Hydrological Time Series Analysis of River Nagavali, Srikakulam District, Andhra Pradesh

A DISSERTATION

Submitted for the partial fulfilment of the

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MASTER OF TECHNOLOGY

in

DISASTER MITIGATION AND MANAGEMENT

By

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CANDIDATE'S DECLARATION

I hereby declare that the work carried out in this dissertation report entitled, **Hydrological time series analysis of river Nagavali, Srikakulam district, Andhra Pradesh** is presented in partial fulfilment of the requirements for the award of degree of "Master of Technology" in Centre of Excellence in Disaster Mitigation and Management, Indian Institute of Technology Roorkee, under the supervision of **Dr.Sumit Sen**, Assistant Professor, Department of Hydrology and**Dr.AshutoshChamoli**, Assistant Professor Department of Earth Sciences, Indian Institute of TechnologyRoorkee.

The matter presented in this report has not been submitted by me for the award of any degree of this or any other institute.

Data:

Place: Roorkee (Rupak Kumar)

CERTIFICATION

This is to certify that the above statement made by the candidate is correct to the best of my knowledge and belief.

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ABSTRACT

Spectral analysis and detection of abrupt changesinhydrological variables are receiving considerable attention to understand the impacts of climate change and socio-economicchanges.Spectralanalysisprovides better understanding of the change in pattern of the prominent climatic variables in a river basin. Precipitation is a prominent factor of the hydrologic cycle and has a direct influence on the water resources of a region. If the precipitation pattern changes,it affects soil moisture, groundwater reserve and streamflow. Thus, proper understanding of spectral analysis and correlation of precipitation and its change in pattern will provide better management and planning of water resources in a region.

In this study, the surrounding area ofSrikakulamdistrict of Andhra Pradesh which is prone to flood due to River Nagavalihas been studied.Daily datasets of rainfall (1990 to 2009) and discharge (1990 to 2009) are analysed to understand their time frequency behaviour. In order to help hydrological aspect, the analysis of rainfall and discharge data was doneusingauto-correlation, cross-correlation, fast Fourier transform and wavelet transform. The fast Fourier transform and wavelet transform were applied to these time series in order to determine dominant spectral components.The cross-correlation coefficient values are showingmaximum after the time delay of 1 day and 2 days, which relates to the time delay of 1 day to 2 days between the rainfall and discharge time series. The autocorrelation and fast Fourier transform (FFT) power spectrum show that the periodicity for both the discharge and rainfall time series data is 372.4 days.The wavelet spectrum shows the periodicity of 370 days approximately for both the rainfall and discharge time series.

Key words – Rainfall Data; Discharge Data; Auto-Correlation; Cross-Correlation; Fast Fourier Transform (FFT); Wavelet Transform (WT).

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CHAPTER 1
INTRODUCTION

1.1 Time Series

A time domain series consist of set of data points arranged statistically in the form of list or graph in time ordered form. Generally, most common definition used by researchers' is equally separated points in time, whicharetakensuccessively to form time series. Thus, it comprises of discrete setoftime series data.Time series analysis consisting of various methods in order toanalyse time series data forextractinguseful and meaningful statistics and other features of the data.In time series analysis, the methods like regression analysis is often used to develop theoretical data in which it is often observed that how the current values of one or more independent time series affect the current value of another time series. The time seriesconsist of such type of analysis is not called, "time series analysis", which focuses comparing values of a multiple dependent time series or single time series at different points in time. The analysis of interventions on a single time series leads to develop of interrupted time series analysis. Examples of time series are discharge of river, height of tides in ocean, counts of sunspots, etc.

1.2 Hydrological Time Series

In hydrological time series data analysis, the various processes states rainfall, streamflow, evaporation etc. involved generally influenced due to transfer of water in hydrological cycle. It infers that the processes in hydrological cycle can have some variation. The existence of spectral and cross-spectral density functions can encode their variations. Earlier in this, satisfactory attention has not been paid to this problem by studies. The inverse Fourier transforms ofspectral and cross-spectral density functionscan be represented by auto-covariance and cross-covariance function.Hence, if we take the Fourier Transform of the auto-covariance and cross-covariance we get spectral and cross-spectral density function. If an input and output function taken under consideration, then subsequent and antecedent influences of the controlling processes can be identify considering the input event as a point of reference. The proposed functions i.e. the Fourier transform get the estimation of spectral density, amplitude and phase that are not affected by a controlling process. Thesebasicpropertieshave been used for removing the ambiguity by applying a novel methodology based on the spectral representation of partial correlation. The partial spectral density, partial amplitude and partial phase functions have been presented in mathematical concept.

It is observed the quantification and identification of the influences is difficult in each process affecting spectral or cross-spectral density function. Like, if random variable is influence by the same process, then they appear to be correlated, either at a different point in time or at given points in time. This ambiguity in result arises because of the processes encoded in the values of cross-correlation and auto-correlation coefficients. The ambiguity in the time domain is transferred to the frequency domainbecause the Fourier transform of auto-covariance function gives spectral density function, whereas the Fourier transform of cross-covariance functions gives cross-spectral density function. Anew method in hydrometeorology has not been applied yet which involves the spectral representation of partial cross-correlation matrix. It is used in order to obtain information about processes by analysing the discharge time series, other than rainfall It may also be used in groundwater transfer in karst aquifers. It allows the separation of those parameters which modifies the input and output signal by their variations before and after each input event.

Hydrological time series analysis and forecasting can be used as an effective tool in order to determine the variation in hydrological processes. In recent years wavelet modelling has become popular tool amongst hydrologist for hydro-metrologicaltime series forecasting because of its superiority to handle the non-stationary variability of hydrological processes. In this method during data pre-processing the real hydrological time series are decomposed into a set of sub signals by discrete or continuous wavelet methods. Each sub signal plays a different role in original time series and shows a different behaviour. Fourier transform and serial correlation analysis are the most widely used among those methods used for the hydrological time series analysis.

1.3 Synthetic Data

Synthetic data are those data which are generated by users rather than the data obtained by real world events. These types of data obtained through indirect measurement. Synthetic data is generated algorithmically and is used as a test data for operation and production point of view in order to validate mathematical models. Now a day it is used as a input to machine learning models. The synthetic data that is created usually involve the processes of data anonymization i.e. if synthetic data is subset of anonymized data. Then,synthetic data is used in various fields as a useful tool, whichaims to generate specific properties of the data. Most of the time human information (addresses of home, driving license number, ration card number, identity number, IP number, etc.) is used as a form of individual aspects.

1.4 Real Time Data (RTD)

Real time seriesisa concatenated information for users which is immediately and effectively used after the collection of data. The timeliness of the information is shared and provided without any delay. Real-time computing is used to process such data, although it can also be used as a storage data for analysis. Real-time data is different from dynamic data. Whether the data is dynamic or static, its presence does not affect the real-time data. The application of RTD is generally used for navigation or tracking purposes.

1.5 Spectral Analysis

Spectral analysis uses numerous statistical techniques. It is very necessary for analysing and characterizing sequenced data. Sequenced data observations that have been taken in one, two or three-dimensional space. Sequenced data are observations that have been taken in one dimensional space, two dimensional spaces, three dimensional spaces or time. It has certain limitation in observation of sequenced data and due to analyses proceed efficiently, the observation become equally spaced. Spectral analysis defined as to get the different lengths (or scales) oscillation by the disintegration of a sequence. Observation in this process, which is called the data domain are converted into the spectral domain. There are several reasons for applying this observation. Some are explained in points below:

(a) In the spectral domain, computation is efficient.

(b) The statistical descriptors should be mandatory to appear by scales and important factors may be suggested which affects or produces such data.

1.5.1 Correlation

Correlation is a technique of statistics that can show whether and how strongly pairs of variables are related. Although this correlation means that data may include undoubting correlations. You can also suspect, your data having correlations or not, but you cannot know which are the strongest. The greater understanding of data can be led by an intelligent correlation analysis. Correlation techniques have a several different types. The Survey System's Optional Statistics Module includes commonly used type, called the Pearson or product-moment correlation. The module, which includes a disparity on this type called partial correlation. It can be useful when you look at the relationship between two variables due to removing the effect of one or two other variables.

1.5.2 Auto-Correlation and Cross-Correlation

Auto-correlation is also called as serial correlation. It is the correlation of a signal. In which the delayed signal copy itself because it is a function of delay. Usually, it shows the similarity between observations, similarity like function of the time lag between them. For finding repeating patterns, the mathematical tool is used to analysis of auto-correlation, such as the noise obscure the presence of a periodic signal, or its harmonic frequencies identifies the missing fundamental frequency in a signal implied. It is usually used inanalysing function or series of value, processing of signal, such as time domain signals.

Cross-correlation is a mathematical representation in the degree of similarity between two-time series data with lag time associated with one-time series data to other time series data over successive time intervals. Its value lies between -1 to +1.

1.5.3 Fast Fourier Transform (FFT)

Fast Fourier transform (FFT) is an algorithm that samples a signal over a period of time (or space) and divides it into its frequency components. At distinct frequencies, these componentsshownsingle sinusoidal oscillations for each with their own phase and amplitudeofdominant frequencies.Figure1.1 shown as time and frequency domain.

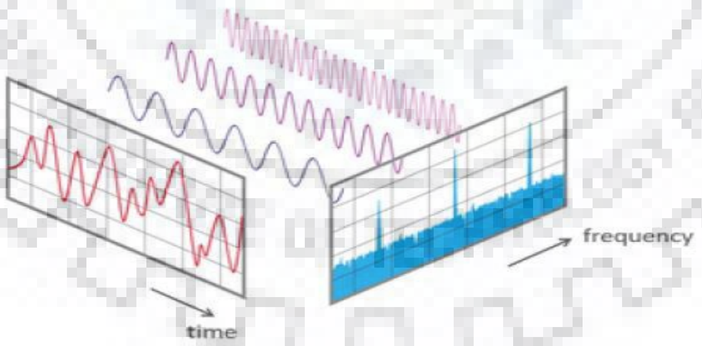

Figure 1.1: View of Signal in the Time and Frequency Domain

1.5.4 Wavelet Analysis

The fundamental objective of wavelet analysis is to attain a complete representation of the localized and transient phenomena happening at different temporal scales. In general, wavelet analysis can be divided into two categories as discrete wavelet analysis and continuous. Both the scale contents of a signal is to determine earlier and how they vary in time. It is generally applied to disintegrate a series into sub-signals known as proper wavelet and disintegration level for discrete wavelet analysis, and then to conduct various time series analysis, such as wavelet decomposition, wavelet de-noising and wavelet aided complexity description and wavelet analysis can be applied in hydrologic forecasting.

Discharge and water levels in natural processes and signals are characterized with notable departure from stationary and time–varying auto-correlation properties. These hydrological time series include intermittent processes where extreme events do not occur evenly. For this process, Fourier analysis have several limitations. Major shortcoming is to identify the frequencies present in the signal but they do not their moment of occurrence. Time–frequency or time-scale localization of the process gives a probable solution of wavelet analysis

1.6 Motivation and Objectives

As natural disaster can be in the form of floods which are devastating in nature for our society.These disasters harm not only life of people but also lead to property loss and livelihood of a community. This type of disaster continuously taking place at “Srikakulam” district of Andhra Pradesh.Therefore,this study focused on the following objectives: - (1)to find the auto-correlation and cross-correlation coefficients and lag time between the rainfall and discharge time series data,(2)tofind the periodicities of discharge and rainfall time series data, by using Fast Fourier Transform (FFT) and continuous wavelet transform (CWT), and (3)to comparison of results byFastFourierTransform and Wavelet transform. Overall the study motivated me to work of a real-world problem on flood issue of river Nagavali.

1.7 Overview of Dissertation

Introduction: In the first chapter, importance of various tools of time series analysis which includes spectral analysis, autocorrelation, correlation, FFT and wavelet analysis are discussed. This chapter also discussed the things which motivated me for selection of this research topic.

Literature Review: This chapter summarises the available literature presents in the journal articles in the area of the hydrological time series and its related tools for investigation. It also identifies the various statistical tools which were used by various authors for time series data analysis and also identifies the current research gaps which is required to check the behavioural analysis of observatory data of rainfall and discharge.

Study Area: This chapter describes about the study area selected for the current research. It describes about the reason for selection of that particular area and also describes forwhere the data were collected for the present research endeavour.

Methodology: This chapter describes about the methodology selected for the current research.

Results and Discussion: In this chapter, the results of various data analysis by using statistical tool and software packages are presented and described in detail and analysis of same is reported.

Conclusions: Finally, in the last chapter, conclusions of this research endeavour are presented.

CHAPTER 2

LITERATURE REVIEW

Adarsh and Janga Reddy (2015) studied the pattern of hydro-climatic rainfall data in four meteorological subdivisions of southern India using linear regression, non-parametric Mann Kendall (MK) test and Sen Slope and discrete wavelet transform estimation method. It is found that increasing trend in annual rainfall time series of three sub-divisions Tamil Nadu, Karnataka and Telangana and a decreasing pattern in Kerala sub-division. They also observed that discrete wavelet transforms (DWT) with SQMK method applied on post monsoon rainfall in Kerala has short term dominant periodicities due to natural phenomenon of QBO and ENSO.

Rodriguez-Iturbe and Nordin (1968) studied of long-term water and sediment discharges for four stations of the Rio Grande in New Mexico, USA. The technique used in the analysis is spectral analysis for seven years of monthly discharge and sediment data. In their study. It was found that the annual cycles of water discharge and sediment discharge were significantly correlated. Observations stand that variation was systematic from one station to other station which was due to erratic tributary inflow and variable irrigation demands.

Y.-F. Sang et al. (2016) showed the important issue related wavelet analysis. The discrepant use of continuous and discrete wavelet methods, choice of mother wavelet, choice of temporal scale, and uncertainty evaluation in wavelet-aided forecasting, these four important issues related to wavelet analysis were discussed.

Rao et al. (2009) studied on the rise of sea level and vulnerability of the coastal area of Andhra Pradesh cost, India through remote sensing and GIS. According to the study, due to global warming rise in the sea level predicted to be about 18 to 59 cm by the 2100 (IPCC 2007). Five physical variables, namely coastal geomorphology, coastal slope, shoreline change, mean spring tide range, and significant wave height were used to assess the vulnerability level of Andhra Pradesh (AP) coast as an example to demonstrate. After integrating the differential weighted rank of above said five physical variable coastal vulnerability index was prepared and was observed that 43% of the 1030 km-long AP coast is under very high-risk, followed by another 35% under high-risk if the level of sea rises by ~0.6 m displacing more than 1.29 million people living within 2.0 m elevation in 282 villages in the region.

Sovi et al. (2012) studied on hydrological time series gauge data of River Sava Republic of Croatia. Considerable influence of flood in Urban, agricultural and nature protected areas in the Republic of Croatia caused by the River Sava. The techniques used in the analysis was spectral analysis and wavelet analysis. It is observed that the FFT and STFT not provide clear information of 1year ½ year 1-month periodicity of long time series signal and nor particular year of event was happened and wavelet analysis gives better resolution in both time and frequency domain and find which year event was happened.

Another investigation done by**, Ilyés, Turai, and Sz 2018,** examined the 110 years data of rainfall using spectral and wavelet analysis. The author's main aim was tobasicallyunderstand the spectral characteristics of precipitation variability as groundwater recharge is the most important source. Monthly and annual rainfall data was used for better understanding of the periodicity of the rainfalls. From two different cities in the Carpathian Basin, Precipitation time was examined to records over a 110-year period, which was obtained from the Hungarian Meteorological Service. They implemented the discrete Fourier-transformation (DFT) and wavelet time series analysis, local cycles and developed was defined to forecast for the Debrecen area. The time-period distributions (spectra) were calculated by using DFT for monthly and annual rainfall data. 16 dominant periods in Debrecen and 17 in Pécswere shown from the annual rainfall data using time period distribution. The most prominent cycles were observed to be 3.6 and 5 years respectively at the two stations. It was also observed that several other cycles were locally presented in the data sets. Wavelet analysis was used to investigate the time dependence of the cycles in the 110-year data set for two Hungarian cities that is Debrecen and Pécs.

Shahabi, Reza, and Kermani (2015) discussed about flood frequency analysis using density function of wavelet (Case study: Polroud River). The author discussed a method which was to be used to perform flood frequency analysis (FFA) in which assumption of stationary was not considered to be important (or not valid). FFA was developed byusing wavelet transform model. Using two different wavelet functions, a full series was applied to FFA and then a investigation approach used a combined method. In the combined method, all discharge data which were less than the lowest value of annual maximum (AM) discharge were removed. Further author explained the use of energy function of wavelet for FFA model development. The data was further classified into some details and an approximation through various decomposition levels and wavelet functions. The approximation series was utilized to FFA. This was achieved using discharge data which were collected from the Polroud River in Iran. Daily maximum discharge data analysis was performed on the total station in the north of

Iran. With the help of wavelet analysis, the data from 1975 to 2007 was evaluated. It was observed on the basis of study that the wavelet full series model resulted (density function) too small as compared to the results of combined method and they were both lesser than traditional methods (AM and PD). On the other hand, the results of combined method were closed to the energy function method when they were compared with the full series data results. The AM and PD methods were used to assess wavelet models. Finally, it was concluded that the basin hydrologic conditions and data's nature were very important parameters in order to increase and improve FFA and the best method of analysis is to be selected.

Y. F. Sang (2013) explained that the de-noising is a very important issue in hydrological time series analysis. It arises due to the defect in the method and it became very difficult to analyse it. So, he discussed about the Hydrologic Time Series based on Energy-Based Wavelet De-Noising. He proposed to develop energy-based wavelet de-noising method. It compares the background energy distribution with energy distribution series to remove the noise. Unlikely wavelet threshold de-noising (WTD) method, the proposed method was based on energy distribution of series. Since the noise is the stochastic phenomena. Hence, the Noise can be easily distinguished from the deterministic components in series, so, the uncertainty of de-noising result can be easily estimated quantitatively by using proper confidence interval, but WTD method is unable to do this. Both WTD and the De-noising method were used to analyse both observed series and synthetic series, but the WTD method were found easily operable than de-noising process. Finally, it was concluded that wavelet de-noising influence the three key parameter namely wavelet choice, decomposition level choice and noise content. Hence, it is to be taken care in choosing the wavelet when analysis is to done by the proposed method. As deterministic sub-signal has the smallest temporal scale, the suitable decomposition level for wavelet de-noising should be corresponded to series. Suitable de-noising result cannot be obtained by Energy-Based Wavelet De-Noising method or WTD if too much noise is interfering in a series but pure random series the series could be shown but not autocorrelation characters, so there is no need of de-noising.

Y.-F. Sang (2012) discussed about the applications of wavelet transform in hydrological time series data analysis. Six key aspect were reviewed, the continuous wavelet transform methods were briefly introduced. The six key aspect were as follow, wavelet aided multi-temporal scale analysis of hydrologic time series, the wavelet aided deterministic component identification in hydrologic time series, wavelet aided complexity quantification of hydrologic time series, wavelet aided de-noising of hydrologic time series, and wavelet aided hydrologic time series simulation and forecasting, and wavelet cross-correlation analysis of hydrologic time series. Finally, it was concluded those three aspects: methodical researches, applications and combination of several personal opinions on the possible future researches of wavelet transform and its applications in hydrology were given.

Chou (2011) technique used to find some hidden characteristics of the original rainfall time series which were applied to the decomposed rainfall time series could be explain by using multi-scale entropy (MSE) analysis, if the wavelet transform was used to breakdown the rainfall time series. His analysis shows that the Mann-Kendall (MK) rank correlation test of MSE curves of residuals at various resolution levels could be used to determine the number of resolution levels in the wavelet decomposition. The complexity of rainfall time series at four stations based on a multi-scale was compared. Finally, the author revealed that the suggested number of resolution levels could be obtained using MK test and MSE analysis. According to author, similarly the complexity of rainfall time series at various locations could also be analysed to provide a reference for water resource planning and application.

Chou (2011) considered the signal of water quality by taking the nitrogen contained in to calculate the wavelet and Fourier analysis. He analyses the water quality of two sites S1 and S2 in the period 1988-2003 in Baihe River lying Miyun reservoir stream watershed. Further he analysestheFourier and Wavelet analysis and compare and explore the cyclic patterns and temporal pattern characteristics of the two sites. The cyclic patterns of two sites were discovered by using the result shown by the Fourier analysis. He observed the Two year of the cyclic pattern for the siteS1 but no significant cyclic pattern was observed for the site S2. Later he calculated the temporal pattern characteristics at distinguished scales which were obtained through wavelet analysis, which were at small scale for the site S1, while at moderate and small scales for the site S2. The study of surface water quality temporal change pattern could be analysing through the wavelet analysis and Fourier transform method.

Gossel and Laehne (2013) discussed an overview of methods and sample applicationsof time series analysis in geosciences. For his work, he compared the Time series analysis methods with four geo-scientific datasets. For the high-resolution analysis of the periodicity and the non-equidistant data set he adopted the new method such aswavelet analysis, STFT and period scanning to bridge the gap, between high resolution analysis of periodicities and non-equidistant data sets. The result of samples obtained after study include not only time series but also spatial data. The author at the end revealed about new research possibilities related to application of variograms which could be as an addition to or instead of autocorrelation opens for storage parameters.

Y.-F. Sang et al. (2009) discussed that original feature of the time series is influenced by the presence of the noise, this noise content reduces the significance of the time series and important task in many practical applications. So, he proposed Entropy-Based Wavelet De-noising method for Time Series Analysis. According to him that by traditional noise attenuating method may not be give the desired result because their inherent shortcomings. The author reported the first set of keys but difficult wavelet de-noising problems which were discussed, and then wavelet de-noising process assessed by applying information entropy theories i.e. principle of maximum entropy (POME) and wavelet energy entropy was use to explain the stochastic character of the noise, to describe the degrees of complexity of the main series in original series data a new entropy-based wavelet de-noising method was proposed. To justify the performance of the new method that he proposed results were analysed for the both several different synthetic series and typical observed time series. Results were indicated through a comprehensive discussion that compared with traditional wavelet de-noising methods, the new proposed method was found to be more efficient, robust and universal. Finally, it was concluded that the results obtained for the new proposed method were observed to be more reasonable and globally optimised.

Schaefli, Maraun, and Holschneider (2007) studied about the recent developments in wavelet spectral analysis and their application to hydrology. As it was quite often known about the extreme hydrological events triggered by exceptional co-variations of the relevant hydro meteorological processes and in individually by exceptional co-oscillations at various temporal scales. In order to detect and analyse such exceptional co-oscillations, Wavelet and cross wavelet spectral analysis observed to be most promising timescale resolved analysis methods. The author focussed on the state-of-the-art methods of wavelet spectral analysis, which is related to subtleties, potential pitfalls and recently developed solutions in order to overcome and shows how reliable new insights could be revealed from wavelet spectral analysis, lead to into hydro-meteorological processes for real-world applications.

Schaefli, Maraun, and Holschneider (2007) studied about the applications of the wavelet transforms for analysis of runoff time series and precipitation. The analysis of runoff data and precipitation was done in order to help the hydrological regionalization through the wavelet transform. Water administration personnel seek to help and to take decisions on predictions in un-gauged basins by using this analysis, with the help of providing more details which concerns about the information related to precipitation and runoff patterns within a region. Piranhas-Açu River basin, located in semiarid north-eastern Brazil used the data from rainfall and runoff stations and in order to determine the zones within the region, the wavelet transforms were applied to these time series.

C. Santos et al. (2001) wavelet analysis-based application was done for the total monthly rainfall data of Matsuyama city; the rainfall variability data was observed. The main frequency components, besides the rainfall variability analysis in the time series were studied by the global wavelet spectrum, reveals that the annual frequency is the main component of the monthly rainfall in Matsuyama city. Thus, an average of all scales between 8 and 16 months were use as the examiner tool for the modulation of the 8-16 monthly band, giving a measure of the time versus average monthly variance, where the periods with high or low variance could be identified.

Guimaraes Celso; Oliveira Carlos; Machado Ricardo (2003) discussed rainfall data analysis with the help of wavelet transform in which wavelet analysis based application was done with a long time series of the total monthly rainfall of different region from several places. Such type of analysis was performed in order to completely characterize for the distinct time-frequency rainfall variability that was observed in several areas. Apart from rainfall variability analysis, global wavelet spectrum was employed to study the main frequency components in the time series that revealed how the monthly rainfall frequency of each place was composed. That analysis was more accurate than the standard Fourier analysis.

CHAPTER 3

STUDY AREA AND DATA AVAILABILITY

3.1 Description of Study Area

Nagavali river basin selected for the study is situated in between Mahanadi and Pennar river basins of south India. Nagavali river basin covers 63% of total area in the state of Orissa and 37% in Andhra Pradesh in India. The river originates from Lakhbahal of district Kalahandi, of Orissa. The twelve principal tributaries that join the NagavaliRiver on both sides are Jhanjavati, Barha, Baldiya, Satnala, Sitagurha, Srikona, Gumudugedda, Vottigedda, Suvarnamukhi, Vonigedda, Relligedda and Vegavati.The part of river basin up to gauge site Srikakulam, falling in the state of Andhara Pradesh is taken as the study area the present study. Here are five water resources projects in the catchment as Jhanjavatiproject, Thotapallibarrage, Madduvalasa reservoir, Narayanapuram barrage andVamsadhara and Nagavali inter link canal have been undertaken in the catchment.

Figure 3.1: Srikakulam District Map

3.2 Geographical Location and Climate

The total catchment area of Nagavali river basin, upstream to the point where river join the Bay of Bengal, is 9510 km^{2}and the geographical co-ordinates are18.33^0 – 19.17^0 of Northern latitude and 83.83^0 – 84.83^0 of Eastern longitude. Total geographical area and forest covered area of the Srikakulam district are 5837 km^2 and 687 km^2 that is 11.8% of total geographical area of the district.The basin is influenced by the south-west monsoon during the months of June to October, and by occasional cyclones due to the formation of depression in Bay of Bengal. Because of the topographical and other characteristics of the catchment, the runoff time is limited and flash flood frequently created. The temperature varies from 10^0 C to 43^{0}Cin the plains of basin andhumidityis above the 95% during the monsoon.

3.3 Topology and Soil

The Nagavali River is full of undulations and has narrow basin. The soil of the area is classified as black soils, mixed red, yellow soils, forest soils and coastal sands.TheKankar and the Murum mostly covered the catchment surface.

3.4 Data Availability

3.4.1 Hydro-metrological Data

The hydro-metrological data has been collected by IMD, Pune and India WRIS website. Precipitation data of three rain gauge stations and discharge data in Srikakulam district of Andhra Pradesh which is shown in Figure 3.1. The rainfall is measure in unit of mm/day. The discharge recorded in units of cumec.

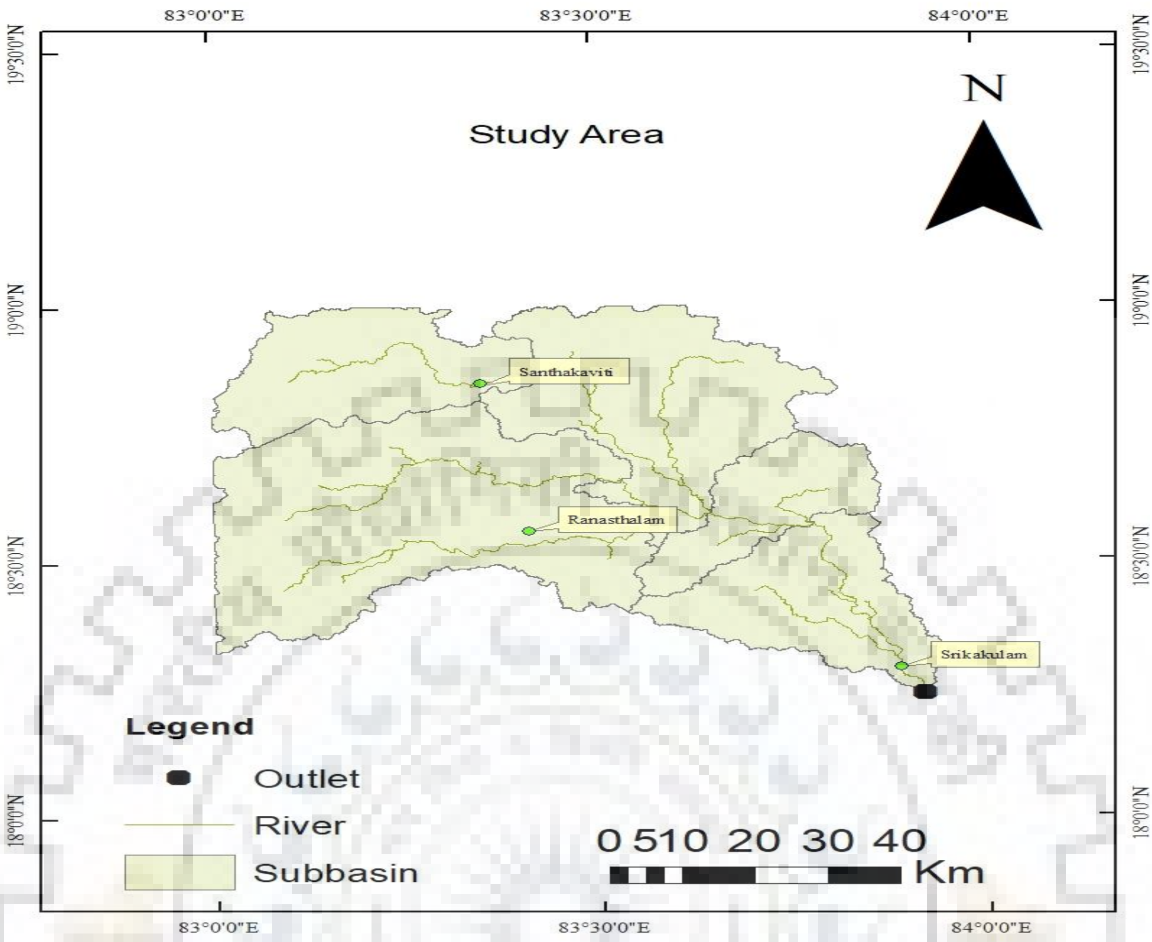

Figure 3.2: Study Area ofNagavaliRiver Basin

Table 3.1 Source of rainfall and discharge data information

DATA TYPE	SOURCE	DETAIL
Rainfall(mm)	IMD	1990 to 2009 (Daily data)
Discharge (m^3/sec)	http://www.india-wris.nrsc.gov.in	1990 to 2009 (Daily data)

CHAPTER 4

METHODOLOGY

To achieve the objectives of this study, the following steps were followed.

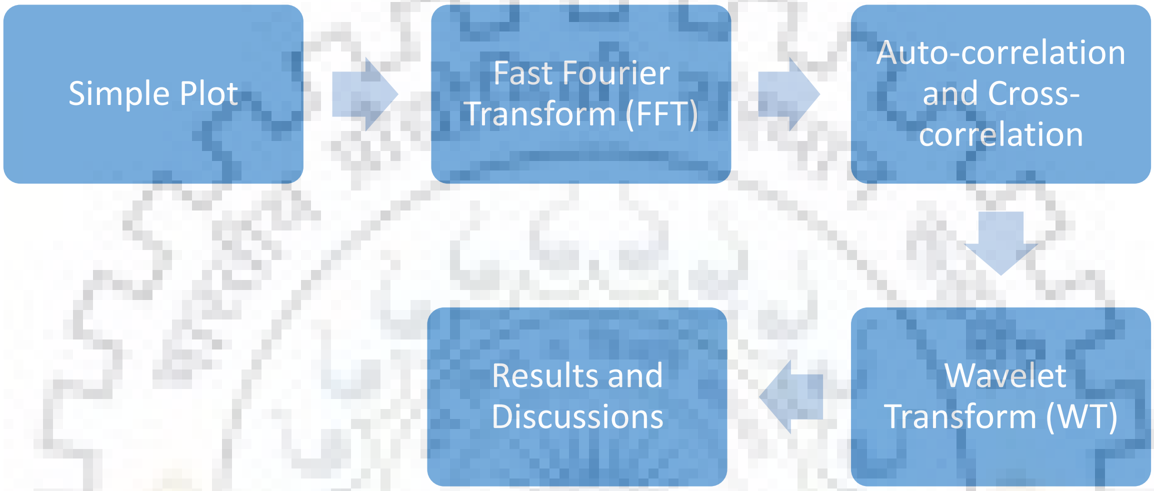

Figure 4.1: Flow Chart of Methodology

4.1 Simple Plot

Without applying, any algorithms in signal simply plot the graph.

4.2 Correlation

4.2.1 Auto-CorrelationFunction(Correlogram)

Auto-correlation function is a mathematical representation in the degree of similarity between certain time series with lagged time associated with itself over successive time intervals. It measures the correlation of signal x (t) with itself shifted by some time delay. Its value lies between -1 to +1.

$$r_k = \frac{\sum_{i=1}^{N-k}(x_i - \bar{x})(x_{i+k} - \bar{x})}{\sum_{i=1}^{N}(x_i - \bar{x})^2}$$

Where,r_k= auto-correlation coefficient at lag time k

4.2.2 Cross-correlation Function

Cross-correlation is a mathematical representation in the degree of similarity between two-time series data with lag time associated with one-time series data to other time series data over successive time intervals. Its value lies between -1 to +1.

$$\mathbf{corr_{xy}(k) = \frac{cov_{xy}(k)}{cov_{xy}(0)}}$$

Where,

$$\mathbf{cov_{xy}(k) = \frac{1}{N-k-1}\sum_{i=1}^{N-k}(x_i - \bar{x})(y_{i+k} - \bar{y})}$$

4.2.3 Fast Fourier Transform (FFT)

FFT function is an effective tool for computing the Discrete Fourier transform (DFT) of a signal in MATLAB produces a discrete frequency domain representation.

The faster version of the Discrete Fourier Transform (DFT) is known as FFT. The FFT utilizes some smart algorithms to do the same thing as the DFT, but in much less time. The DFT has its importance in the area of frequency (spectrum) analysis because it converts the discrete signal in the time domain and into its discrete frequency domain representation. The computation of Fourier Transform with a microprocessor or DSP based system is not possible without a discrete-time to discrete-frequency transform. The DFT is given as

$$\mathbf{x_k = \sum_{K=0}^{N-1} x_n e^{-i2\pi kn/N}}$$

Where, k= 0…1…2…N-1

The DFT cannot be said similar to the DTFT, though both start with a discrete-time signal. This is becausethe DTFT is continuous in the frequency domain while DFT produces a discrete frequency domain representation. These two transforms have many similarities in common. Hence to analyse DFT, the understanding of the basic properties of DTFT will be helpful, like Periodicity: The DTFT, X ($e^{j\Omega}$), is periodic having period extended from f = 0 to fs, where fs is the sampling frequency. So, taking advantage of this redundancy, the DFT is only defined in the region between 0 and fs. Symmetry: By examining the region between 0 and fs, it can be seen that there is even symmetry around the centre point, 0.5fs,ortheNyquist frequency.

$$\textbf{Nyquist frequency} = \frac{\mathbf{f_s}}{\mathbf{2}}$$

4.2.4 WaveletTransform

The wavelets transform contains the information in time and frequency domain of signal.

$$\mathbf{CWT_x^{\psi}(\tau, s) = \psi_x^{\psi}(\tau, s)} = \frac{\mathbf{1}}{\sqrt{|\mathbf{s}|}} \int \mathbf{x(t)\, \psi^*\left(\frac{t - \tau}{s}\right) dt}$$

Where τ, s,and $\psi(t)$are translation, scale, and transforming parameters respectively and x(t) is the time domain signal which is to be transformed in frequency domain.

The term waveletstandsmall wave. The wave refers that this function is oscillatory and the small refers that this (window) function has finite length (compactly supported)in the transformation processes the different region are derived from the main function which is also known as the mother wavelet i.e. we can say that, the mother wavelet is a prototypefor generating the other window functions.

The term **Translation** gives the information about the location of the windowand corresponds to time information in the transformed domain.

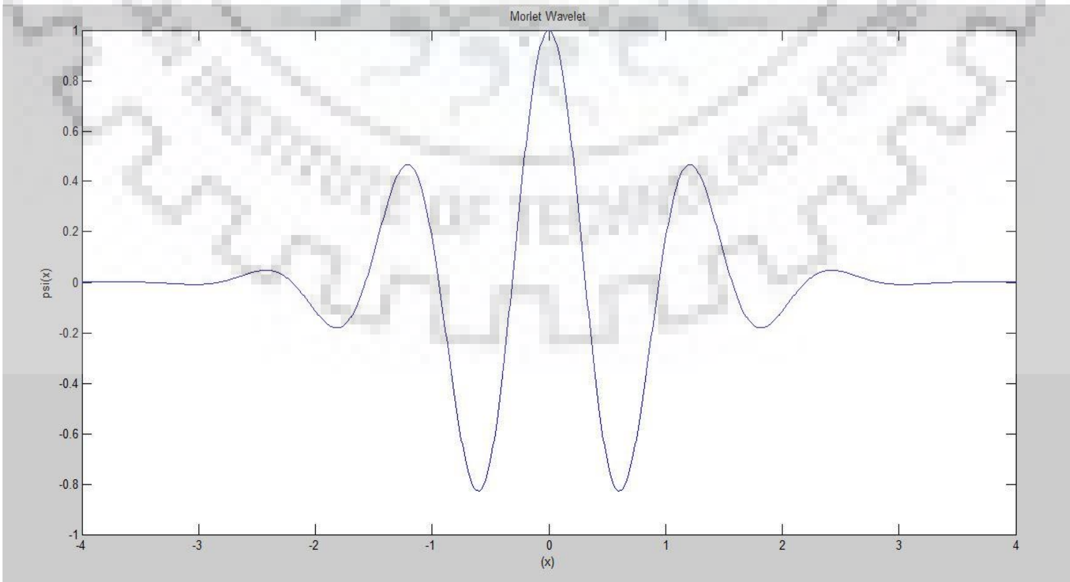

Figure 4.2: MorletWavelet

4.3 Scale Factor in Wavelet Analysis

Thescaleparameterin the wavelet analysis is similar to the scale used in maps. As in the case of maps, bigger scales correspond to detailed view and smaller scales correspond to less detailed view. Similarly, in wavelet analysis the higher scales give low frequency and correspond to better frequency resolution but less time detailed and lower scales gives higher frequency and correspond to better time resolution and less frequency resolutions. This can be expressed in mathematical form, if **f(t)** is a given function, then **f(st)**correspondsto an expanded (dilated) version of **f(t)** if **s < 1** and contracted (compressed) version of **f(t)** if **s > 1**

4.3.1 Time andFrequency Resolutions

For understating the time and frequency resolution which is shown in Figure 4.3, the area of each boxesis constant but heights and widths of the boxes changes,so that the area should be constant.Each box having equal portion of time-frequency plane but gives different proportions to frequency and time. The height of boxes is shorter at low frequency which corresponds to better frequency resolutions, because there is less uncertainty regarding the value of exact frequency but their widths are wider which corresponds to deficient time resolution, because there is more uncertainty regarding the value of exact time. The heights of boxes are higher at high frequency which corresponds to deficient frequency resolutions, because there is more uncertainty regarding exact frequency but their widths are narrower which correspond to better time resolutions, because there is less uncertainty regarding the value of exact time exact time.

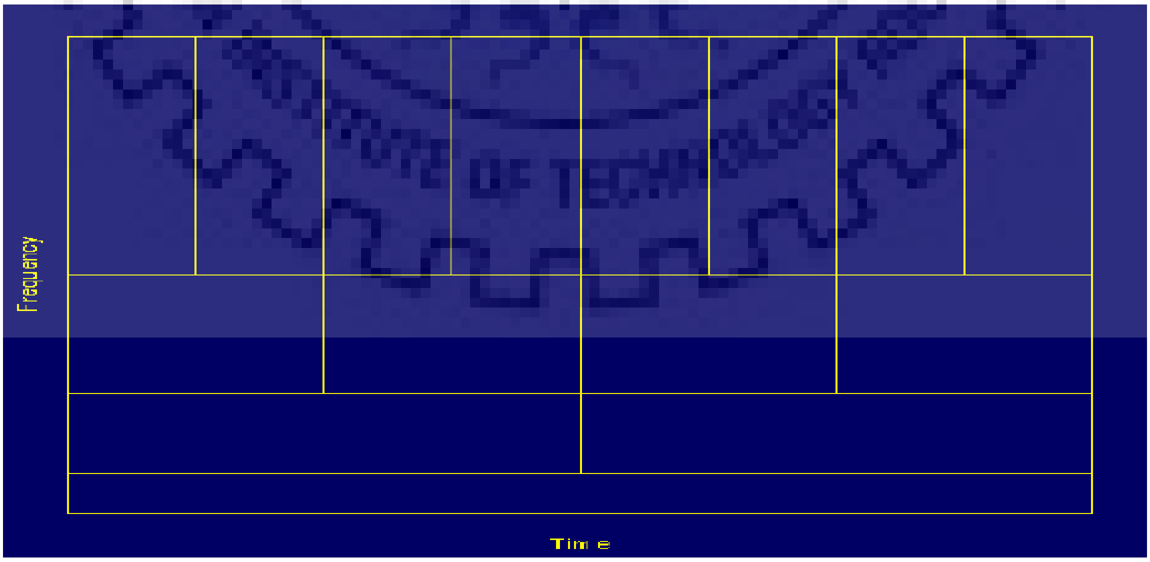

Figure 4.3: Time and Frequency Resolution

CHAPTER 5
RESULTS AND DISCUSSION

5.1 Synthetic Data

Synthetic data are generated based on known frequency and periodicity, i.e., Sine waves of known frequency can be used to develop and test the methodology for better understanding before application on real time series data. In other words, say that it is used as recipes for the analysis to the reader^{s}onreal data after learning their application on synthetic data.

5.1.1 Stationary Synthetic Signal Plot

For stationary synthetic signal, we have considered the signal having time range from 0 sec to 1 sec with step size 0.001 sec having two frequency component of 20 Hz and 50 Hz.

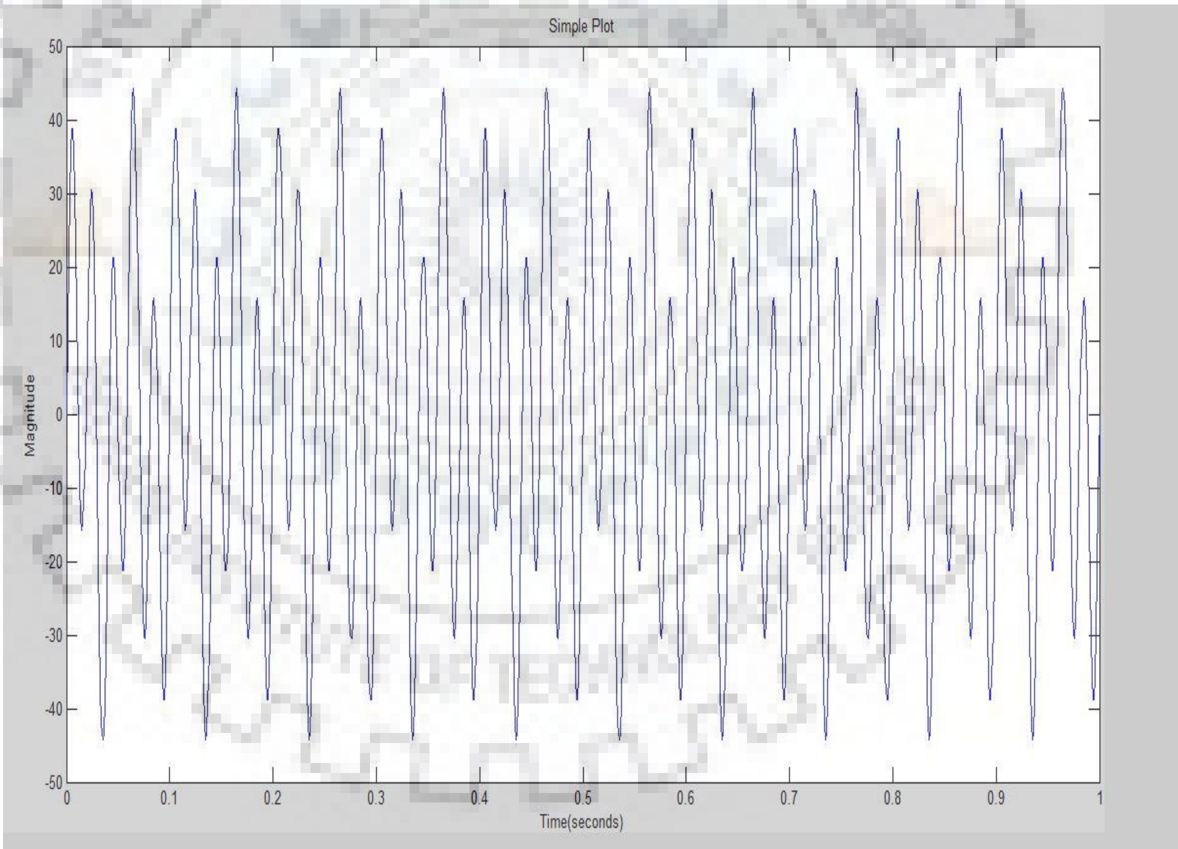

Figure 5.1: Synthetic Signal

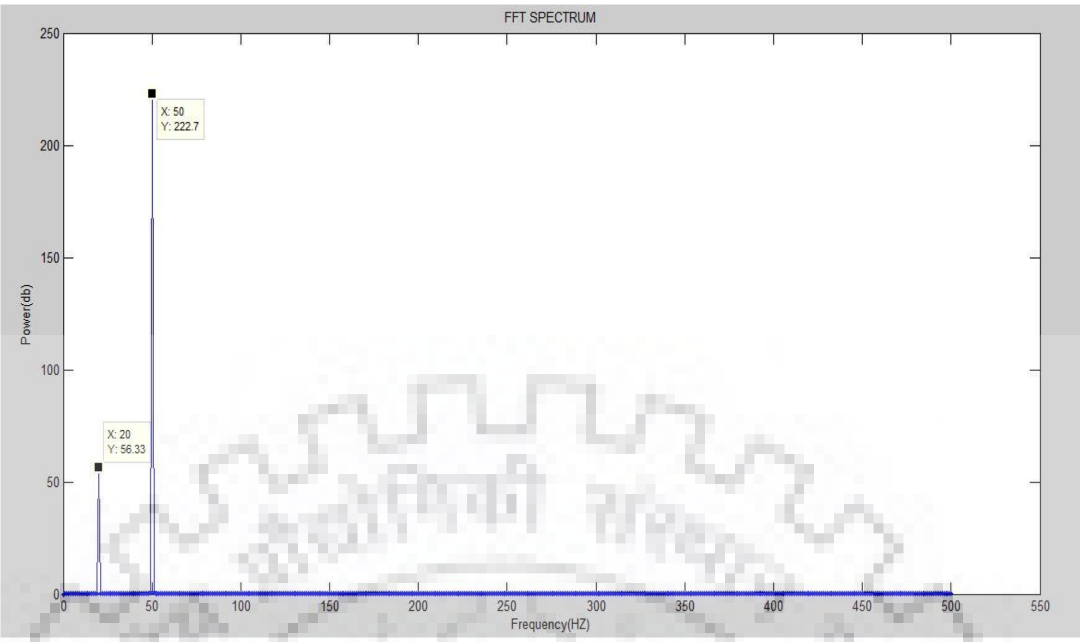

Figure 5.2: Fast Fourier Transform of Synthetic Signal

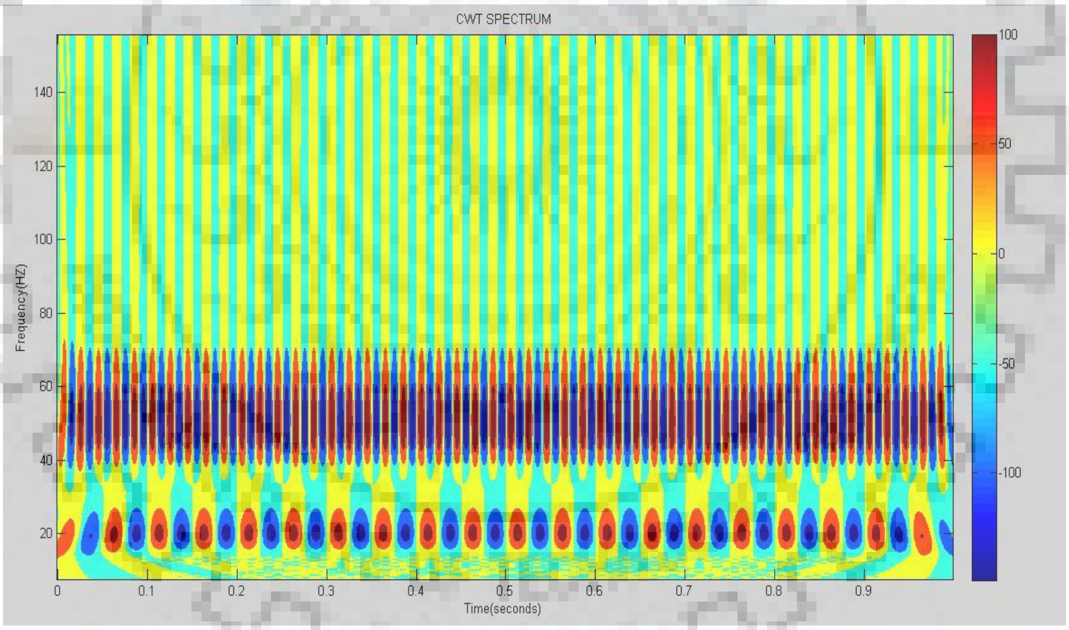

Figure5.3: Continuous Wavelet Transformof Synthetic Signal

After running the code for stationary signal in MATLAB (in appendix code A1) we have obtained the Fig 5.1 which shows the stationary signal without any turbulence. It is same for the whole-time range which has beentaken. Fig 5.2 shows the Fast Fourier Transform for the synthetic data which clearly show the two-frequency component at 20 Hz and 50 Hz. Fig 5.3 show the Continuous Wavelet Transform (CWT) by using Morlet wavelet function which is localizing the time and frequency of the taken synthetic signal.

From CWT it is clear that for the lower frequency which is 20 Hz in our case loop size is wider, i.e.less time resolution. As we go to the higher frequency which is 50 Hz in our case we can see that loop width has decreased which corresponds to higher resolution in time domain.

5.1.2 Non-Stationary Synthetic Signal Plot

For non-stationary synthetic signal, we have considered the first signal having time range from 0 sec to 1 sec with step size of 0.001 and other signal having time range from 0.4 second to 0.7 sec with step size of 0.001 addition of these two signalsanon-stationary signal was provided.

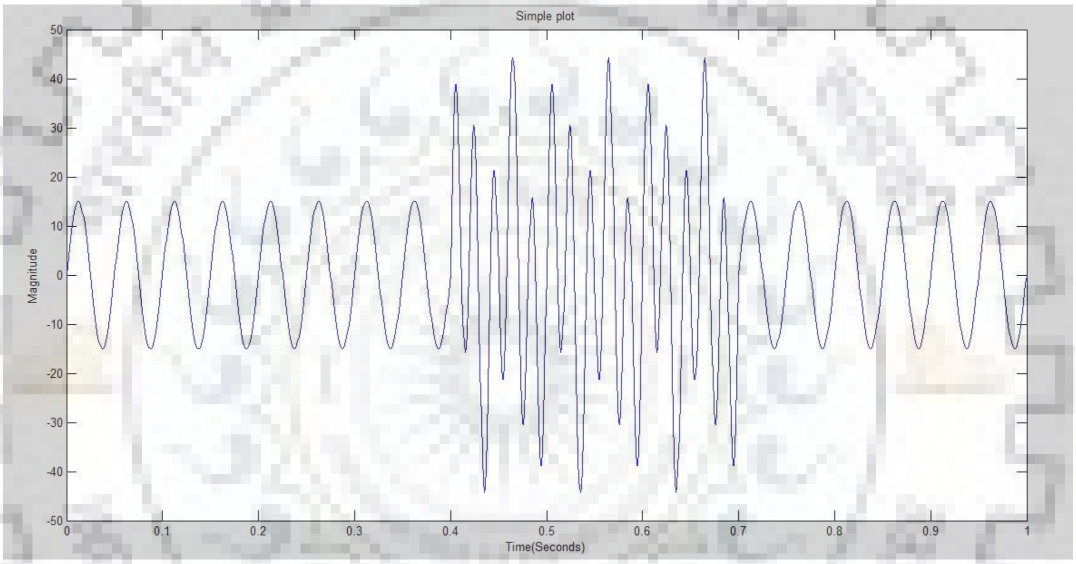

Figure5.4: Simple Plot of Non-Stationary Signal

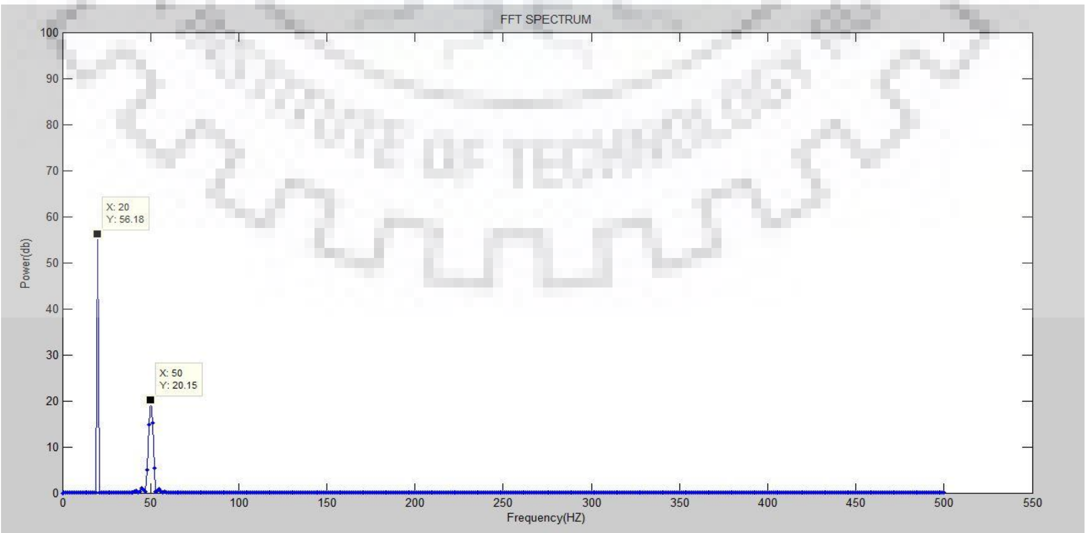

Figure 5.5: Fast Fourier Transform of Non-Stationary Synthetic Signal

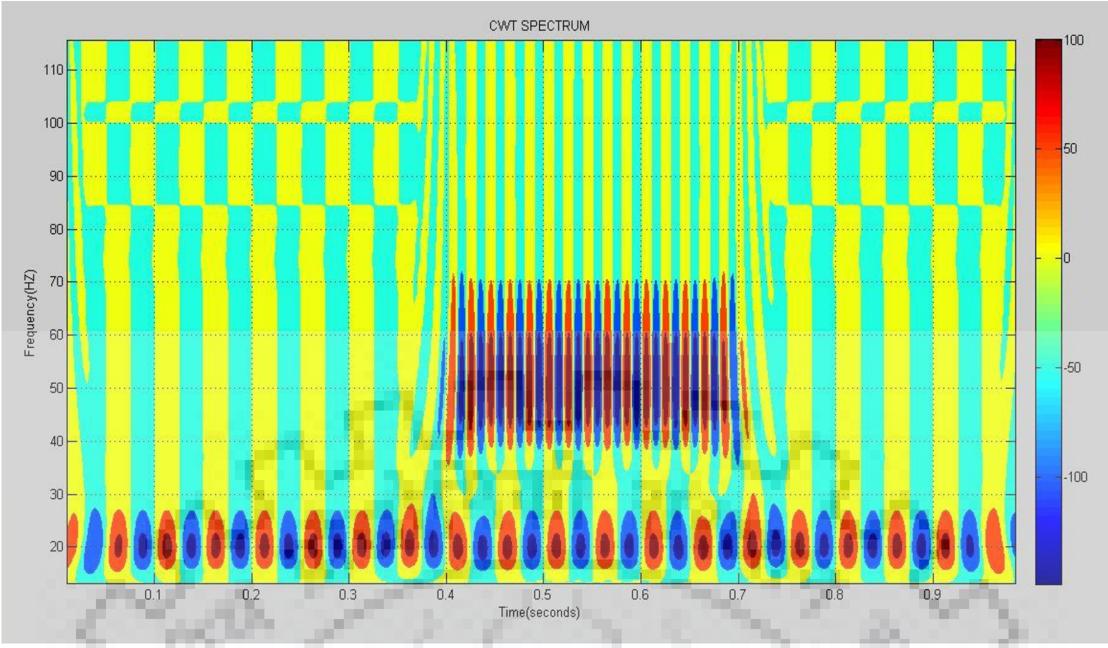

Figure5.6: Continuous Wavelet of Non-Stationary Synthetic Signal

After running the code for non-stationary signal in MATLAB (in appendix code A1) wehaveobtained the Figure 5.4, 5.5 and 5.6. Fig 5.4 shows the non-stationary signal and the frequency 50 Hz exist for limited time range. Fig 5.5 shows the Fast Fourier Transform for the synthetic data which clearly shows the two frequency components of 20 Hz and 50 Hz but do not give the information about how much time length turbulence is occurred. Fig 5.6 shows the continuous Wavelet transform using Morlet wavelet function, which is localizes the time and frequency of the synthetic signal and clearly shows the time boundaries of different frequencies.

5.2 Real Time Series Data

5.2.1 Data

The discharge time series and precipitation time series show episodic periodicities (Figure 5.7 and 5.8).

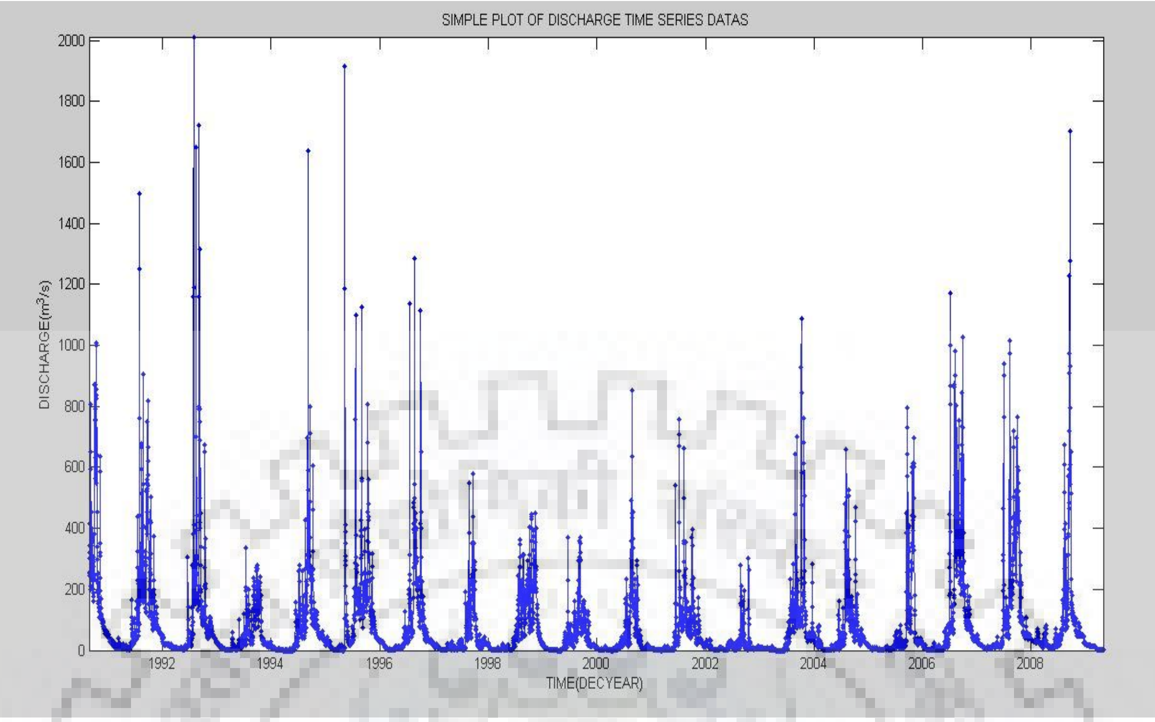

Figure 5.7: Discharge Time Series Data

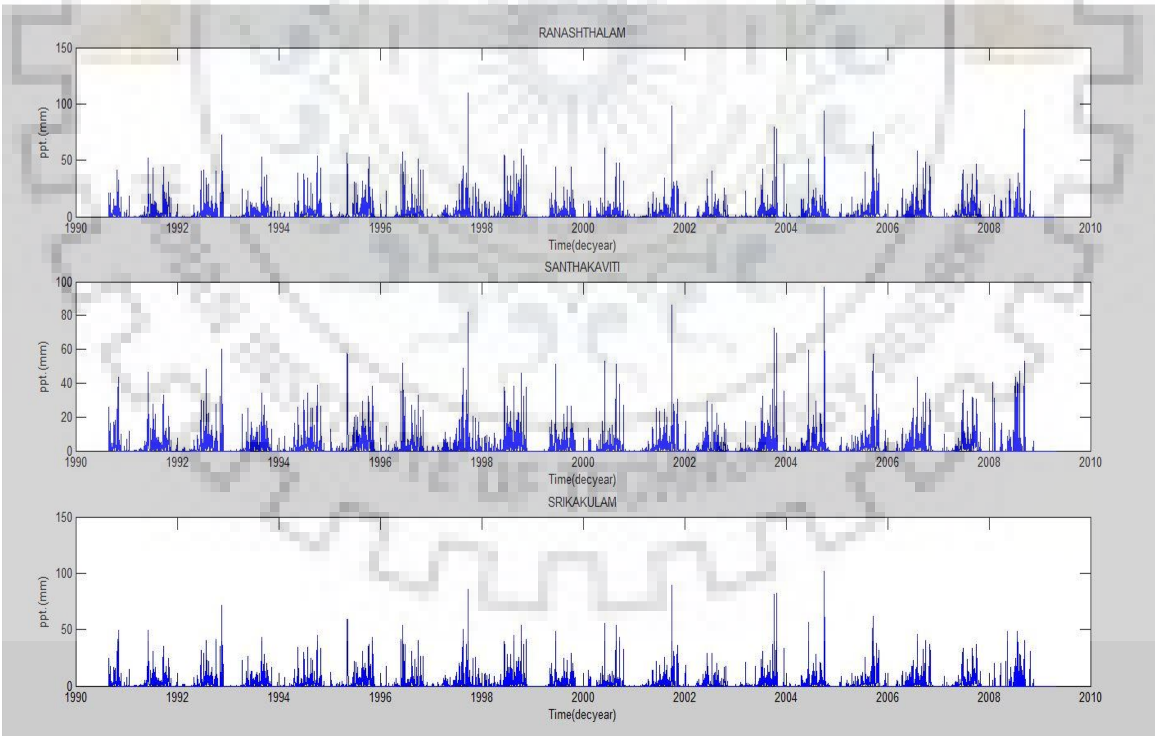

Figure5.8: Rainfall Time Series Data of Three Rainfall Stations

5.2.2 Fast Fourier Transform (FFT)

Figure 5.9 and 5.10 shows the Fast Fourier Transform (FFT) spectrum of discharge data and rainfall data of Ranasthalam, Santhakaviti and Srikakulam rain gauge station respectively, gives the periodicity 372.4 days.

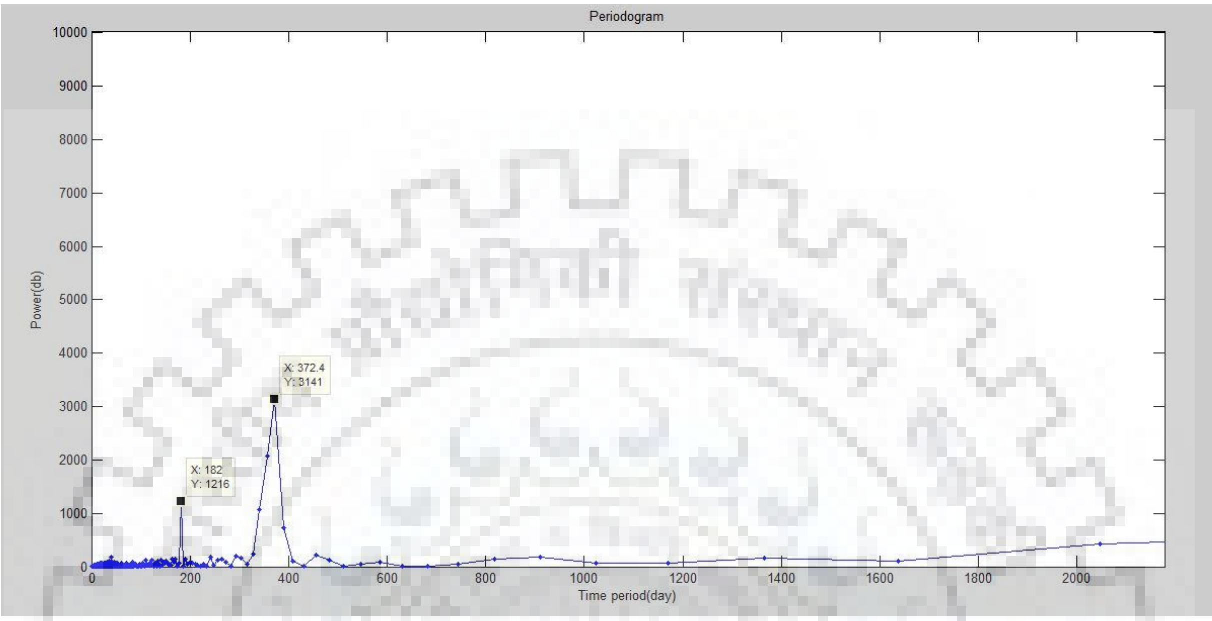

Figure 5.9: Fast Fourier Transform of Discharge Time Series Data

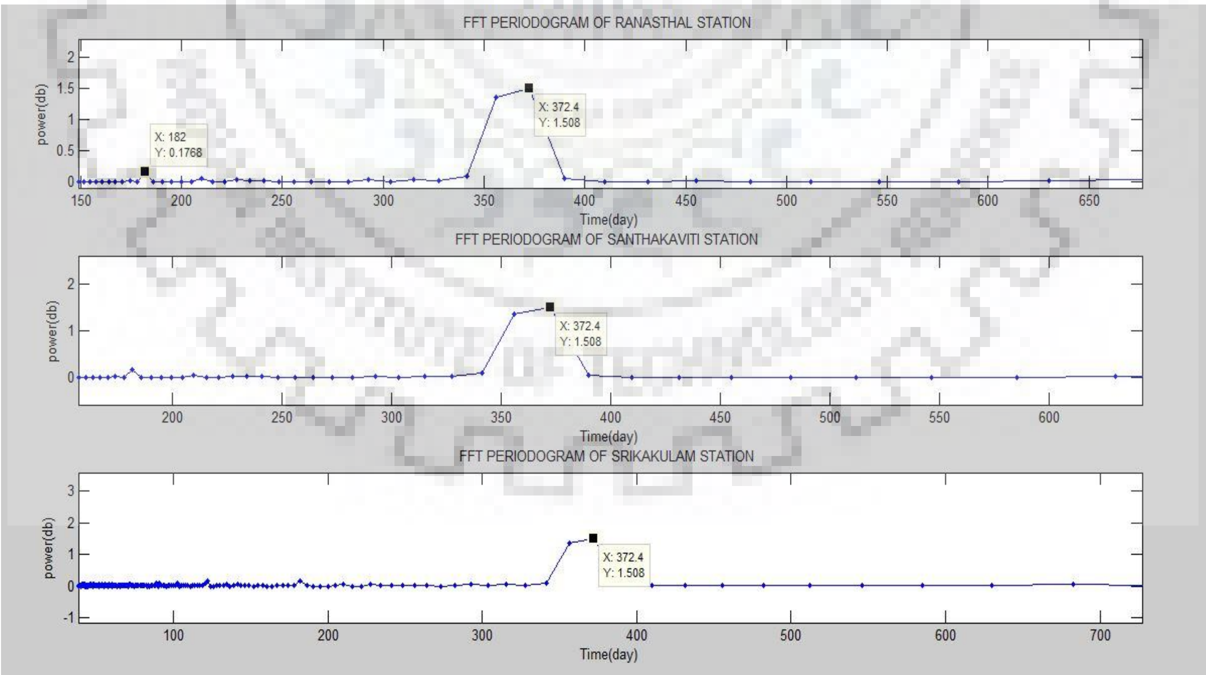

Figure 5.10: Fast Fourier Transform three Rainfall Stations Time Series Data

5.2.3 Auto-Correlation andCross-Correlation

Figure 5.11 and 5.12 shows the auto-correlation of discharge data and rainfall data of Ranasthalam, Santhakaviti and Srikakulam rain gauge station respectively, and periodicity is 375 days.

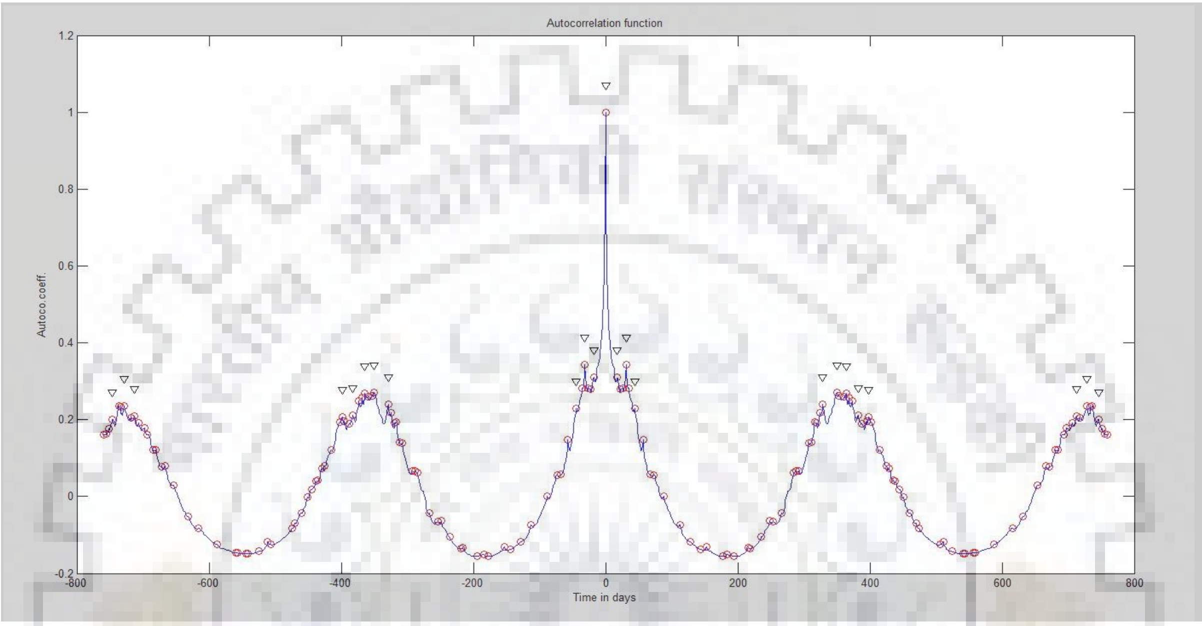

Figure5.11: Auto-Correlation of Discharge Time Series Data

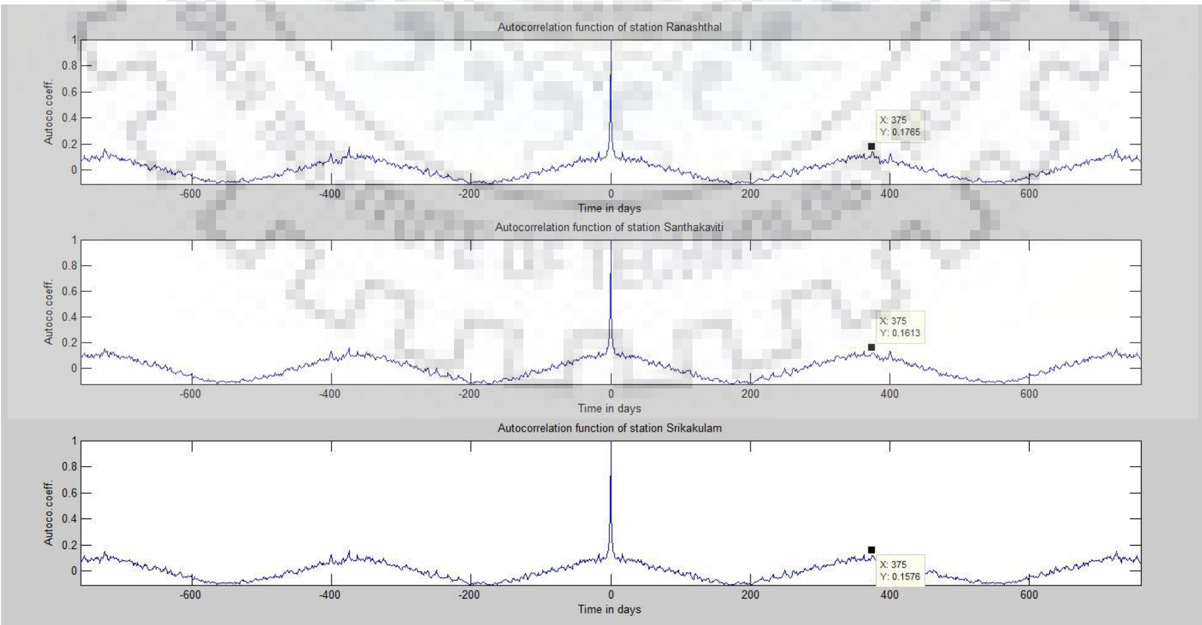

Figure5.12: Auto-Correlation of Time Series Data of three Rainfall Stations

Figure 5.13 and 5.14 shows the cross-correlation between the rainfall data with different rain gauge stations, Ranasthalam-Santhakaviti, Ranasthalam-Srikakulam and Santhakaviti-Srikakulam and discharge data with rainfall data of three different rain gauge stations respectively. Maximum cross-correlation coefficients were found between Ranasthalam rain gauge station with Snthakaviti rain gauge station followed by Ranastham rain gauge station with Srikakulam rain gauge station and then Santhakaviti rain gauge station with Srikakulam rain gauge station are 0.88, 0.92 and 0.96 at 0-time lags and 0.48, 0.47 and 0.47 at 1 day lag time respectively. Maximum correlation coefficients between rain gauge stations with discharge are 0.42, 0.42 and 0.40 at 1-day lag time and 0.41, 0.41 and 0.4 at 2 days lag time, respectively.

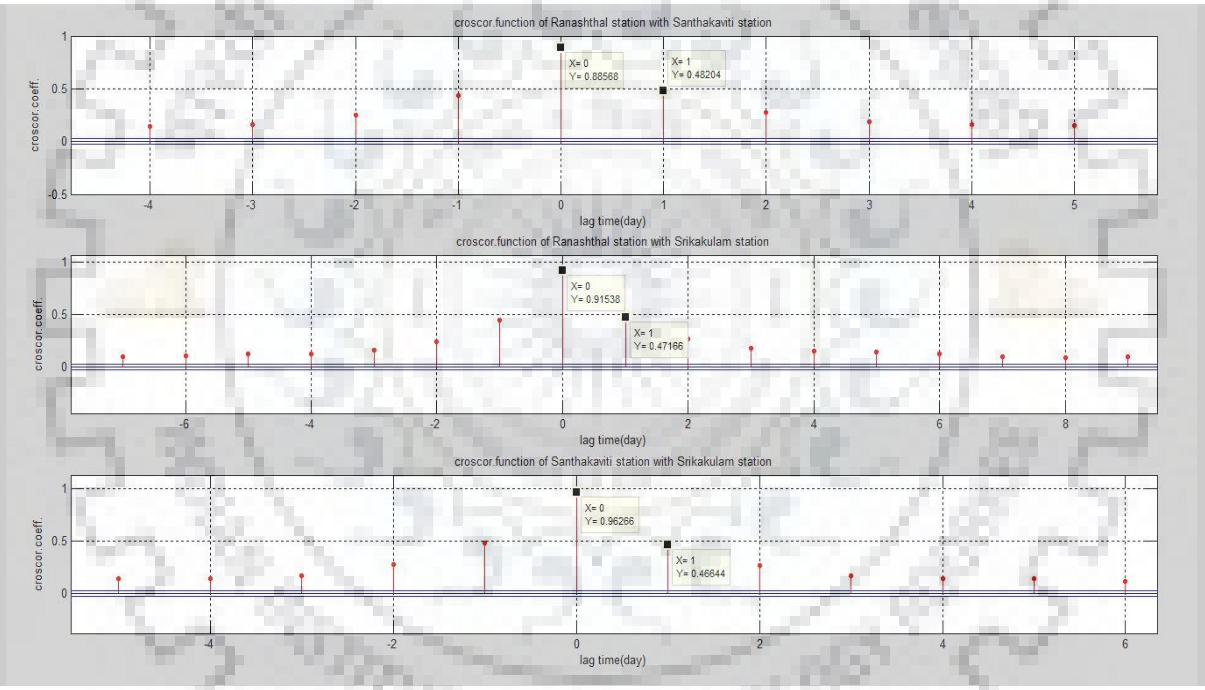

Figure 5.13: Cross-Correlation within Rainfall Stations Time Series Data

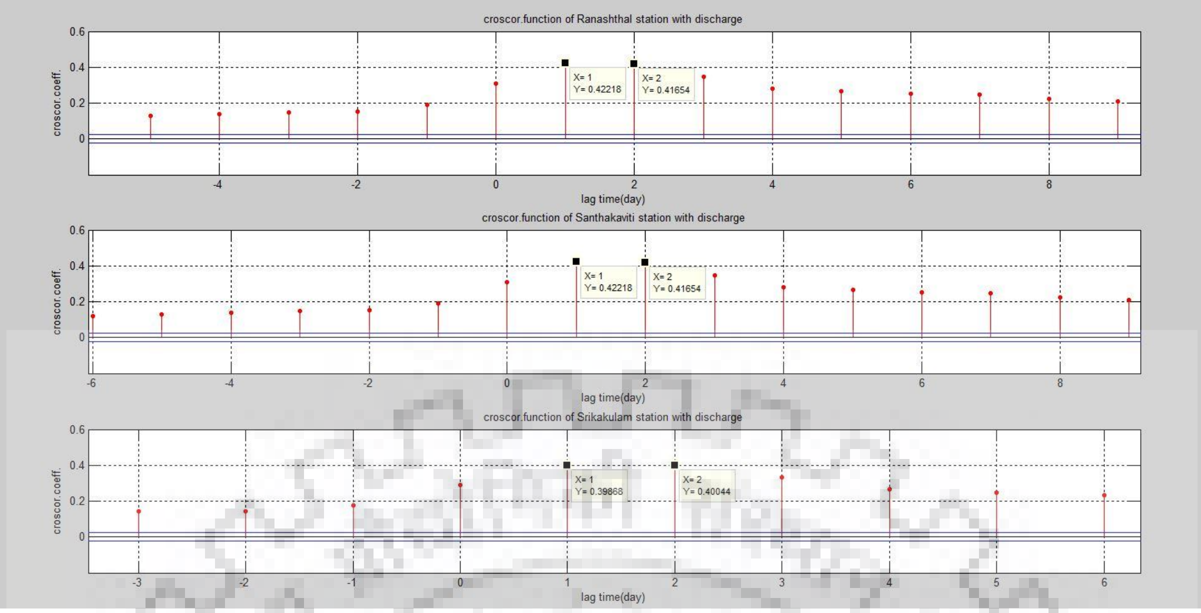

Figure5.14: Cross-Correlation between the Discharge Data and Rainfall Time Series Data

Figure 5.15, 5.16, 5.17, and 5.18 shows the continuous wavelet transform (CWT) of discharge and rainfall of three rain gauge stations Ranasthalam, Santhakaviti, and Srikakulam respectively and gives the central periodicity near about 370 days, which is close to the periodicity obtained by FFT (372.4 days).

In this case have additional information's like time localization and in which particular period of time impulse is more or less shown by intensity of colour as shown in above Figures. Intensity of red colour is more in the loop that means in particular year corresponding to that loop impulse is more and vice-versa.

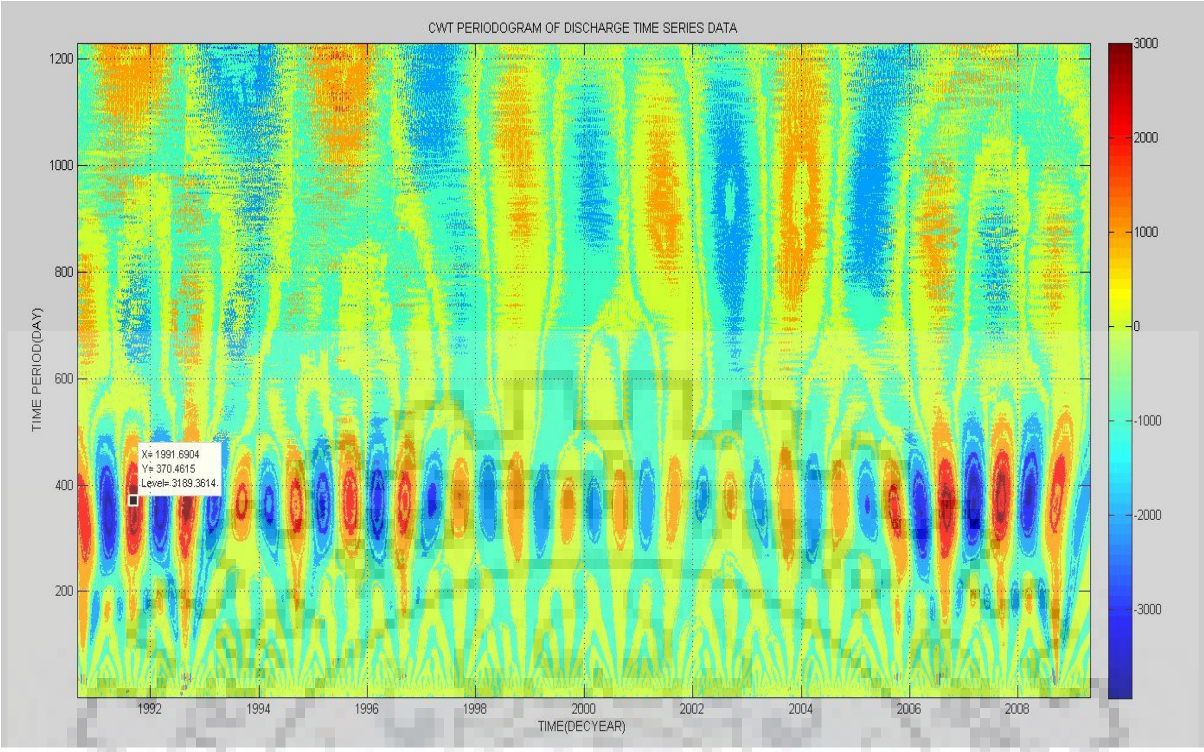

Figure5.15: Continuous Wavelet Transform of Discharge Time Series Data

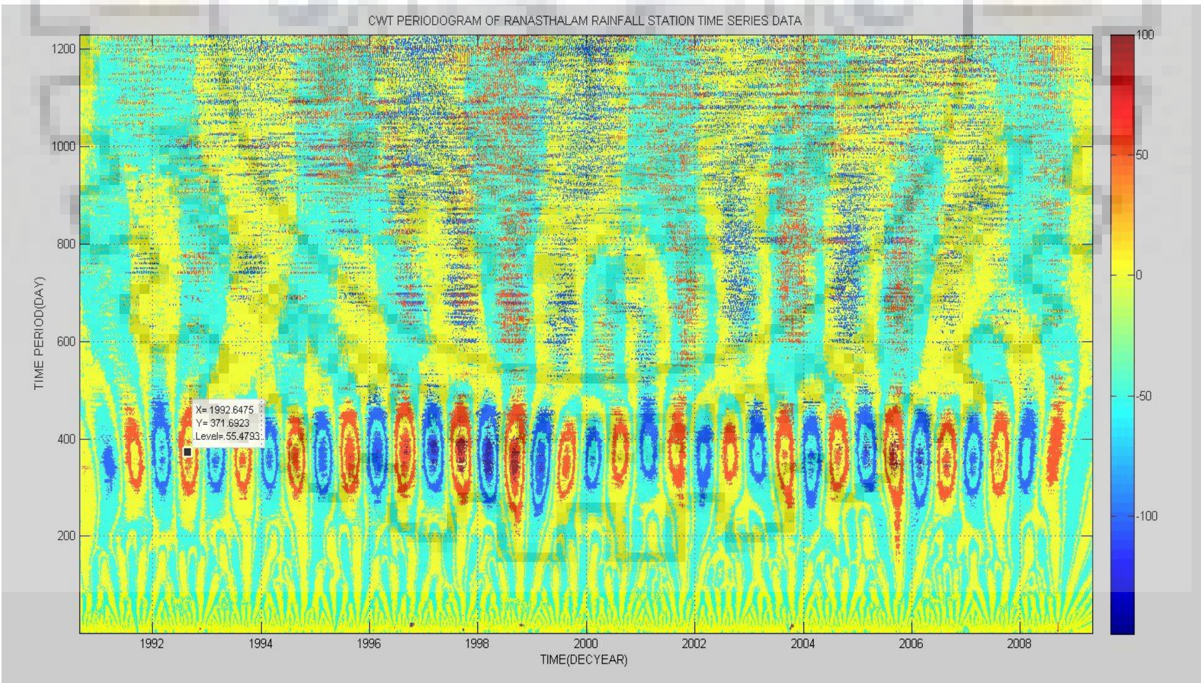

Figure5.16: Continuous Wavelet Transform of RanasthalamRainfall Station Time Series Data

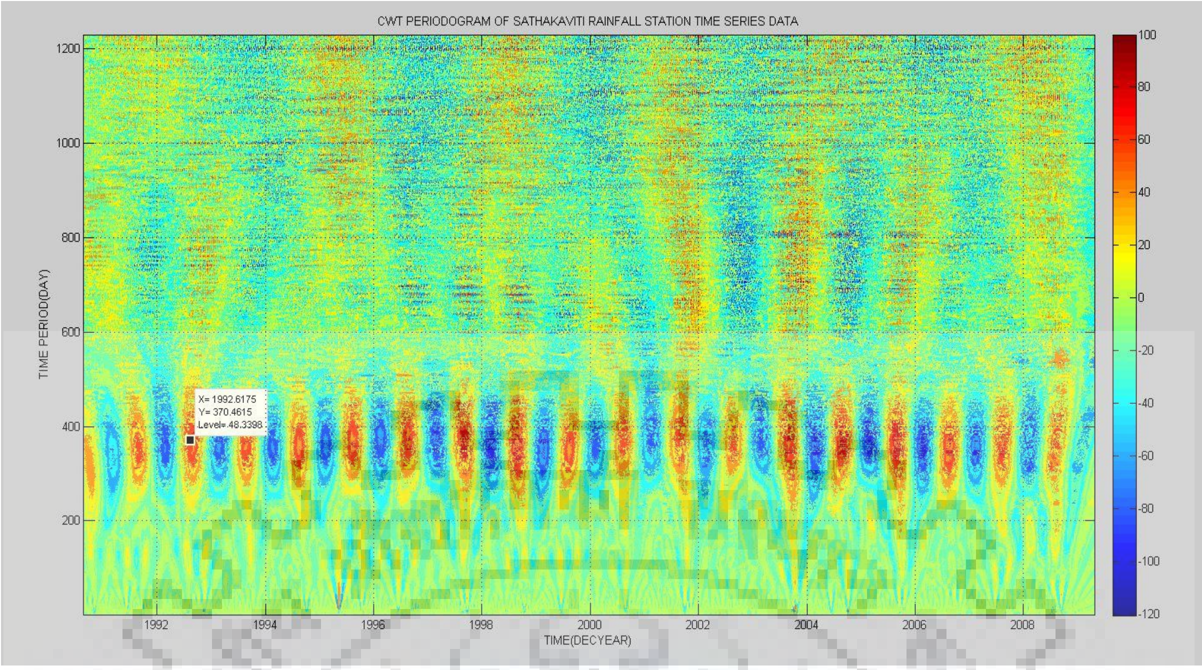

Figure5.17: Continuous Wavelet Transform of SanthakavitiRainfall Station Time Series Data

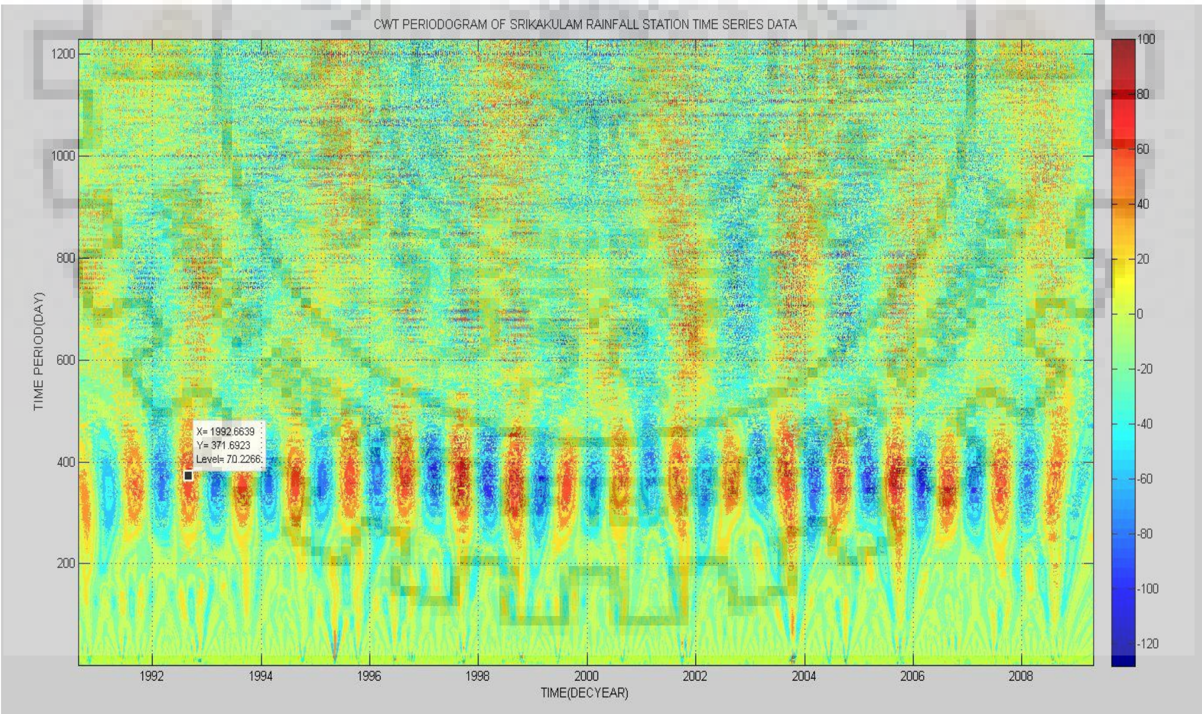

Figure 5.18: ContinuousWavelet Transform of SrikakulamRainfall Station Time Series Data

CHAPTER 6

CONCLUSIONS

The time frequency analysis of the daily discharge and rainfall time series data of Srikakulam Nagavali river basin in eastern coast of Andhra Pradesh India is carried out to study the variability in the data sets using correlation (auto-correlation and cross-correlation), fast Fourier Transform (FFT) and Wavelet transform. The cross-correlation coefficient shows maximum time delay of 2 days lag time between the rainfall and discharge time series. The power spectrum and correlogram shows the dominant periodicity of 372.4 daysfor both the discharge and rainfall time series data (Figure 5.9, 5.10, 5.11 and 5.12). Thewavelet power spectra show power concentrations between the 288– 440 days band with central periodicity of 370 days for both discharge and rainfall time series data set (Figure 5.15, 5.16, 5.17 and 5.18). The calculated periodicity is more or less same using FFT and wavelet transform respectively. The wavelet spectrum further identifies the relatively low intensity of discharge and precipitation during 1993 and 1998-2002 time span respectively in comparison to other episodes. Our analysis suggests annual periodicity in the discharge and rainfall time series data set (Figure 5.13).

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APPENDIX

A1. MATLAB code for Stationary synthetic signal

```
closeall;clearall;clc;
t = 0:0.001:1;
dt=0.001;
s = 15*sin(2*pi*20*t)+30*sin(2*pi*50*t);
plot(t,s); % Gives the Plot for the Fig. 5.1
xlabel('Time(seconds)');
ylabel('Magnitude');
title('Simple Plot')
figure
nt=length(t);
p=fft(s)/nt;
z=p.*conj(p);
df=2*pi/(nt*dt);
f=(0:nt/2);
plot(f,z(1:nt/2+1),'.-'); % Gives plot for the Fig. 5.2
Ylabel('Power(db)');
Xlabel('Frequency(HZ)');
title('FFT SPECTRUM');
axis([0 550 0 250]);
figure
scale=1:300;
```

```
f=scal2frq(scale,'morl',0.001);

c = cwtext(s,1:300,'morl');

contour(t,f,c,'fill','on'); % Gives the Plot for the Fig. 5.3

xlabel('Time(seconds)');

ylabel('Frequency(HZ)');

title('CWT SPECTRUM')
```

A2. Matlab code for Non Stationary synthetic signal

```
closeall;clearall;clc;

t=0:0.001:1;

dt=0.001;

nt=length(t);

t1=0.4:0.001:0.7;

t2(400)=0;

t1(601)=0;

t3=[t2,t1];

s1 = 15*sin(2*pi*20*t);

s2=30*sin(2*pi*50*t3);

s=s1+s2;

plot(t,s);% Gives the Plot for the Fig. 5.4

xlabel('Time(Seconds)');

ylabel('Magnitude');

title('Simple plot')
```

```
fs=1/dt;

df=2*pi/(nt*dt);

nfft=2^nextpow2(nt);

X=fft(s)/nt;

p=X.*conj(X);

f=(0:nt/2);

figure

plot(f,p(1:nt/2+1),'.-');% Gives the Plot for the Fig. 5.5

title('FFT SPECTRUM');

axis([0 550 0 100]);

xlabel('Frequency(HZ)');

ylabel('Power(db)');

figure

scale=1:300;

f=scal2frq(scale,'morl',0.001);

c = cwt(s,1:300,'morl');

contour(t,f,c,'fill','on');% Gives the Plot for the Fig. 5.6

gridon;

xlabel('Time(seconds)');

ylabel('Frequency(HZ)');

title('CWT SPECTRUM');
```

A3. Matlab code for real time series data

```
closeall;clearall;clc;

s=xlsread('runoffx.xlsx');

s1=xlsread('rainfallx.xlsx');

x1=s1(:,5);

x2=s1(:,6);

x3=s1(:,7);

d=s(:,1);

mo=s(:,2);

ye=s(:,3);

t1=decyear(ye,mo,d);

x=s(:,6);

plot(t1,x,'.-b');% Gives the plot for discharge  data series Fig. 5.7

xlabel('Time(Decyear)');

ylabel('Discharge(m^3/sec)');

subplot(3,1,1)

plot(t1,x1);% Gives the plot for Ranasthal station rainfall data series  Fig. 5.8 (top)

xlabel('Time(Decyear)');

ylabel('Ppt.(mm)');

subplot(3,1,2)

plot(t1,x2);% Gives the plot for Santhakaviti station rainfall station Fig. 5.8 (middle)

xlabel('Time(Decyear)');

ylabel('Ppt.(mm)');

subplot(3,1,3)

plot(t1,x3);% Gives the plot for Srikakulam station rainfall station Fig. 5.8 (bottom)
```

```
xlabel('Time(Decyear)');
ylabel('Discharge(mm)');
t=(t1-t1(1)).*365;
dt=t(2)-t(1);
t=(t1-t1(1)).*365;
dt=t(2)-t(1);
fs=1/dt;
nt=length(t);
nfft=2^nextpow2(nt);
df=2*pi/(nt*dt);
f=fs/2*linspace(0,1,nfft/2+1);
z=fft(x,nfft)/nt;
p=z.*conj(z);
figure
plot(1./f,2*p(1:nfft/2+1),'.-');% Gives the plot for discharge data series  the Fig. 5.9
xlabel('Time period(day)');
ylabel('Power(db)');
title('Periodogram');
%%%%rainfall
z1=fft(x1,nfft)/nt;
p1=z1.*conj(z1);
z2=fft(x2,nfft)/nt;
p2=z2.*conj(z2);
z3=fft(x3,nfft)/nt;
```

```
p3=z3.*conj(z3);

figure

subplot(3,1,1)

plot(1./f,p1(1:nfft/2+1),'.-');% Gives the plot for Ranasthal station rainfal data series. In Fig. 5.10 (top)

xlabel('Time period(day)');

ylabel('power(db)');

title(' PERIODOGRAM OF RANASTHAL STATION BY FFT ');

subplot(3,1,2)

plot(1./f,p1(1:nfft/2+1),'.-');%Gives the plot for Santhakaviti station rainfal data series. In Fig. 5.10 (middle)

xlabel('Time period(day)');

ylabel('power(db)');

title(' PERIODOGRAM OF SANTHAKAVITI STATION BY FFT ');

subplot(3,1,3)

plot(1./f,p1(1:nfft/2+1),'.-');%Gives the plot for Srikakulam station rainfal data series. In Fig. 5.10 (bottom)

xlabel('Time period(day)');

ylabel('power(db)');

title('PERIODOGRAM OF SRIKAKULAM STATION BY FFT');



%%%%%%%%%%%% auto-correlation.

closeall;clearall;clc;

s=xlsread('rainfallx.xlsx');
```

```
s1=xlsread('runoffx.xlsx');
x1=s(:,5);% Ranasthalam rainfall station
x2=s(:,6);% Santhakaviti rainfall station
x3=s(:,7);% Srikakulam rainfall station

x4=s1(:,6);
d=s1(:,1);
mo=s1(:,2);
ye=s1(:,3);
t1=decyear(ye,mo,d);
xnorm1=x1-mean(x1);
xnorm2=x2-mean(x2);
xnorm3=x3-mean(x3);
xnorm4=x4-mean(x4);
fs=1;
t=(0:length(x1)-1)/fs;
[autocor1,lags1]=xcorr(xnorm1,380*2*fs,'coeff');
[autocor2,lags2]=xcorr(xnorm2,380*2*fs,'coeff');
[autocor3,lags3]=xcorr(xnorm3,380*2*fs,'coeff');
[autocor4,lags4]=xcorr(xnorm4,380*2*fs,'coeff');
[pksh4,lcsh4]=findpeaks(autocor4);
short=mean(diff(lcsh4))/fs;
[pklg4,lclg4]=findpeaks(autocor4,'MinpeakDistance',ceil(short)*fs,'MinpeakHeight',0.2);
long4=mean(diff(lclg4))/fs;
```

```
pks4=plot(lags4(lcsh4)/fs,pksh4,'or',lags4(lclg4)/fs,pklg4+0.07,'vk');

holdon;plot(lags4/fs,autocor4); % Gives the plot for Fig. 5.11

xlabel('Time in days');shg

ylabel('Autoco.coeff.');

title('Autocorrelation function');size(s1)

figure

subplot(3,1,1);

plot(lags1/fs,autocor1);% Gives the plot for Ranasthal rainfall data series Fig. 5.12 (top)

xlabel('Time in days');

ylabel('Autoco.coeff.');

title('Autocorrelation function of station Ranashthal');axis tight;

subplot(3,1,2);

plot(lags2/fs,autocor2);% Gives the plot for Santhakaviti rainfall data series Fig. 5.12 (middle)

xlabel('Time in days');

ylabel('Autoco.coeff.');

title('Autocorrelation function of station Santhakaviti');axis tight;

subplot(3,1,3);

plot(lags3/fs,autocor3);% Gives the plot for Srikakulam rainfall data series Fig. 5.12 (bottom)

xlabel('Time in days');

ylabel('Autoco.coeff.');

title('Autocorrelation function of station Srikakulam');axis tight;


%%%%%%%%%% Cross-correlation and continuous wavelet transform (CWT).

closeall;clearall;
```

```
s1=xlsread('runoffx.xlsx');

x1=s1(:,6);

s2=xlsread('rainfallx.xlsx');

x2=s2(:,5);

x3=s2(:,6);

x4=s2(:,7);

d=s1(:,1);

mo=s1(:,2);

ye=s1(:,3);

t=decyear(ye,mo,d);

numlags=min(20,min(length(x2),length(x1))-1);

[xcf1,lags1,bounds1] = crosscorr(x2,x1,numlags);

subplot(3,1,1);

crosscorr(x3,x1,numlags);% Gives the plot for croscor. of disc. withRanasthal rainfall station Fig. 5.13 (top)

xlabel('lag time(day)');

ylabel('croscor.coeff.');

title('croscor.function of Ranashthal station with discharge');

[xcf2,lags2,bounds2] = crosscorr(x3,x1,numlags);

subplot(3,1,2);

crosscorr(x3,x1,20);% Gives the plot for croscor. of disc. with  Santhakaviti rainfall station Fig. 5.13(middle)

xlabel('lag time(day)');

ylabel('croscor.coeff.');

title('croscor.function of Santhakaviti station with discharge');
```

```
subplot(3,1,3);

[xcf3,lags3,bounds3] = crosscorr(x4,x1,20);

crosscorr(x4,x1,20); % Gives the plot for croscor. of disc. with Srikakulam rainfall station Fig. 5.13 (bottom)

xlabel('lag time(day)');

ylabel('croscor.coeff.');

title('croscor.function of Srikakulam station with discharge');

figure

numlags=min(20,min(length(x2),length(x3))-1);

[xcf1,lags1,bounds1] = crosscorr(x2,x3,numlags);

subplot(3,1,1);

crosscorr(x2,x3,numlags);% Gives the plot for croscor.ofRanasthal station with Santhakaviti station Fig. 5.14 (top)

xlabel('lag time(day)');

ylabel('croscor.coeff.');

title('croscor.function of Ranashthal station with Santhakaviti station');

[xcf2,lags2,bounds2] = crosscorr(x2,x4,numlags);

subplot(3,1,2);

crosscorr(x2,x4,20);% Gives the plot for croscor.ofRansthal station with Srikakulam station Fig. 5.14(middle)

xlabel('lag time(day)');

ylabel('croscor.coeff.');

title('croscor.function of Ranashthal station with Srikakulam station');

[xcf3,lags3,bounds3] = crosscorr(x3,x4,20);

subplot(3,1,3)
```

```
crosscorr(x3,x4,20);% Gives the plot for croscor.ofSanthakaviti station with Srikakulam station Fig. 5.14 (bottom)

xlabel('lag time(day)');

ylabel('croscor.coeff.');

title('croscor.function of Santhakaviti station with Srikakulam station');

scales=1:1000;

c1=cwt(x1,1:1000,'morl');

c2=cwt(x2,1:1000,'morl');

c3=cwt(x3,1:1000,'morl');

c4=cwt(x4,1:1000,'morl');

f=scal2frq(scales,'morl',1);

figure

contour(t,1./f,c1,'fIll','on');% Gives the plot for Fig. 5.15(a)

gridon;

xlabel('Time(decyear)');

ylabel('Time period(day)');

title('WAVELET SPECTRUM OF DISCHARGE' )

figure

contour(t,1./f,c2,'fill','on');% Gives the plot for Fig. 5.16

gridon;

xlabel('Time(decyear)');

ylabel('Time period(day)');

title('WAVELET SPECTRUM OF RANASTHALAM RAINFALL STATION');

figure;

contour(t,1./f,c3,'fill','on');% Gives the plot for Fig.5.17
```

```
gridon;

xlabel('Time(decyear)');

ylabel('Time period(day)');

title('WAVELET SPECTRUM OF SANTHAKAVITI RAINFALL STATION')

figure;

contour(t,1./f,c4,'fill','on');% Gives the plot for Fig. 5.18

gridon;

xlabel('Time(decyear)');

ylabel('Time period(day)');

title('WAVELET SPECTRUM OF SRIKAKULAM RAINFALL STATION')
```