, and hence, the infinite memory result. Mandelbrot (1971) was the first to suggest that R/S analysis could be useful in studies of economic data and provided an economic rationale. In Mandelbrot (1972), it was further argued that R/S analysis was superior to autocorrelation and variance analysis since it could consider distributions with infinite variance and was superior to spectral analysis because it could detect non periodic cycles.

The problem with Mandelbrot's analysis was the adherence to processes with infinite memory. In the mathematics of fractal geometry developed in Mandelbrot (1982), fractals will continue to scale to infinity. Peters (1991), on the other hand, argued that in nature, fractals will stop scaling at a finite point (e.g., the passage ways in your lungs will stop branching at some finite point). Consistent with Peters (1991), it can be reasonably argued that economic time series have finite memory and R/S analysis must be used over sub-periods in order to discover the length of the finite memory or the average non periodic cycle. Most academic studies to this point have assumed Mandelbrot's infinite memory process and performed the R/S analysis only on the complete sample. Mandelbrot, however, does acknowledge the existence of finite memory. In Mandelbrot and Wallis (1969), it is noted that observations far removed in time can be considered independent and that the R/S analysis will asymptotically approach a random process. With shorter lags, the dependence will be evident, but a "break" will occur at longer lags and independence will be obtained. Since Mandelbrot and Wallis (1969) do not observe such a "break" in geophysical records, they considered, for practical purposes, that these time series exhibit infinite memory. Mandelbrot (1972) discussed that there can be short term R/S dependence where a time series has a finite but long memory. It may well be that the time series has a finite memory and R/S analysis will indicate dependence, but, at longer lags, a "break" toward random behavior occurs. From a very long run viewpoint, Mandelbrot (1972) considered this dependence to be a special transient, but went on to say that this does not lessen the importance of the finite memory component. In fact, Mandelbrot and Wallis (1969), as well as Peters (1991), used R/S analysis to detect the well known 11 year cycle in sunspot activity. They add a warning that processes with a strong periodic element will affect the Hurst phenomenon, but again they did examine the data for infinite memory and felt that these "subharmonics" complicate the issue.

In economics, following Peters '(1991) argument, one would expect to find finite memory processes, and the "break" in the R/S analysis detect these finite memory for non periodic cycles. Peters (1991) used R/S analysis and a Hurst (1951) regression to examine stock market indices for persistent finite memory and found evidence of a four year cycle. However, his analysis may be biased by short term Markovian dependence. Davies and Harte (1987) showed that conventional R/S analysis using a Hurst regression can be biased toward accepting a long term dependence hypothesis even when the true process is first order autoregressive. As a result, Lo (1991) developed a modified R/S test that allows for short-term dependence, non normal distributions, and conditional heteroscedasticity under the null hypothesis. In addition, Cheung (1993) used Monte Carlo simulation to show that the modified R/S test is robust to non stationary variance and ARCH (autoregressive conditional heteroscedasticity) effects. The only problem is that the Lo (1991) modification does assume an infinite memory process.

Fortunately, like R/S analysis, it too can be used on different sub-periods (Cheung and Lai (1993). In the last decades, the hydrologic and water resources community goes behind the trails of the climatological community in an attempt to trace the future of water resources under climate change. As climatic records do not verify a Markovian behaviour, its adoption has been combined with a decomposition of a climatic series into components, one of which is Markovian e.g., Mann and Lees (1996), performed such a decomposition on stochastic grounds – by spectral methods – whose physical fundamental may be disputable. The Markovian dependence (also known as autoregressive of order 1– AR(1)) is the most typical and simple example of the so-called short-term persistence (STP, also known as short-term dependence). STP is contrasted with long term persistence (LTP, also known as Hurst phenomenon, Joseph effect, long memory, long-range dependence, scaling behavior, and multi-scale fluctuation). From a practical point of view, LTP indicates that the process is compatible with the presence of fluctuations on a range of timescales, which may reflect the long term variability of several factors such as solar forcing, volcanic activity and so forth. LTP can be also conceptualized as a tendency of clustering in time of similar events (droughts, floods, etc).

2.1 Stochastic characteristic of hydroclimatic processes.

The stochastic characterization of the underlying processes is important in constructing such models. In general, the stochastic characteristics of hydroclimatic processes such as precipitation and runoff depend on the type of data at hand. Hydroclimatic time series may consist of a single time series (univariate series) or multiple time series (multivariate series). Data may be available on a continuous time scale or at discrete points in time. For instance, most hydrologic series of practical interest are discrete time series defined on hourly, daily, weekly, monthly, bimonthly, quarterly, and annual time intervals.

Hydroclimatic time series are generally autocorrelated. Autocorrelation in some series such as streamflow usually arises from the effect of surface, soil, and groundwater storages that cause the water to remain in the system through subsequent time periods (Salas, 1993). For instance, basins with significant surface storage in the form of lakes, swamps, or glaciers, produce streamflow series that are autocorrelated. Likewise, subsurface storage, especially groundwater storage produces significant autocorrelation in the streamflow series derived from groundwater outflow. Conversely, annual precipitation and annual maximum flows (flood peaks) are usually uncorrelated. Sometimes significant autocorrelation may be the result of trends and/or shifts in the series (Salas and Boes, 1980; Eltahir, 1989).

Hydroclimatic series may be cross-correlated. For example, the precipitation series at two nearby sites, or the streamflow series of two nearby gaging stations in a river basin are expected to be cross-correlated because the sites are subject to similar climatic and hydrologic events. As the sites considered become farther apart, their cross-correlation decreases. However, because of the effect of some large-scale atmospheric-oceanic phenomena such as El Nino Southern Oscillation (ENSO), significant cross-correlation between sea surface temperature (SST) and streamflow between sites thousands of miles apart can be found (Eltahir, 1996). Furthermore, one would expect a significant cross-correlation between a streamflow time series and the corresponding areal average precipitation series over the same basin. Hydroclimatic time series are intermittent when the variable under consideration takes on nonzero and zero values throughout the length of the record. For instance precipitation that is observed in a recording rain gage is an intermittent time series. Likewise, hourly, daily, and weekly rainfall are typically intermittent time series, while monthly and annual rainfall are usually non intermittent. However, in semiarid and arid regions even monthly and annual precipitation and monthly and annual runoff may be intermittent as well.

Traditionally, certain annual hydroclimatic series have been considered to be stationary, although this assumption may be incorrect as a result of large-scale climatic variability, natural disruptions such as a volcanic eruption, and anthropogenic changes such as the effect of reservoir construction on downstream flow, and the effect of landscape changes on some components of the hydrologic cycle. On the other hand, hydroclimatic series defined at time intervals smaller than a year, such as months, generally exhibit distinct seasonal (periodic) patterns due to the annual revolution of earth around the sun, which produces the annual cycle in most hydroclimatic processes.

2.2 Behavioral properties

a. Overall statistical properties.

The most commonly used statistical properties for analyzing stationary or non stationary hydroclimatic time series are the sample mean $\bar{y}$, variance s^2, coefficient of variation *cv*, skewness coefficient g , lag-*k* autocorrelation coefficient r_k and the spectrum *g(f)*. Coefficients of variation of annual flows are typically smaller than one, although they may be close to one or greater in streams in arid and semiarid regions. The coefficients of skewness g of annual flows are typically greater than zero. In some streams, small values of g are found suggesting that annual flows are approximately normally distributed. On the other hand, in some streams of arid and semiarid regions, g can be greater than one.

The lag-*k* autocorrelation coefficient r_k may be determined as

$$r_k = \frac{c_k}{c_o} \quad k\ 0,2. \qquad (2.1a)$$

$$c_k = \frac{1}{N}\sum_{i-1}^{N-k}(y_{i+k} \quad \bar{y})(y, \quad \bar{y}) \qquad (2.1b)$$

where N is the sample size and k is the time lag. The plot of r_k versus k, i.e., the correlogram, may give an idea of the degree of persistence of the underlying time series, and it may be useful for choosing the type of stochastic model that may represent the series. When the correlogram decays rapidly to zero after a few lags, it may be an indication of small persistence or short memory in the series, while a slow decay of the correlogram is an indication of large persistence or long memory.

b. Periodic (seasonal) statistical properties.

stochastic properties of hydroclimatic time series, as mentioned above may be determined from either annual series or for seasonal series as a whole, specific seasonal (periodic) properties may provide a better picture of the stochastic characteristics of certain hydroclimatic time series that are defined at time intervals smaller than a year such as monthly stream flow data. Let the seasonal time series be represented by $y_{v,r}$ $v = 1, ..., N$; $r = 1, ..., w$ in which v, is the year, r is the season, N is the number of years of record, and w is the number of seasons per year (e.g., w = 12 for monthly data). Then, for each season r, one can determine a number of statistics such as the seasonal mean $\bar{y}_r$ variance s^2_r, coefficient of variation cv, and skewness coefficient g_r. Furthermore, the season-to -season correlation coefficient $r_{k,r}$ may be estimated by

$$r_{K,t} = \frac{c_{k,t}}{\left(c_{0,t-k}c_{0,t}\right)^{1/2}} \qquad k=0,1,2, \qquad t=1, \quad ,\omega \qquad (2.4a)$$

$$r_{K,t} = \frac{1}{N}\sum_{V=1}(\bar{y}_{v,t} - y)(\bar{y}_{v,t-k} - \bar{y}_{t-k}) \qquad (2.4b)$$

The statistics $\bar{y}_r$, s_r, g_r, and $r_{k,r}$, may be plotted versus time $r = 1, ...,\omega$ to observe whether they exhibit a seasonal pattern. Generally, for seasonal stream flow series $\bar{y}_r > s_r$, although for some streams $\bar{y}_r$, may be smaller than s_r, especially during the "low-flow" season. Furthermore, for intermittent stream flow series, generally the mean is smaller than the standard deviation, i.e., $\bar{y}_r < s_r$, throughout the year.

The values of the skewness coefficient g_r, for the dry season are generally larger than those for the wet season indicating that data in the dry season depart more from normality than data in the wet season. Values of the skewness for intermittent hydrologic series are usually larger than skewness for similar non intermittent series. Seasonal correlations $r_{k,\tau}$, for stream flow during the dry season are generally larger than those for the wet season , and they are significantly different than zero for most of the months. On the other hand, seasonal correlations for monthly precipitation are generally low or not significantly different from zero for most of the months (Roesner and Yevjevich, 1966), while for weekly, daily, and hourly precipitation they are generally significant and greater than zero.

Complex long-term dependence (long memory) of seasonal flows may be evident when the correlations $r_{k,\tau}$, are significant and decay slowly as k increases beyond ω seasons (beyond a year). These correlations are usually small or not significant for many streams, but in river systems, such seasonal correlations may persist for several years. In addition, some streamflow hydrographs such as daily and weekly hydrographs may possess directionality (nonreversibility), which means that some of their statistical properties change when direction of time is reversed. (Fernandez and Salas, 1986)

2.3 Component of hydroclimatic analysis

Hydroclimatic time series may exhibit trends, shifts or jumps, seasonality, autocorrelation, and non-normality. These attributes of hydroclimatic time series are referred to as components (Salas, 1993). In general, natural and human-induced factors may produce gradual and instantaneous trends and shifts (jumps) in hydroclimatic series. For example, a large forest fire in a river basin can immediately affect the runoff, producing a shift in the runoff series, whereas a gradual killing of a forest (e.g., by an insect infestation that takes years for its population to build up) can result in gradual changes or trends in the runoff series. A large volcanic explosion such as the one at Mount St. Helens in 1980 or a large landslide can produce sudden changes in the sediment transport series of a stream. Trends in non-point-source water quality series may be the result of long-term changes in agricultural practices and agricultural land development. Likewise, shifts in certain water quality constituents may be caused by agricultural activities such as sudden changes in the use of certain types of pesticides. Changes in land use and the development of reservoirs and diversion structures may also cause trends and shifts in stream flow series.

2.4 Long term phenomenon

Long-term memory refers to the continuing storage of information. In Freudian psychology, long-term memory would be called the preconscious and unconscious. This information is largely outside of our awareness, but can be called into working memory to be used when needed. Some of this information is fairly easy to recall, while other memories are more difficult to access. Long-term memory (LTM) is memory in which associations among items are stored, as part of the theory of a dual-store memory model. According to the theory, long term memory differs structurally and functionally from working memory or short-term memory, which ostensibly stores items for only around 20–30 seconds and can be recalled easily. This differs from the theory of the single-store retrieved context model that has no differentiation between short-term and long-term memory. According to Miller (1956), whose paper popularized the theory of the "magic number seven," short-term memory is limited to a certain number of chunks of information, while long-term memory has a limitless store. According to the dual-store memory model set forth by Atkinson and Shiffrin (1968), memories can reside in the short-term "buffer" for a limited time while they are simultaneously strengthening their associations in long-term memory. When items are first presented, they enter short-term memory, but because it has limited space, as new items enter, old ones leave. However, each time an item is rehearsed while it is in short-term memory, it is also increasing its strength in long-term memory. In long-term store, items are recalled through retrieval cues in a two-step process. First, context is used as a cue to probabilistically select an item to be potentially recalled. Second, that item is probabilistically determined to be recalled or not.

Long-term correlations have been first observed by H.E. Hurst, who found ``long-range statistical dependencies" in river-runoff records, and mathematically described by Mandelbrot (B.B. Mandelbrot, J.R. Wallis, Noah, Joseph 1968). In the last decades, it has become clear that long term correlations are abundant in nature, characterizing, for example, temperature records (D. Rybski, A. Bunde, H. von Storch (2007), hydrological records, physiological records , economic records and even records of human activity [P. (Ivanov et al., 2007). In long-term correlated records, large events well above the average are more likely to be followed by large events, and small events well below the average by small events. This persistence occurs on all time scales. For example, a week where the temperature is high, is more likely to be followed by a warm week than by a cold week, a warm month is more likely followed by a warm month than by a cold one, and the same holds on annual and decadal scales, and probably even on centennial scales (Rybski et al., (2006). This persistence on all scales is characterized by an autocorrelation function that decays in time by a power law, $C(s) \sim s^{-\gamma}$ with an exponent γ between 0 and 1.

While investigating the discharge time series of the Nile river for the design of the Aswan High Dam, Hurst (1951) discovered a special behavior of hydrological and other geophysical time series, which has become known as the " Hurst phenomenon". This behavior is essentially the tendency of wet years to cluster into wet periods, or of dry years to cluster into drought periods. The term "Joseph effect" introduce by Mandelbrot (1997) has been used as an alternative for the same behavior . Since its discovery, the Hurst phenomenon has been verified in the several environmental quantities, such as wind power variations (Haslett & Raftery. 1989), global mean temperature (Bloom field, 1992), flow of the River Nile (Eltahir, 1996), flows from the river warta, Poland (Radziejewski & Kundzewicz, 1997), monthly and daily inflows of lake maggiore, Italy (Montanari et al., 1997), annual stream flow records across the continental United States (Vogel et al., 1998), an indexes of North Atlantic Oscillation (Stephenson et al., 2000). In addition, the Hurst Phenomenon has gained new interest today due to its relationship to climate changes (e.g., Evans, 1996).

Biologically, short-term memory is a temporary potentiation of neural connections that can become long-term memory through the process of rehearsal and meaningful association. Not much is known about the underlying biological mechanisms of long-term memory, but the process of long-term potentiation, which involves a physical change in the structure of neurons, has been proposed as the mechanism by which short-term memories move into long-term storage. The time scale involved at each level of memory processing remains under investigation. As long-term memory is subject to fading in the natural forgetting process, several recalls/retrievals of memory may be needed for long-term memories to last for years, dependent also on the depth of processing. Individual retrievals can take place in increasing intervals in accordance with the principle of spaced repetition. This can happen quite naturally through reflection or deliberate recall (also known as recapitulation), often dependent on the perceived importance of the material.

There are actually three different types (or aspects or parts) of long-term memory, the Episodic memory, Semantic, and procedural memory. (a)**Episodic memory:** This refers to our ability to recall personal experiences from our past. When one recount events that happened during his/her childhood, a ballet or food taken at breakfast, one is employing long-term episodic memory. As the name suggests, this aspect of memory organizes information around episodes in our lives. When one tries to recall the information, one attempts to reconstruct these episodes by picturing the events in our minds. Episodic memory enables us to recall not only events, but also information related to those events. For example, a baseball coach faced with an unusual situation requiring a rule interpretation might think like this: "I remember a similar situation in a professional baseball game... When was it...? Last year... Reds vs. Giants... It was a night game, and the Giants had runners on first and second, when a line drive bounced and hit the umpire... What was the call...? I think they gave the batter a single and let the runners advance one base.... But I thought when the ball hit the umpire it remained in play.... Now I remember! If the umpire is in front of the fielders, it's a dead ball and a single. If the umpire would have been behind the fielder, it would have remained in play...."

(b) Semantic memory: Semantic memory stores facts and generalized information. It contains verbal information, concepts, rules, principles, and problem-solving skills. While episodic memory stores information as images, semantic memory stores information in networks or schemata. Information is most easily stored in semantic memory when it is meaningful - that is, easily related to existing, well-established schemata. By using information on numerous occasions after it has been initially learned, we solidify the connections among elements of information, make it easier to retrieve when we need to use it, and make it more likely that this information will be available to help us accept and store additional information in the future.

(c)Procedural memory: Procedural refers to the ability to remember how to perform a task or to employ a strategy. The steps in various procedures are apparently stored in a series of steps, or stimulus-response pairings. When one retrieve information from procedural memory, one retrieve one step, which triggers the next, etc.

These various parts of long-term memory do not operate in isolation from one another. While it is not clear how they work together, it is clear that they are related and overlap. For example, a teacher who is asked to write a letter of recommendation for a former student might wish to retrieve information about the ability of that student compared to other students. To do this, he/she might first use episodic memory to form an image of that student as a real person performing real activities in his/her class several years ago, and this image might help her recall specific details of class performance and term papers written by that student. Likewise, a college student writing a paper in a history course on mercantilism might first listen to or read a semantic presentation on the topic, perform an episodic memory search to recall instances in his own life when he himself experienced what the teacher was talking about, recall the semantic definitions of related terms from another course, and continue this process until he felt he could understand and integrate the new information. The key ingredient that facilitates long-term storage is meaningfulness. This term refers not to the inherent interest or worthiness of information, but rather to the degree to which it can be related to information already stored in our long-term memory. One concept or piece of information is more meaningful than another if the learner can make a larger number of connections between that piece of information and other information already in long-term memory. Theoretically, the capacity of long term memory could be unlimited, the main constraint on recall being accessibility rather than availability.

In statistical terms, the presence in a time series of long term fluctuations implies dramatically increased uncertainty, especially on long timescales, in comparison to classical statistics. This is easy to understand, as the observed record could be a small portion of a longer cycle whose characteristics might be difficult to infer on the basis of the available observations. In this respect, in processes characterized by LTP, the results of the statistical analysis may be difficult to decipher. As a consequence, the application of statistical tools to climatic time series should be carefully considered and classical statistics should be carefully revisited to locate points that may produce misleading or incorrect results. In stochastic terms, STP and LTP are conceptualized in terms of conditional probabilities for the future given past observations. Thus, in a Markovian process, the future is not influenced by the past when the present (a time instant) is known whereas in a process exhibiting LTP, the influence of the past (the entire history) never ceases. Both Markovian dependence and LTP, can result from physical principles. For example, the maximum entropy principle results in Markovian dependence if the maximization of entropy is done on a particular timescale and in LTP if the maximization is done on a range of timescales (Koutsoyiannis, 2005b). Despite dominance of the Markovian behavior in climatologists' views, its two aforementioned features (non influence of the past, exclusiveness of a single scale of fluctuation) and other features might make it implausible. Probability, statistics and stochastic processes provide mathematical tools to describe LTP conveniently and efficiently. To fight a common misconception, it should be stressed that the use of such tools should not be confused with admitting that things happen spontaneously and randomly or without a cause. It is well known today (from chaos literature) that even a simple nonlinear system with purely deterministic dynamics may trace an irregular trajectory, whose future may be unpredictable in deterministic sense. Unpredictability or future uncertainty depends then on the degree of nonlinearity and the dimensionality (number of degrees of freedom) of the deterministic system as well as the time horizon of prediction. For chaotic systems, the deterministic dynamics cannot produce a good prediction for a large time horizon. This is particularly the case in high-dimensional systems, where a stochastic approach may give better results (mean predictions and uncertainty limits) than a pure deterministic approach. This is reflected for instance in the recently developed method of ensemble weather predictions, a method based on the idea of Monte Carlo (i.e. stochastic) simulation, whose use has now been generalized in meteorological services.

An example of this type, more closely related to the subject of this study, has been proposed by Koutsoyiannis (2006). This example deals with a simple toy model that was devised to mimic the evolution of long hydroclimatic time series. The model is purely deterministic (involving no random component) and nonlinear, and has only two degrees of freedom. Application of the model demonstrates that (a) extremely simple deterministic dynamics can produce trajectories exhibiting LTP; (b) large-scale climatic fluctuations (like upward or downward trends) can emerge without any apparent reason; and (c) deterministic dynamics do not help predict climatic evolution, even in the case of the caricature model with only two degrees of freedom. Thus, this demonstration justifies (a) the utility of a stochastic description even for systems with perfectly known purely deterministic dynamics and (b) the presence of LTP in all examined hydro climatic series.

To date, there is considerable empirical evidence for the presence of LTP in hydroclimatic and other geophysical records, as well as time series from other fields. In fact, the history of LTP started more than half a century ago, after its discovery in geophysics by Hurst (1951), although, in a mathematical (stochastic processes) and physical context (turbulence), the concept has been pioneered a decade earlier by Kolmogorov (1940), and Shiryaev (1989).

Throughout these decades, the studies providing indications that LTP may be omnipresent in several natural (hydroclimatic, geophysical, biological) and human associated (social, economical and technological) processes have been so numerous that it is difficult to shape a complete picture; yet it is worth giving some recent examples (which contain additional references). LTP properties of temperature at a point, regional or global basis, have been studied by Bloomfield (1992), Koscielny-Bunde et al., (1996, 1998), Pelletier and Turcotte (1997), Koutsoyiannis (2003), Monetti et al., (2003) and Koutsoyiannis et al., (2006). Similar analyses have been conducted for other climatological time series including wind power and indexes of North Atlantic Oscillation (Haslet & Raftery, 1989; Stephenson et al., 2000) as well as proxy series such as tree-ring widths or isotope concentrations (Pelletier and Turcotte, 1997;

Koutsoyiannis, 2002; Beran and Feng, 2002; Craigmile, 2004b). Numerous studies have indicated LTP in hydrological time series and particularly in river flows (Eltahir, 1996; Montanari et al., 1997; Pelletier and Turcotte, 1997, Koutsoyiannis, 2002, 2003; Radziejewski and Kundzewicz, 1997; Sakalauskienė, 2003; Yue and Gan, 2004; Koscielny-Bunde, 2006). Similar findings have been reported in diverse scientific fields such as biology (Peng et al., 1994), physiology (Hausdorff et al., (1997), economics (Ray and Tsay, 2000), and Internet computing (Karagiannis et al., 2004). The similarity of behaviours in such diverse complex systems should not be regarded as coincidence; rather some fundamental explanation behind this should be investigated, as is for instance the Central Limit Theorem (CLT) for the emerging of the normal distribution in diverse processes. Perhaps, this explanation is the principle of maximum entropy, which also produces the normal distribution independently of CLT (Koutsoyiannis, 2005a, b). Most recently, the presence of LTP in temperature data has been considered by Cohn and Lins (2005) and Rybski et al.,(2006). Both have found that instrumental records and reconstructed time series of temperature are compatible with the hypothesis of LTP and therefore suggested that this property should be taken into account in statistical tests. Earlier, Koutsoyiannis (2003) arrived at similar conclusions, arguing that there is the need in hydroclimatic research to adapt classical statistics, which is based on the Independent-Identically-Distributed (IID) paradigm, so as to account for the observed LTP behavior. Also a variety of methods shed light on the statistical problems related to LTP (Beran and Feng, 2002; Kantelhardt et al., 2002; Craigmile, 2004a, b).

In this respect, Cohn and Lins (2005) and Rybski et al., (2006) have suggested a necessary rectification of the prevailing incorrect practices. Both have proposed statistical tests, which they have illustrated essentially on the same climatic record; for example, the instrumental temperature record of the Northern Hemisphere between 1856 and 2004 (due to Climatic Research Unit – CRU). The LTP and trend properties of this record had been studied earlier by Smith (1993), Beran and Feng (2002), and Craigmile et al., (2004a). Cohn and Lins (2005) and Rybski et al., (2006) focused on the well known detection problem (whether or not climatic changes have occurred) and attribution problem (whether or not observed changes are related to anthropogenic forcing of the climate system). Interestingly, however, their conclusions on these problems are opposite. Rybski et al., (2006) concluded that the hypothesis that at least part of the recent warming cannot be solely related to natural factors can be accepted with a very low risk. Cohn and Lins (2005) stated that, given what is known about the complexity, long-term persistence, and non-linearity of the climate system, this warming can be due to natural dynamics. This disagreement may indicate that our understanding of the behavior of LTP and its consequences in climatic analyses and statistical testing is not complete yet and that additional insights are needed. In conclusion, Long memory is a hydrological property that can lead to prolonged droughts or the temporal clustering of extreme floods in a river. Analysis of 28 Long (up to 145 years), continuous instrumental runoff series from six European, American, and African rivers revealed that this effect increases downstream. Simulations reproduce the increase qualitatively and show that a river network aggregates short-memory precipitation and converts it into long-memory runoff. In view of the projected charges in climate and the hydrological cycle, these findings show that decadal- scale variations in drought or flood risk can be predicted for individuals rivers with higher predictability downstream. Spatial aggregatiom may also explain the emergence of long memory in other networks, such as the brain or those formed by computers.

However Literature has proven over the years that there are several approaches in determining long term memory; examples are: Classical rescaled range, modified rescale method, Aggregated variance method (Avm), aggregated standard deviation method (Asd), detrended fluctuation analysis, (DFA).

a. Aggregated standard deviation method (asd)

The method is based on the analysis of the variability of the data aggregated at different time scales. Specifically, let X_i be a stationary process on discrete time i (referring to years in our case) with (true – or population) standard deviation σ and let

$$X_i^{(k)} = \frac{X_i + \cdots + X_{i-k+1}}{K} \qquad (2.5)$$

denote the aggregate (average) process at time scale k, with (true) standard deviation $\sigma^{(k)}$(the notation implies that $X_i^{(1)} \equiv Xi$). For sufficiently large k, $X_i^{(k)}$ represents the climatic process; Now, LTP is expressed by the elementary scaling property

$$\sigma^{(k)} = \frac{\sigma}{K^{1-H}} \qquad (2.6)$$

where H is the Hurst exponent, which for stationary and positively correlated processes varies in the range (0.5, 1). H = 0.5 means independence and increasing values represent increasing LTP intensities.

b. Detrended fluctuation analysis (dfa)

The Detrended Fluctuation Analysis (DFA) is a well-established method for determining the scaling of long-term correlations in the presence of trends without knowing their origin and shape (M.S. Taqqu, V. Teverovsky, W. Willinger (1995). The DFA depends less on finite size effects and can eliminate systematically polynomial trends. In DFA, one considers the cumulative sum (``profile") of the ω_i and studies its fluctuations around polynomial best fits in time windows of size s.

In general, the DFA procedure consists of three steps:

(1) Determine the profile:

$$Y(i) = \sum_{k=1}^{i} \omega_k \qquad (2.7)$$

of the (deseasoned) record .ω_i of length N and cut it into N_s = int (N/s) non-overlapping segments of equal length s (an illustrative Figure can be found, e.g., in Kantelhardt et al., (2001).

(2) In each of these segments v determine the local polynomial trend (of given order n) by a least-square fit and determine the variance $F_s^2(v)$ around it.

(3) Average over all segments and take the square root to obtain the DFA(n) fluctuation function:

$$F^{(n)}(s) = \left[\frac{1}{N_s}\sum_{v=1}^{N_s} F_s^2(v)\right]^{1/2}. \qquad (2.8)$$

For different detrending orders n, one obtains different fluctuation functions $F^{(n)}(s)$. For long-term correlated data without deterministic trend, the $F^{(n)}(s)$ all scale the same,

$$F^{(n)}(S) \sim S^{\alpha n} \tag{2.9}$$

with

$$\alpha_n = \begin{cases} 1 - \gamma/2 & \text{for } 0 < \gamma \leq 1 \\ 1/2 & \text{for } \gamma > 1. \end{cases} \tag{2.10}$$

By definition, DFA_n eliminates trends of order n in the profile which represent trends of order n - 1 in the original record.

2.5 Detecting long memory and modelling.

The presence of long memory in a time series can be detected by estimating the valve of the Hurst exponent *H*. This can be done by applying different heuristic methods. These methods are in many cases robust, but they are not able to supply any additional information about the spectral density function of the data. They are easy to use and can provide the first indication of whether long memory is present in the data. In the past, heuristic methods, such as the R/S estimation procedures have been mostly applied to annual time series. Past studies have often come to conclusion that the flow data can also be well fit by a short – memory model. However, annual time series tend to be short. This fact and potential lack of reliability of the R/S method when dealing with short sample size have motivated further analysis using other probable robust approaches.

Seasonal stochastic processes are frequently applied to hydrologic time series in order to model data affected by a non-deterministic periodic component. This approach allows one to fit many climatological records that exhibit seasonal patterns because of the periodicity of the weather. Seasonal autoregressive integrated moving average (ARIMA) models, already considered by Box and Jenkins (1976) and fully described by Brockwell and Davis (1991), are widely applied. Another formulation of these models was proposed by salas et al., (1982), who developed an estimation procedure for ARIMA models with periodic coefficients. However, all these models failed in modeling data affected by long-term persistence, because they are not able to reproduce the autocorrelation pattern of data affected by long memory. This can be an important limitation, since long-memory was found by many authors to be present in hydrological records. (Lawrance and Kottegoda, 1977; Momtanari et al., 1996,1997). Seasonal long-memory models were considered by Gray et al., (1989), who developed the so – called GARMA (Gegenbauer autoregressive moving average) model, a stochastic process able to model long-lasting and non deterministic periodic components. This model is not able to take into account both seasonal and non seasonal long memory. Another periodic long-memory model was introduced by porter – Hudak (1990) and hassle (1994), who developed a seasonal fractional differencing filter.

Recently, Giraitis and Leipus (1995) developed a generalized form of the FARIMA model, which combines periodic and non periodic long memory. Both the seasonal fractional differencing filter and the GARMA model are special cases of the generalized FARIMA model which allow the modeling of a wide variety of periodic processes. This very flexibility however, sometimes makes the identification procedure difficult to perform. Thus, the identification of some special cases of the generalized FARIMA process, having a clearly identifiable covariance structure (Such as the GARIMA model), can help the analyst in choosing the right formulation of the model for the data.

CHAPTER THREE

3.0 MATERIALS AND METHOD

3.1 Study area

Kaduna state is located on the southern end of the high plains of northern Nigeria, bounded by parallels 9^0 03' N and 11^0 32' N, and extends from the upper River Mariga on 6^0 05' E to 8^0 48' E on the foot slopes of the scrap of jos plateau. Stream valley incisions and dissections of the high plains are evident in several areas, especially in the Zaria region, they are due more to anthropogenic influences and climatic factors than regional geologic instability.

The state experiences a typical tropical continental climatic with distinct seasonal regimes, oscillating between cool to hot dry and humid to wet. These two seasons reflect the influence of tropical continental and equatorial maritime air masses which sweep over the entire country. However, in Kaduna state , the seasonality is pronounced with the cool to hot dry season being longer, than the rainy season. Again the spatial and temporal distribution of rain varies, decreasing from an average of about 1530mm in Kafanchan and kagoro areas in the southeast to about 1015mm in Ikaramakarfi districts in the northeast. High storm intensities (ranging from 60mm hr 1 to 99mm hr 1) plus the nature of surface run of build up the good network of medium sized river systems. High Evaporation during the season, however, creates water shortage problems especially in Igabi, Giwa, Soba, Makarfi and Ikara LGAs.

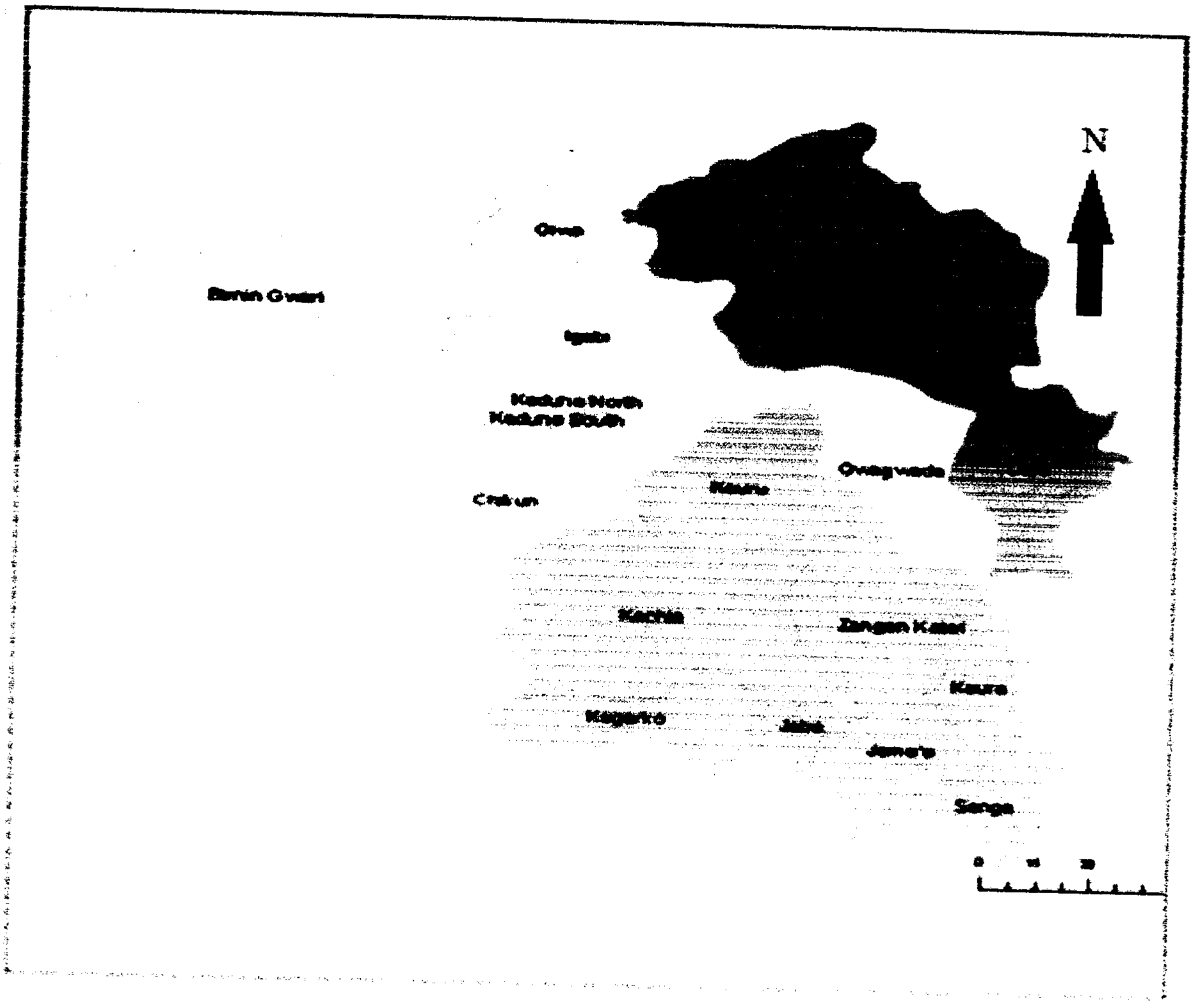


Plate 3.1: Map of Kaduna State showing Local Government Areas.

3.2 Data assembly and management

3.2.1 Data Used

In this study, streamflow, Temperature, rainfall, and evaporation data from Kaduna is used, a total of 26years (1980-2005) to be precise. For purposes of this study, the daily flow data were aggregated to monthly flow series by taking the average of each month's flow.

3.2.2 Data Preprocessing

To investigate the long-term memory, seasonality or periodicity must be removed. Processes which induce non stationarity in the mean are particularly problematic, since these are most likely to lead to spurious detection of long memory. Generally seasonal or periodic variations in the mean, variance, and covariance are to be expected. These are sources of non stationarity and should be carefully accounted for when modeling the data. To remove the seasonality in the daily and monthly series, the series were standardise; standardisation was done by applying

$$m(i) = \frac{x_i - \bar{X}}{s_i} \qquad 3.1$$

Where, $\bar{X}$ is the daily mean, s_i the standard deviation, and x_i is the data series

3.3 methodology

3.3.1 Classical rescale range (R/S)

The classical R/S-analysis aims at inferring from an empirical record the value of the Hurst parameter for long-range dependent process that presumably generated the record at hand. In practice, classical R/S-analysis is based on a heuristic graphical approach where the resulting R/S values are plotted against the lag in a log-log plot (pox plot) to yield a straight line with slope equal to H (i.e., the Hurst exponent) in this context, the R/S statistic is the range of partial sums of deviations (R) of times series from its mean, rescaled by its standard deviation (S). Thus, given a sample of N observations and $2 \le n \le N$, one can define

$$<x>_n = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad 3.2$$

$$X(i,n) = \sum_{j=1}^{i}\left[x_j - <x>_n\right] \qquad 3.3$$

$$R(n) = \max_{1\le i\le n} X(i,n) - \min_{1\le i\le n} X(i,n) \qquad 3.4$$

$$S(n) = \left[\frac{1}{n}\sum_{i=1}^{n}\left(x_i - <x>_n\right)^2\right]^{1/2} \qquad 3.5$$

Hurst (1951) found that

$$E[R(n)/S(n)] \cong \left(\frac{n}{2}\right)^H \qquad 3.6$$

where the ratio of R (n)/S (n) is defined here as Q(n), and H is the Hurst exponent while n is the number of segments or blocks; similarly, X and $< x >$ represent the demeaned and mean of the data points in each blocks respectively. To this end, for any lag n and $2 \le n \le N$, there are Int [N/n] estimates of $R(n)$ and $S(n)$ where the eventual value of $R(n)/S(n)$ is averaged over all the estimates of $R(n)/S(n)$, precisely over all Int [N/n].

In this study, equations (3.2-3.6) were estimated for both the daily and monthly series. In doing so, suppose w is a series of natural integers such as 1, 2, 3, and N is total observations, n series is set as 4, 5, . . ., $w \le N/2$ for both daily and monthly flow series while the R/S statistic was calculated for 155 for monthly and 288 for daily logarithmically spaced values of n respectively.

3.3.2 Aggregated variance method

For the given time series X_i of length N, the corresponding aggregated series is defined by

$$X^{(m)}(k) = \frac{1}{m} \sum_{i=(k-1)m+1}^{km} X(i) \qquad k = 1,2,\ldots, \qquad (3.7)$$

for successive values of m. Its sample variance is

$$\widehat{\mathrm{Var}} X^{(m)} = \frac{1}{\frac{N}{m}} \sum_{k=1}^{\frac{N}{m}} (X^{(m)}(k) - \mathrm{E}X^{(m)})^2 \qquad (3.8)$$

In this study, equations (3.7 and 3.8) are estimated for both the daily and monthly series. The sample variance $\widehat{\mathrm{Var}} X^{(m)}$ should be asymptotically proportional to m^{2H-2} for large N/m and m,where m is number of blocks and the resulting points should form a straight line with slope $\beta = 2H - 2$ and $-1 \leq \beta < 0$. suppose w is a series of natural integers such as 1, 2, 3, and N is total observations, m series is set as 2, 3 . . ., $w \leq N/2$ for both daily and monthly flow series while the Variance was calculated for 155 for monthly and 290 for daily logarithmically spaced values of n respectively.

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

4.1 Presentation of result

Fig4. 1 Pox plots of the Daily flow (m^3/s): (a) R/S analysis, (b) Aggregated Variance method; n and m are number of blocks in the respective methods

Fig 4.2 Pox plots of the Monthly flow (m^3/s): (a) R/S analysis, (b) Aggregated Variance method

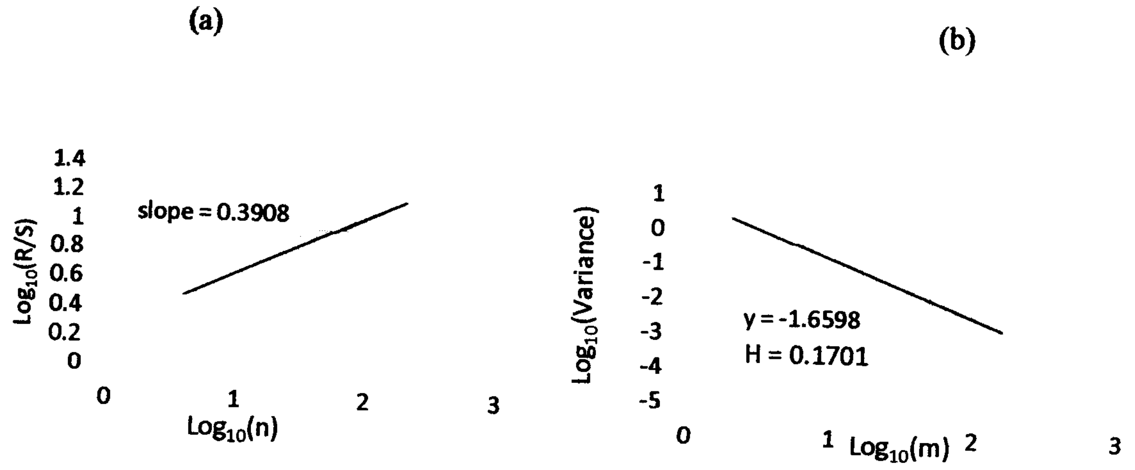


Fig 4.3 Pox Plot of the Monthly Evaporation (mm) : (a) R/S analysis, (b) Aggregated Variance method

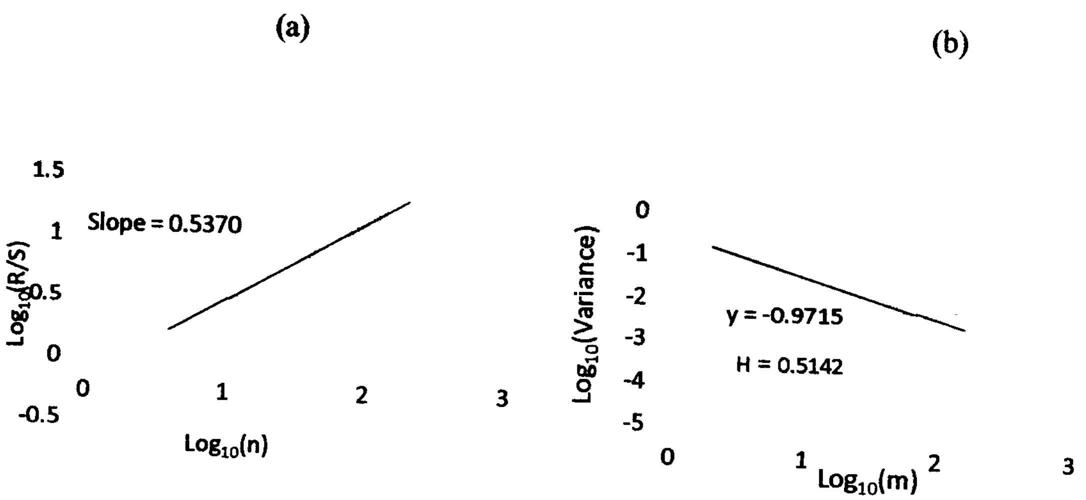
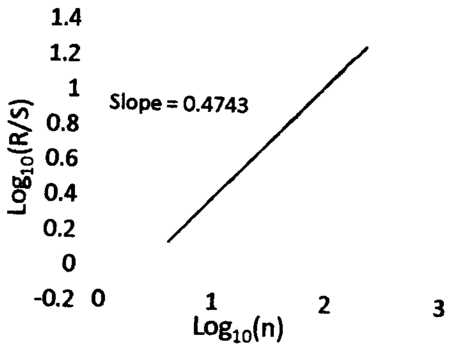


Fig 4.4 Pox Plot of the Monthly Rainfall (mm) : (a) R/S analysis, (b) Aggregated Variance method

(a)



(b)

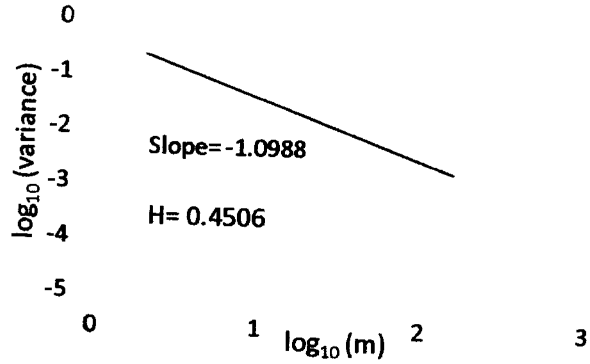


Fig 4.5 Pox Plot of the Monthly Temperature(mm) : (a) R/S analysis, (b) Aggregated Variance method

4.2 Summary of results

Table 4.1 Rescaled range statistic (R/S)

Time series	Hurst exponent (H)
Standardized daily flow (m^3/s)	0.9086
Standardized monthly flow(m^3/s)	0.2145
Standardized monthly evaporation(mm)	0.3908
Standardized monthly rainfall(mm)	0.5370
Standardize monthly temperature(mm)	0.4743

Table 4.2 Aggregated variance method (AVM)

Time series	Slope	Hurst exponent (H)
Standardized daily flow (m^3/s)	-0.3560	0.8220
Standardized monthly flow(m^3/s)	-1.2654	0.3673
Standardized monthly evaporation(mm)	-1.6598	0.1701
Standardized monthly rainfall(mm)	-0.9715	0.5142
Standardize monthly temperature(mm)	-1.0988	0.4506

*Hurst exponent (H) is computed according to the Equation: Slope β= 2H-2 as shown in the chapter three of this work

4.3 **Discussion of result**

The two heuristic methods described in Chapter three were used to evaluate the Hurst exponent in the flow, Evaporation, Rainfall, and Temperature series. Both the R/S and the Aggregated Variance pox plot suggest that Long-memory component may be present in the Daily flow series (Figs 4.1a, 4.1b). But the scenario presented above is completely different for the monthly series (i.e., Stream flow, Evaporation, Rainfall and Temperature (extreme event). The values of *H* obtained applying the R/S statistic and the aggregated variance method respectively for monthly series as mentioned above indicate the absence of long-memory component(Figs 4.2a, 4.2b, 4.3a,4.3b, 4.4a, 4.4b,4.5a and 4.5b). This result accords with the findings of M. Y. Otache (2008) in his Contemporary Analysis of Benue River flow Dynamics and Modelling, Because of the relatively short length of the data series and its probable variability, there is visible presence of associated problems. This highly manifest in nonlinearity and excessive scatter which may cause uncertainty in the slopes and thus render the computed value of the Hurst exponent unrealistic (see 4.1b, 4.2a, 4.2b, 4.3a, 4.3b, 4.4a, 4.4b, 4.5b) especially with the aggregated variance method. In addition, it is important to note base on the findings that the standardisation of both the mean daily and monthly series does greatly explains the variance in the original data.

CHAPTER FIVE

5.0 CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

An analysis has been done to assess the presence or otherwise of long – range dependence in hydro climatic process using the Rescaled range static and the aggregated variance method. Based on the heuristic tests carried out on the stream flow, evaporation, rainfall and temperature series using the classical R/S and the aggregated variance method, in terms of the Hurst exponent values, one comes to the conclusion that the daily flow series may display long-term memory although it is difficult to estimate precisely the measure of persistence. The other series, i.e., the monthly series (i.e., Stream flow, evaporation, rainfall and temperature) examined show that there is no discernible reason to suspect the presence of long-term memory, indicating that there is no significant serial correlations in the series. Considering the fact that limited data is used for analysis in this study and only standardization were done as method of data preprocessing, the results obtained here are inconclusive from practical point of view rather than academic and thus subject to further analysis.

5.2 Recommendations

In considering how important were simulation and modeling in Agricultural and hydroclimatic process, It is therefore recommended that robust heuristic methods, long length of data and importantly, deseasonalisation of data based on classical harmonic analysis be employed.

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