IMPACT OF CLIMATE CHANGE ON STREAM FLOW OF

RIVER BRAHMAPUTRA

AT PANDUGHAT STATION

A Study Report

by

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ABSTRACT

The North East region of India suffers from frequent flood attack, specially the upper Assam area due to high intensity rainfall during the month of June and July every year. However the region also suffers from long dry spell and this problem is still increasing due to the severe impact of climate change in the region. The changing climate is also affecting the morphology of the river Brahmaputra, which is the main source of water for the people of Assam, especially in the Guwahati region. Therefore strategic planning of water resources management is essential for efficient utilization of water in future. Reliable forecasting of future precipitation influenced by climate change scenario is an important field of research.

In this study, the impact of climate change on the stream flow of river Brahmaputra at Pandughat has been simulated. For reanalysis of data Hadley centre Coupled Model version 3 (HadCM3) GCM has been used. The data has been then downscaled using the method of statistical downscaling. To determine the stream flow in the region, HADCM3 monthly weather data under A4 scenario has been used. The downscaled data then, use for future stream flow prediction in the same location.

The second part of the study focuses on statistical Flood Frequency Analysis using both short term and long term data, obtained from the previous part of the study. Here four available statistical distribution methods, has been used namely Gumbel distribution, log-normal type-iii distribution, Pearson type-iii distribution and log-Pearson type-iii distribution. The results obtained from each of the distribution methods then compared with each other. The best suited data has been taken into account, for estimating flood risk of the region in near future. It has been observed that Gumbel and log-normal give appreciable flood estimation data than the other two remaining model.

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1. INTRODUCTION

This chapter introduces to the causes of climate change and its impact on water resource. In the later part of the chapter the objectives of the study has been described along with the future study scope in this field.

1.1 Climate:

Climate is defined as the weather averaged over a long time, generally the standard averaging period is 30 years. However, other periods may be used depending on the purpose. The climate of an area depends on several factors and changes from time to time depending on these factors. Some of the most climate affecting factors are: temperature, humidity, sea level pressure, atmospheric pressure etc.

Climate Change is defined as the change in the statistical properties of the climate system of a region when considered over a long period of time. The cause of the change may be due to human influence or due to nature. One of the major causes of climate change is global warming.

Global warming is the rise in the average temperature of the earth surface due to the increase in the concentration of the greenhouse gases. **Greenhouse gases**, as defined by the **Intergovernmental Panel on Climate Change** (IPCC), are "The gaseous constituents of the atmosphere, both natural and anthropogenic, that absorb and emit radiation at specific wavelengths within the spectrum of thermal infrared radiation emitted by the earth's surface, the atmosphere itself and by clouds." Greenhouse gases include carbon dioxide, methane and nitrous oxide. Several human activities have lead to the increase in concentration of these gases leading to global warming. The earth mean temperature has increased by an amount of $0.8^{o}C$ and according to *fourth assessment report* (AR4) by the IPCC the earth temperature is going to increase further by $1.1^{o}C$ to $2.9^{o}C$ in the 21^{st} century only.

1.2 Impact of Climate Change:

Global warming and sea-level rise are the main impacts of climate change. Arctic sea ice is melting more rapidly than expected as per the IPCC report. The impacts of climate change are:

Sea-level rise due to the high rate of melting in glaciers.

Droughts and floods

In hot region the crop yield decreases but in cold regions it increases.

Increasing health problems like water-borne diseases

Change in the weather pattern.

1.3 Impact of Climate Change on Stream Flow behavior:

The stream flow of most of the East Indian rivers increases in the monsoon period, i.e. during the month of June, July and August and decreases in the non-monsoon period. However, this flow pattern is very much important for the development of irrigation and fish cultivation especially in the rural areas of the region. Due to irregular precipitation pattern and constant rising temperature of the earth, the flow pattern changes, giving very high runoff in some period and very low runoff in other periods of the year. This uneven stream flow leads to various major problems, such as:

Agricultural Drought
Severe flood
Changes in the river morphology
High rate of sediment transport

1.4 Scope of Study in North East India:

The north east region of India is well rich in rainfall as well as rivers. The river Brahmaputra is one of the largest perennial rivers in the world. The source of this river is from the Kailash range of Himalayas. Total length of this river is 2880km and width as high as 18 km. The river starts from Tibet, covering a length of 1600km in Tibet, over 160 km in Arunachal Pradesh, 720km in Assam and rest in Bangladesh. The Pandughat region near Guwahati has been selected as the study area.

In this study, the method of downscaling has been used for predicting the stream flow, at the Pandughat statiuon. The predicted stream flow data is then used for estimating the flood risk using the method of statistical Flood Frequency Analysis. Four probability distributions have been used for this purpose, and the best fitted value has been taken into account.

1.5 Objectives:

- To develop a statistical downscaling model for predicting future stream flow in the Pandughat region.
- To obtain variation in the stream flow pattern in future considering climate change.
- To estimate the flood risk in the region in future.
- To compare the results obtained from various probability distribution methods.

2. DOWNSCALING FROM GCM

2.1 GLOBAL CLIMATE MODELS (GCM):

Global Climate Model (GCM) or general circulation model aims to describe climate behavior by integrating a variety of fluid-dynamical, chemical, or even biological equations that are either derived directly from physical laws or constructed by more empirical means. They are basically mathematical models of the general circulation of a planetary atmosphere or ocean and based on the Navier-Stokes equations on a rotating sphere with thermodynamic terms for various energy sources.

There are both atmospheric GCMs (AGCMs) and ocean GCMs (OGCMs). An AGCM and an OGCM can be coupled together to form an atmosphere-ocean coupled general circulation model (AOGCM). These models are used to perform operations related to climate like weather forecasting, understanding climate & projecting climate change. GCM datasets are available for use from Intergovernmental panel on climate change (IPCC 2007) and Canadian Centre for Climate Modeling and Analysis (CCCma).

2.2 EMISSION SCENARIOS:

Emission Scenarios describes how greenhouse gases emissions could evolve between 2000 and 2100, depending on various hypotheses. The IPCC has published a voluminous book describing the 40 scenarios used, that are grouped in 4 main "families". Each "family", named by an abbreviation (A1, A2, B1, B2), is supposed to reflect a particular evolution of humanity, and the main hypothesis (concerning demography, agricultural practices, technology spreading, etc) are then turned - through simple models - into energy consumption and food production, the latter being then converted into greenhouse gas emissions.

The various hypotheses involved with each of scenarios are described below:

A1 scenario:

- economic growth is fast
- the world population reaches 9 billion people in 2050 then decreases thereafter
- new and efficient technologies are quickly spreading,
- the income per capita and the way of life converge between regions (meaning that Chinese, Indians, and Occidentals all live the same way),
- social and cultural interactions increase heavily (which means that the cultural models are the same for everyone, roughly)

A2 scenario:

- The world evolves in a very heterogeneous way.
- The world population reaches 15 billion people in 2100, and rising.
- economic growth and the spreading of new efficient technologies are very different depending on the region of the world

B1 scenario:

- the world population reaches almost 9 billion people in 2050 then decreases
- the economy is dominated by services and information technologies,
- new efficient technologies spread very quickly and are massively used,

B2 scenario:

- The world population reaches more than 10 billion people in 2100, and rising.
- the dispersion between individual incomes is lower to what it is for A2, but higher to what it is for A1
- The developing and spreading of new efficient technologies is uneven and goes slower than for B1 or A1.

2.3 **DOWNSCALING:**

Downscaling is the process of making the link between the state of some variable representing a very large space and the state of some variable representing a much smaller space. Here it has been used to relate the large scale GCM output of global climate variables to local scale hydrologic variables.

GCM s are very coarse in resolution, approximately 2.5^o x 2.5^o, i.e. about 250 km x 250 km, and are unable to resolve sub-grid scale features such as topography, clouds, land use etc. This represents a considerable problem for the impact assessment of climate change on hydrological dynamics in river-systems. Therefore, to bridge the gap between the large scale and local scale climate data the downscaling technique is use. Downscaling techniques can be classified into two types:

- Dynamic Downscaling
- Statistical Downscaling

Dynamic Downscaling:

Dynamical downscaling is also referred to as numerical downscaling or nested modeling. The dynamical downscaling approach provides an alternative to the statistical downscaling, but without assuming that historical relationships between large scale circulation and local climate remain constant. In dynamic downscaling high-resolution Regional Climate Models (RCM) are use. RCMs are similar to GCMs, but RCM generally improves with the higher-order statistics of the meteorological variables. A drawback of RCM is that it is very expensive and demands large number of computer resources, which increases the complexity of the study.

Statistical Downscaling:

In statistical downscaling, a statistical relationship is obtained between the large scale climate variables and local hydrologic variables. This relationship is then use to obtain the local and regional climate change factors from the future GCM outputs. In this study regression based statistical downscaling has been used.

2.4 ARTIFICIAL NEURAL NETWORK:

Artificial Neural Network can be defined as computational pattern that involves searching and matching procedures, which permit forecasting without an intimate knowledge of the physical or chemical processes, the statistical relationship between the sites on a map or any idea about what it is being modeled. The neural network only seeks the relationship between the input and output data and then creates its own equations to match the patterns in an iterative manner. These equations are then use to obtain future results. The process is done in three different stages, these are:

- Training stage
- Validation stage
- Testing stage

In training stage, the output is related to large number of input nodes so as to obtain a specific relation between them. The network is however adjusted according to the errors. In the validation stage observed data are use to check whether the model is not over trained. In the testing stage observed data that are not used in the training stage are use to check whether the network is giving satisfactory results or not. If the results are satisfactory, the model may be use for live forecasting. In this study, Back propagation – Supervised learning (error based) has been used for the learning process with the Levenberg-Marquardt learning algorithm.

The **Multi Layer Perception** (MLP) Neural Network is one of the most useful neural networks. It basically consists of an input layer and an output layer, along with several neurons, weight, biases and transfer function. In MLP the input (x_i) is multiplied by the weight function (w_i) and summed up together with the bias function (θi). The resulting (n_i) is then taken as input to the transfer function [g(x)], which operates with the result to give the output (y_i).

$$\boldsymbol{n_i = \sum_{j=1}^{n} w_{ji} x_j + \theta_i}$$

$$y_i = g\left\{\sum_{j=1}^{n} \boldsymbol{w_{ji} x_j} + \boldsymbol{\theta_i}\right\}$$

Transfer Function or activation function determines the nature of the neural network. The transfer function may be linear or a non-linear mathematical function and should be selected to satisfy the problem. Several transfer functions are available like linear, log-sigmoid, hyperbolic tangent sigmoid etc. In this study linear transfer function has been use.

3. CASE STUDY IN PANDUGHAT STATION

3.1 STUDY AREA:

Pandu (Pandughat) is within the Guwahati city at a distance of 15.7km from the D.C. Office of the Kamrup Metropolitan district. It is about 123m above sea level. Before the construction of the Saraighat Bridge, it was one of the major commercial ports of Assam for water transportation. Though in the present time water transportation in Brahmaputra has decreased even then Pandu port serves as an important commercial port of Assam.

3.2 DATA USED:

Two types of data were used in this study, namely:

- Observed Stream flow data
- Data from HADCM3 GCM

Observed stream flow data were collected from Central Water Commission. for the Pandughat station from June 1999 to May 2010.

The GCM data were downloaded from the **Intergovernmental Panel on Climate Change** for the **HADCM3 GCM** model for the **fourth assessment report (AR4).** The time period of the AR4 is from 2000 to 2100.

3.3 HADCM3 GCM:

HadCM3 stands for Hadley centre Coupled Model version 3. This model does not require flux adjustment. In this model, spatial resolution for AGCM3 is roughly 2.5^0 of latitude and 3.75^0 of longitude forming the global grid of 96×73 grid cells with 19 levels. In the oceans, this model has a resolution of 1.25^0 of latitude and longitude with 20 vertical levels. This model has been used in lot of projects involving climate change and its prediction. It is also used in IPCC third assessment report. This model has higher resolution compared to other models.

3.4 **OBTAINING LOCATION FROM GOOGLE MAP:**

To determine the exact location of the Pandughat station, GOOGLE map was used. The latitude and longitude 26.169^0N and 91.675^0E respectively.

4. IMPACT OF CLIMATE CHANGE ON STREAM FLOW OF RIVER BRAHMAPUTRA AT PANDUGHAT STATION

In this chapter statistical downscaling has been done using multiple linear regressions. The predictors were selected by Pearson correlation and step wise regression. The results obtained from the downscaling have been compared with the observed data and future stream flow predictions were done.

4.1 MULTIPLE LINEAR REGRESSIONS:

In Multiple linear Regressions, the operation procedure is divided into four basic steps, namely: **Specification, Calibration, Validation** and **Forecast.** In the specification stage model and predictors are selected. In calibration stage the relation between the output data and input data is obtained. The accuracy of the model is checked in the validation stage, while in the forecast stage validated model is to predict the future forecast.

Assumptions: The following assumptions were taken into consideration while using the multiple linear regressions:

- The relation between Y and X_1, X_2,…, Xn are linear.
- The residuals have a constant variance σ and are normally distributed.
- There is no autocorrelation
- The X variables are fixed.

4.2 STANDARDIZATION:

Before calibration, the large scale climate variables need to be processed. In this study, pre-processing of data has been done by the method of standardization. Here standardization has been used to reduce the biases in the mean and variance of the GCM predictors relative to the observed data. In the process of standardization the mean (μ) is subtracted from the i^{th} predictor/predictant and then it is divided by the standard deviation. Here as AR4 assessment was used, the time period was from 2000 to 2010, i.e. 10 years.

$$\nu_{std}(n) = \frac{\nu_i(n) - \mu(n)}{\sigma(n)}$$

Where, ν_{std} is the standardized data of n^{th} predictor

ν_i is the i^{th} variable of the n^{th} predictor

μ is the mean of all the variables of n^{th} predictor

σ is the standard deviation

4.3 SELECTION OF PREDICTORS:

The Predictors are selected by step wise regression method. This method consists of two main approaches, forward selection and backward elimination. The coefficient of determination is obtained between the observed data and a particular predictor. The coefficient of determination lies between 0 and 1. Larger the value, stronger will be the correlation. Here the coefficient of determination is obtained with the help of Microsoft Excel (MS-Excel).

Correlation: It is the statistical relation between the array of two variables. It shows how they are correlation. Here Pearson Correlation is used to determine the coefficient of correlation. larger the value of the correlation, stronger will be the relationship between the two variables.

Pearson Correlation: It is a statistical technique which is use to determine the correlation coefficient between two variables. Its value lies between -1 to +1. Here coefficient of correlation for all the predictors were found using MS-Excel. The values obtained are given in table 1.

Table 1 : Pearson coefficient of correlation using HadCM3 at Pandughat Station

Predictors	Abbreviations	Coefficient of correlation
1.Relative humidity @200 hpa	hur200	-0.5811
2.Relative humidity @500 hpa	hur500	-0.5550
3.Relative humidity @850 hpa	hur850	-0.7374
4. Soil Moisture COntent	mrso	-0.7917
5.Convective Precipitation flux	prc	-0.5169
6.Air pressure at sea level	psl	0.2170
7.Air temperature at 200 hpa	ta200	-0.6211
8 Air temperature at 500 hpa	ta500	-0.7023
9. Air temperature at 850 hpa	ta850	-0.1893
10.Surface Air Temperature	tas	-0.3084
11. Surface Temperature	ts	-0.3135
12.Zonal Eastward wind @ 200 hpa	ua200	0.6956
13 Zonal Eastward wind @ 500 hpa	ua500	0.7157
14. Zonal Eastward wind @ 850 hpa	ua850	0.8338
15. Zonal Eastward wind @ surface	uas	0.6629
16. Zonal Northward wind @ 200 hpa	va200	0.0935
17. Zonal Northward wind @ 500 hpa	va500	-0.5211
18. Zonal Northward wind @ 850 hpa	va850	0.7084
19. Zonal Northward wind @surface	vas	0.4884
20. Geopotential height @200hpa	zg	-0.7403

The above correlation coefficient clearly indicates that 'mrso', 'ua850' have stronger correlation than other predictors. On the basis of the above correlation test and step wise regression these two predictors have been selected for calibration.

4.4 MODEL CALIBRATION AND VALIDATION:

There are several ways for performing calibration. Some of these are:

- Multiple linear regressions without additive constant.

$$y_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_n x_{in}$$

- Multiple linear regressions with additive constant.

$$y_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_n x_{in} + r_i$$

- Multiple linear regression with a multiplying factor

$$y_i = (\beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_n x_{in})\ \mathrm{m}$$

Here, y_i = precipitation, β= coefficient, x_i=predictor, r_i=residual, m_i=multiplying constant.

In this study multiple linear regressions without additive constant has been selected as it gives good calibration.

4.5 STREAM FLOW MODEL:

By using Multiple Linear regression without additive constant, calibration and validation has been done. For calibration of the model used in the present work alternate years from June 1999 to May 2009 has been considered. The calibration is sown in figure:1 and it is found to be satisfactory.

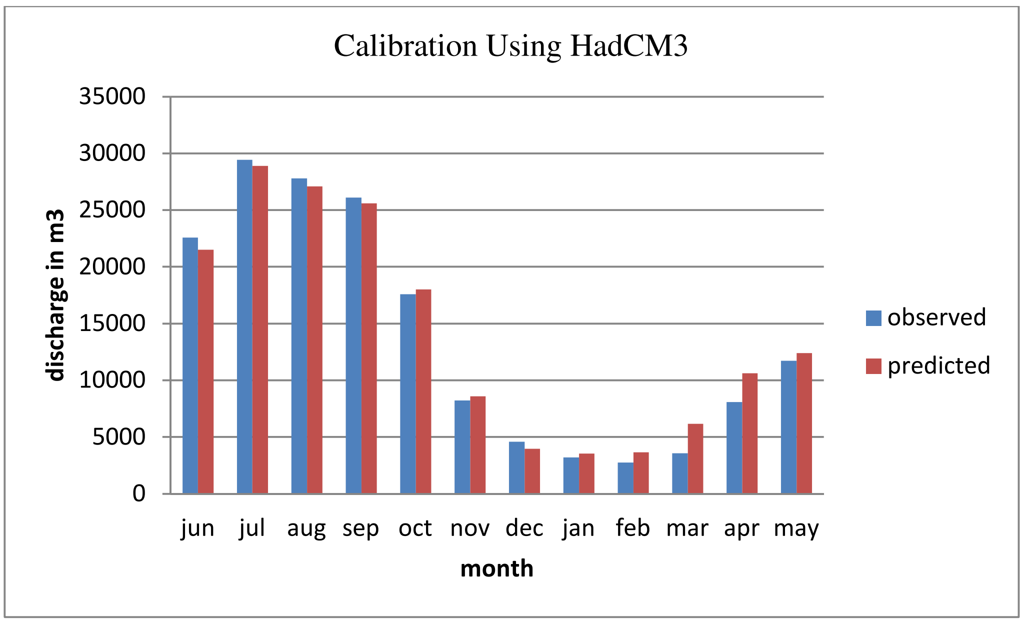

Fig.1: Calibration using HADCM3 for Pandughat station

For validation of the present model used in the work the other alternative five years (June 2000- May 2001 upto June 2008- May 2009) has been taken into account. The validation is shown in fig.2 and the result sows the validation of the present proposed model.

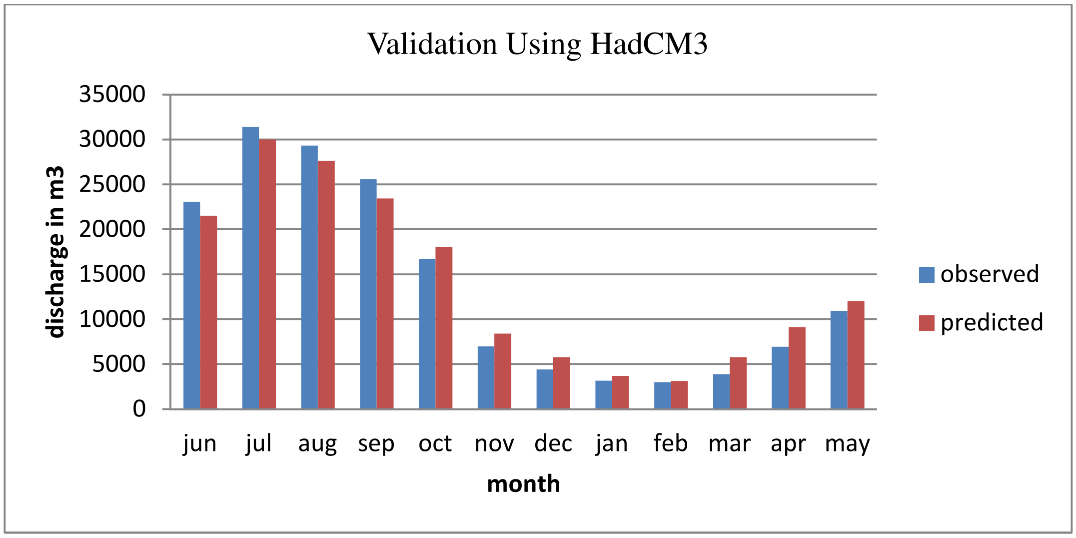

Fig.2: Validation using HADCM3 for Pandughat station

4.6 COMPARISON OF OBSERVED STREAM FLOW AND PREDICTED STREAM FLOW

The stream flow at Pandugat Station is predicted from 2000 to 2010 on monthly basis, using the present model. Then the monthly average of predicted values are calculated and compared with the monthly average observed values for the same time period. The comparison shows good correlation between the two values. However, it is observed that during monsoon period the magnitude of the predicted values are slightly more than the observed values while during the non-monsoon period (stream flow less than 5000m^3/sec) the predicted values are slightly lower than the observed values. The comparison is sown graphically in fig.3

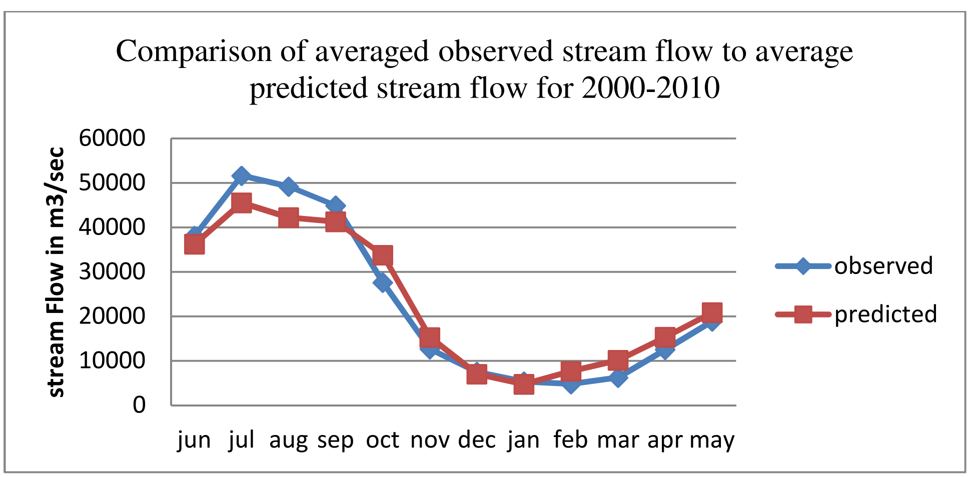

Fig.3 : comparison of average observed stream flow to average calculated stream flow from 2000-2010

4.7 FUTURE DATA GENERATION:

The future stream flow of river Brahmaputra at Pandughat station has been predicted by using the above model. Nine sets of data (for the year 2011-2020, 2021-2030,…, 2091-2100) were predicted. The predicted stream flow has been plotted in fig.4

From fig.4 it is observed that the predicted stream flow pattern is similar to the observed stream flow pattern for the year 2000-2100 (as shown in fig.3).From fig.4 it is also observed that the stream flow rate increases gradually with time. From 2011 to 2050, the maximum stream flow increases by 19.91% and from 2011-2100 and it increases by near about 46.32%.

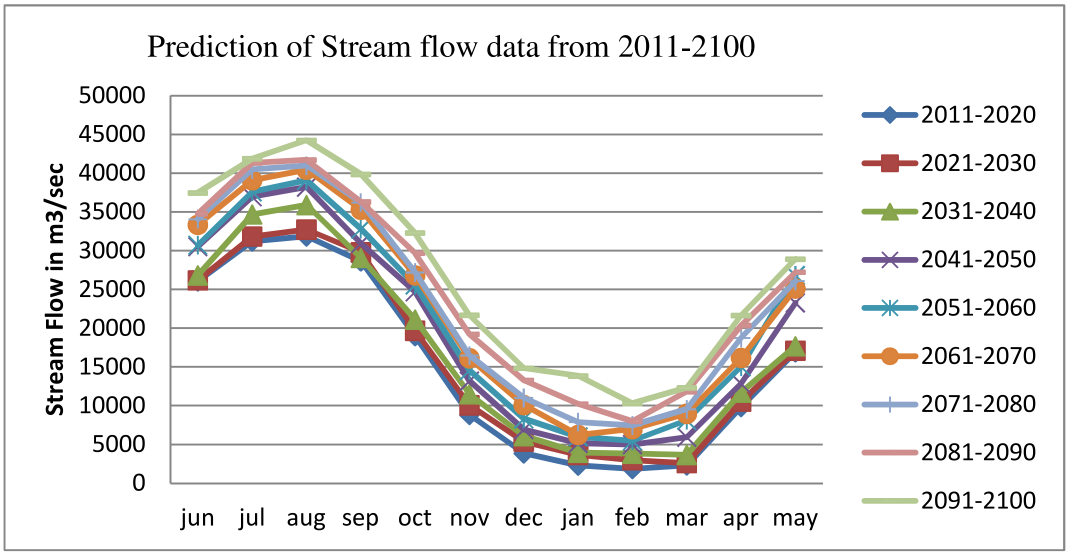

Fig.4: behavior of predicted stream flow from 2011-2100

4.8 Plot of generated stream flow data for each data set:

From fig.5 to fig.13 the decade wise monthly average stream flow is sown from the year 2011 to 2100. It is observed that the maximum monthly stream flow shifts from July to August as we move from 2011 to 2100. Again there is a considerable increase in the annual maximum flow from 2011 to 2100.

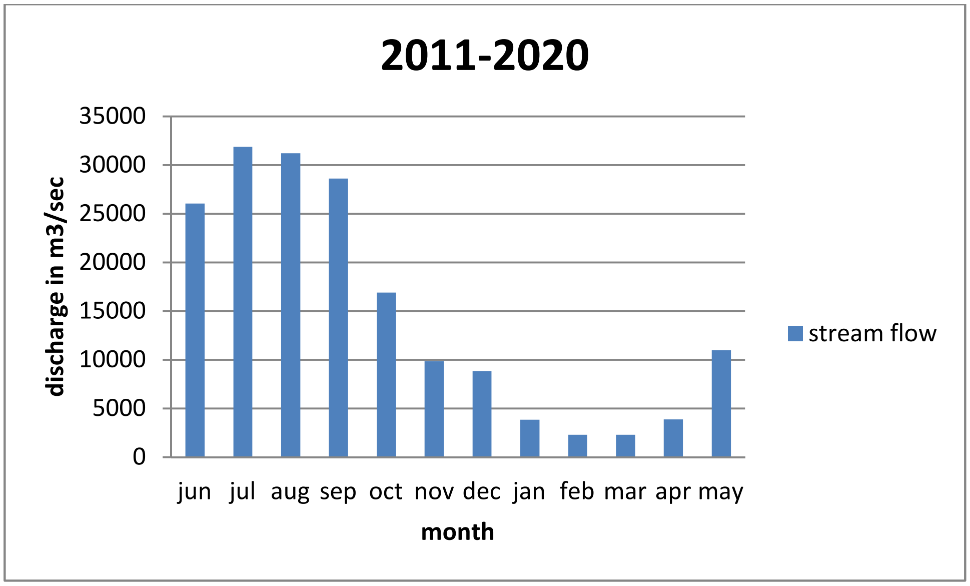

Fig.5: Predicted average Stream flow data from 2011-2020

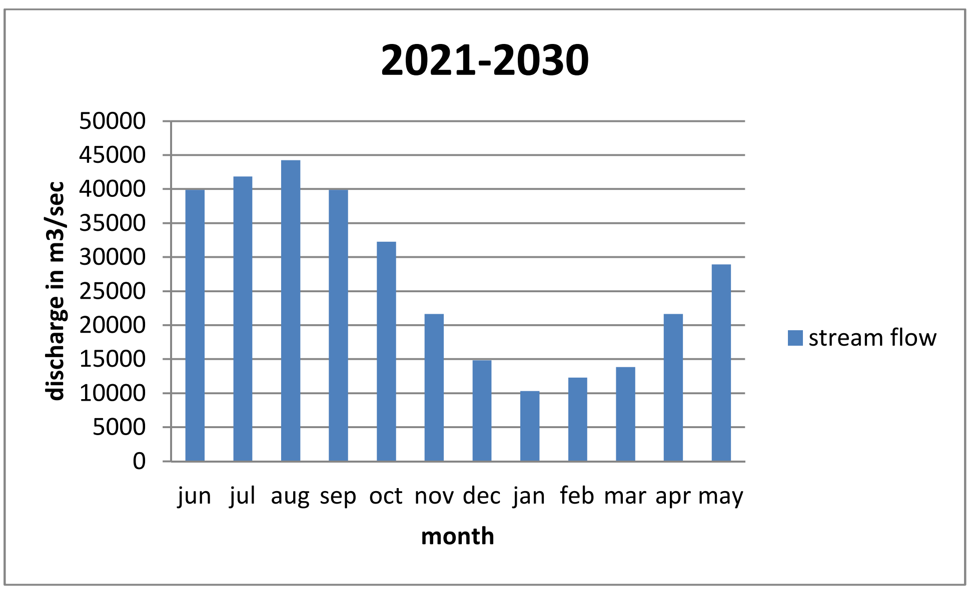

Fig.6: Predicted average Stream flow data from 2021-2030

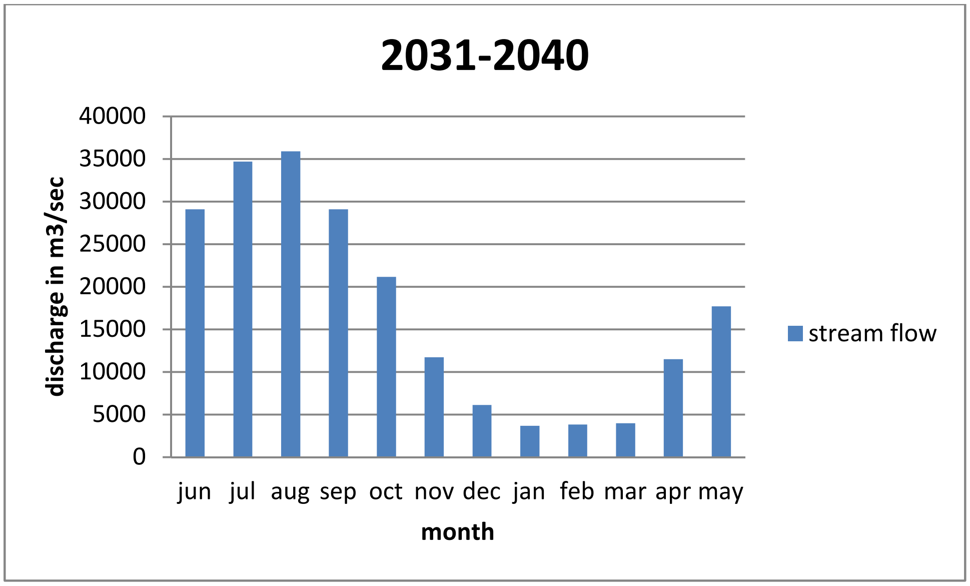

Fig.7: Predicted average Stream flow data from 2031-2040

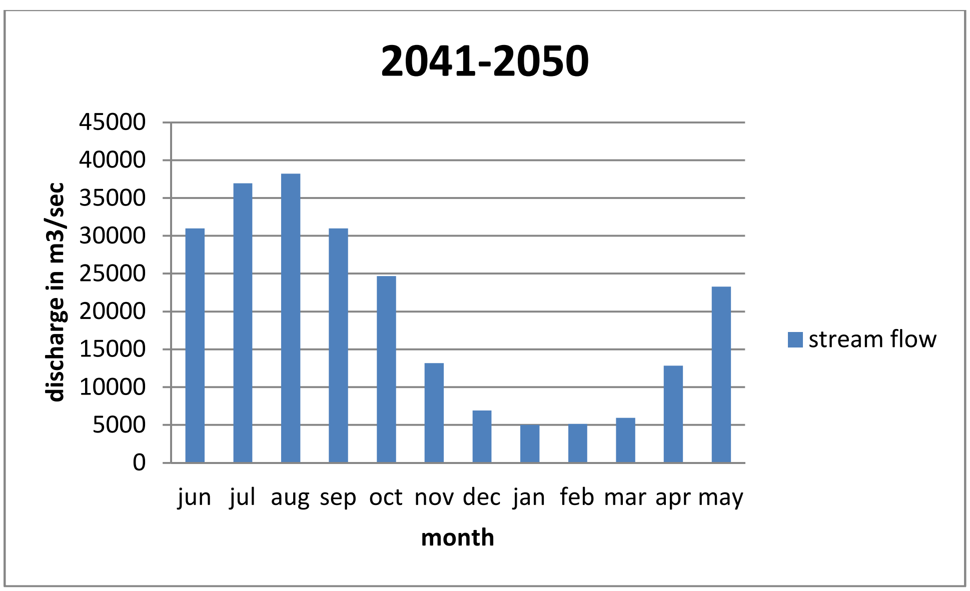

Fig.8: Predicted average Stream flow data from 2041-2050

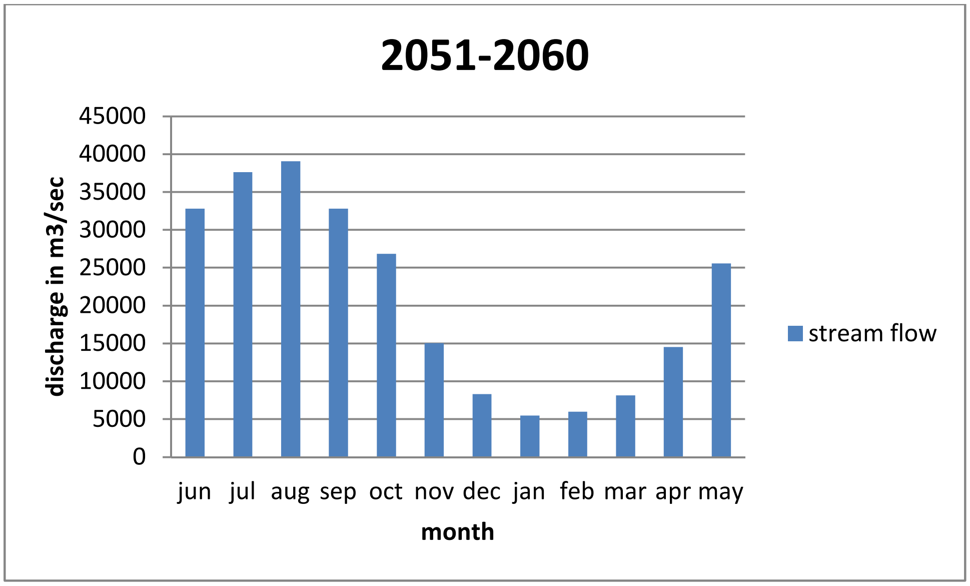

Fig.9: Predicted average Stream flow data from 2051-2060

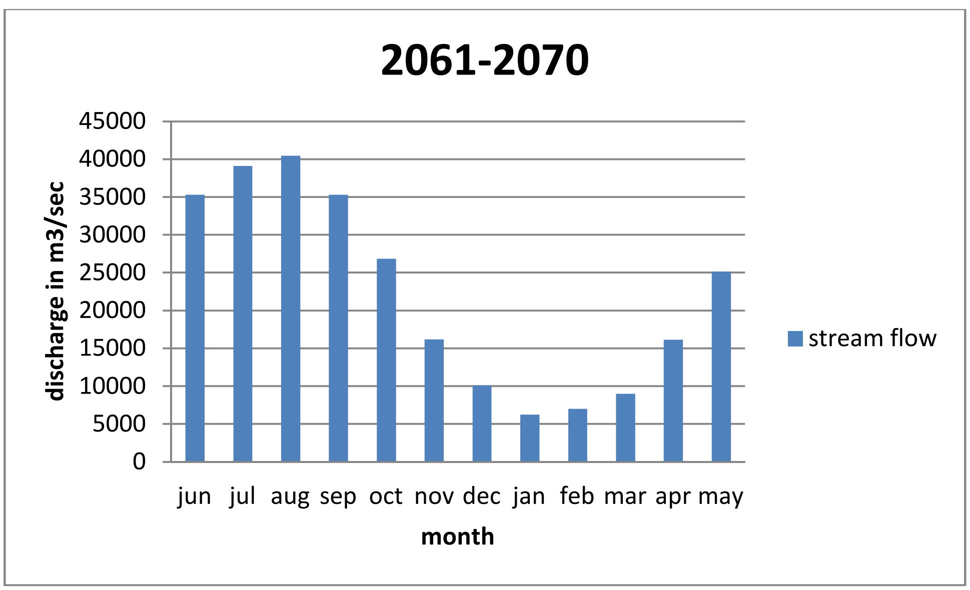

Fig.10: Predicted average Stream flow data from 2061-2070

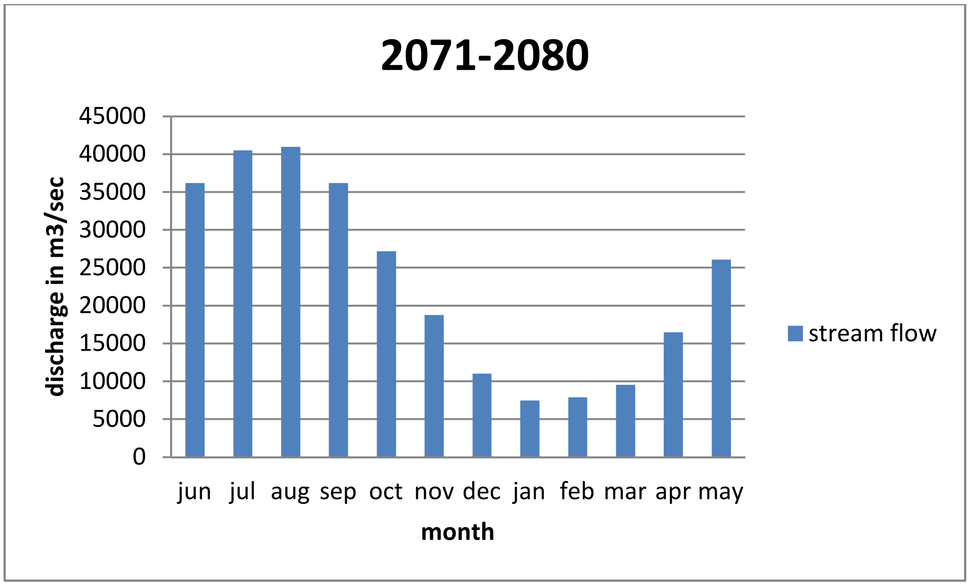

Fig.11: Predicted average Stream flow data from 2071-2080

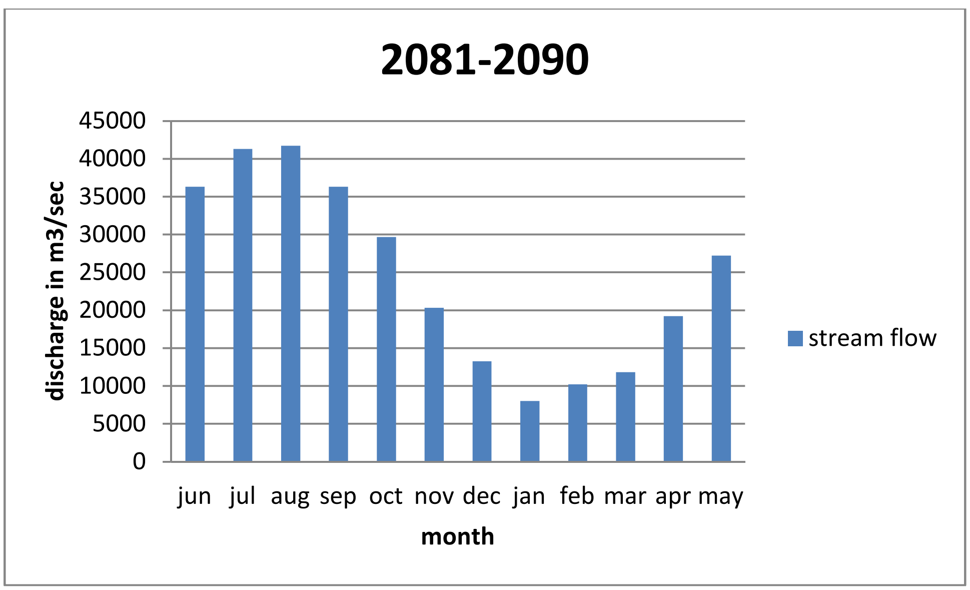

Fig.12: Predicted average Stream flow data from 2081-2090

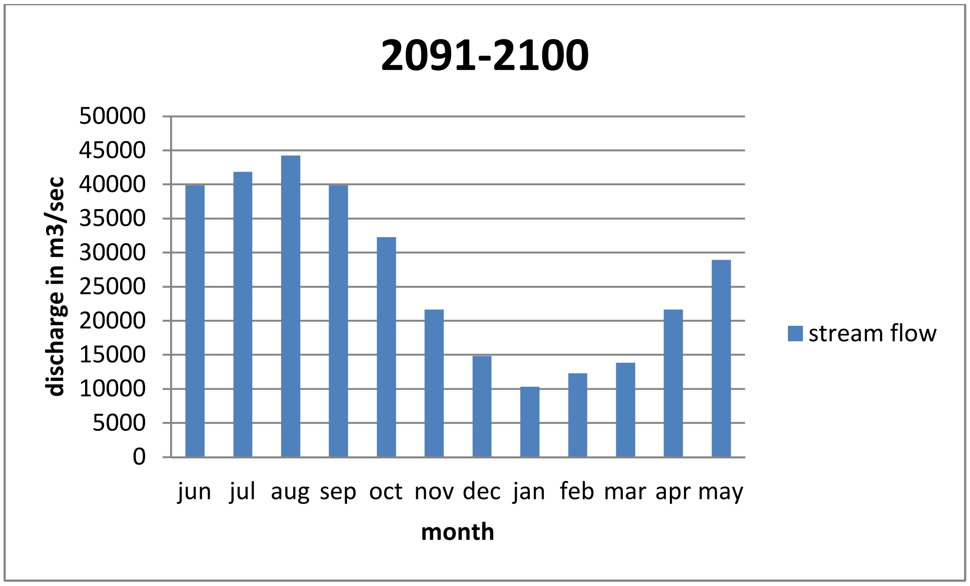

Fig.13: Predicted average Stream flow data from 2091-2100

4.9 AVERAGE MAMXIMUM ANNUAL STREAM FLOW:

The average maximum stream flow for each data set (2000-2010, 2011-2020,…,2091-2100) is sown in fig. 14 below. The result shows an increase of 32.86% in the stream flow from 2000 to 2100.

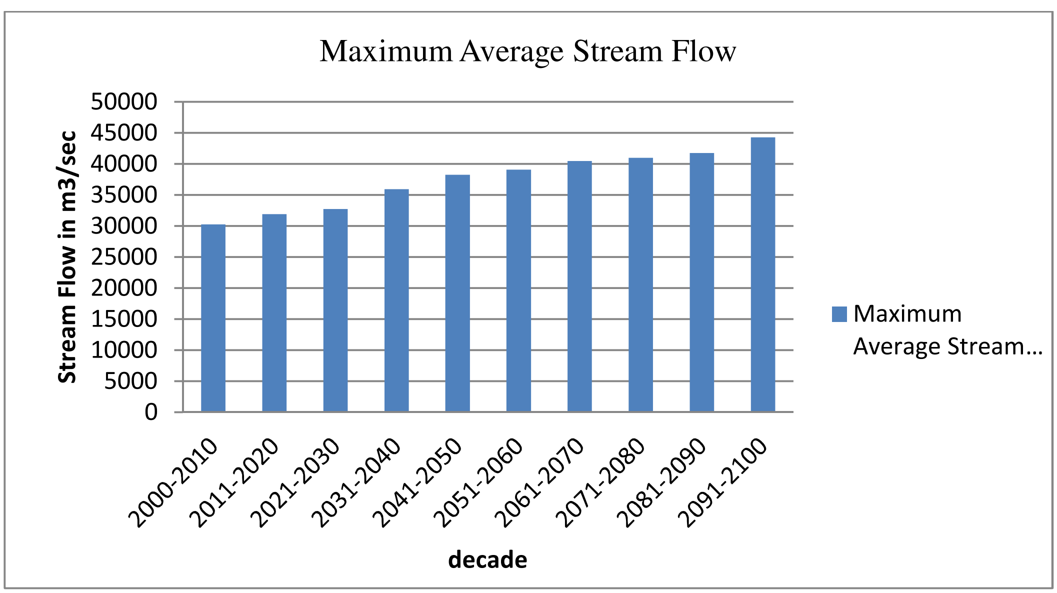

Fig.14: AVERAGED MAXIMUM ANNUAL STREAM FLOW

4.10 SUMMARY:

In this chapter by using the method of statistical downscaling future prediction of stream flow of river Brahmaputra at Pandughat station has been done. For performing the downscaling Multiple Linear Regression has been done. In order to select the predictors, the method of step wise regression has been followed. Here data were collected from IPCC for the fourth assessment report (AR4) for the HadCM3 GCM. From the results it was observed that the stream flow of the river increases considerable in the near future. From 2011 to 2050, the maximum stream flow increases by 19.91% and from 2011-2100 and it increases by near about 46.32%. This shows a very alarming situation as increase in stream flow may result in severe flood leading to heavy loss of life and property in the nearby areas. This may also lead to change in river morphology which may further lead to decrease in ground water level due to excessive runoff.

5. FLOOD FREQUENCY ANALYSIS

Floods are extreme events that cause large scale damage. So it is of utmost importance to develop a mechanism to predict flood occurrence such that its damage can be minimized. In developing countries like India, where data are scare a simple probability distribution can give good flood estimation.

Here, in this study four probability distribution namely Gumbel, log-Pearson type-iii, log-normal type-iii, Pearson type-iii have been used to estimate the flood magnitude and to determine their return period. Furthermore, these distributions have been compared to find out the best fitted distribution. For the same purpose software has been developed to estimate the flood magnitude and its return period.

5.1 GUMBEL DISTRIBUTION:

The Gumbel or Extreme Value type-I distribution was introduced by Gumbel in 1941 and till now it is widely use for frequency analysis in hydrology, meteorology, storm and droughts.

Here, recurrence interval is given by:

$$r_i = \frac{1}{P_i}$$

Where, r_i= recurrence interval of i^{th} variable

P_i= probability of i^{th} variable

Again, probability is given by:

$$P_i = 1 - e^{(-e(-y_i))}$$

Where, P_i= probability of i^{th} variable

And, y_i is given by:

$$y_i = \left\{\frac{(Q_i - \mu).c_1}{\sigma}\right\} + c_2$$

Where, Q_i= ith discharge

μ= mean of all discharge

σ= standard deviation

c_1 and c_2 are constants.

The flood magnitude is obtained by the following relationship:

$$v_n = \mu + (k_n.\sigma)$$

Where, v= flood magnitude.

K_n= frequency factor, which is determined from the following relation:

$$k_n = \frac{(\vartheta_i' - \mu_n')}{\sigma_n'}$$

Where, v_i' = reduced ith variant

μ_n'= reduced mean

σ_n'= reduced standard deviation

n= number of observations

Reduced mean and reduced standard deviations were obtained from data sheets

Again the, reduced variant is obtained from the following relationship:

$$\vartheta_i' = -\log\left\{\log\left(\frac{r_i}{r_i - 1}\right)\right\}$$

The probability distribution function, f(x) is given by:

$$f(x) = \frac{1}{\alpha}\left\{e^{\{-p-e^{-p}\}}\right\}$$

Where, α = location perameter

$$p = \frac{x-\mu}{\sigma}$$

μ= scale perameter (mean)

σ = standard deviation

5.2 LOG-NORMAL TYPE-III DISTRIBUTION:

The log-Normal distribution was introduced by Hazen in 1914 and is used for flood frequency analysis.

Here, flood magnitude is determined by the relation

$$v_n = e^{\mu+(k_n.\sigma)}$$

v= flood magnitude.

K_n= frequency factor, which is determined from the data sheet .

The coefficient of skewness is given by the relation:

$$\sigma' = \{(3CV) + CV^3\}$$

σ' = coefficient of skewness

CV is given by:

$$CV = \sqrt{e^{\sigma^2} - 1}$$

σ = standard deviation

The probability distribution function, f(x) is given by:

$$f(x) = \frac{1}{\sigma(\sqrt{2\pi})x}\left\{e^{-\frac{\{(\log(x)-\mu\}^2}{2\sigma}}\right\}$$

Where, σ= standard deviation

μ = mean

x= variant

5.3 PEARSON TYPE-III DISTRIBUTION:

The Pearson distribution was first introduced by Karl-Pearson in 1924. This distribution is also known as the three variable gamma distribution. Ball and Beard found that this distribution can be use for annual peak distribution.

Here, flood magnitude is determined by the relation

$$v_n = \mu + (k_n.\sigma)$$

Where, v_n = flood magnitude

k_n = frequency factor, obtained from data sheet

The coefficient of skewness is given by the relation:

$$\sigma' = \left\{\frac{n\,.\sum_{i=1}^{n}\left\{Q_i - \mu\right\}^3}{(n-1)(n-2).\,\sigma^3}\right\}$$

σ' = coefficient of skewness

Q_i= i^{th} discharge

μ= mean of all discharge

n= number of observations

σ= standard deviation

The probability distribution function, f(x) is given by:

$$f(x) = |\beta|[\beta(x-\varepsilon)]^{\alpha-1}\frac{e^{-\beta(x-\varepsilon)}}{\Gamma(\alpha)}$$

Where, β=shape parameter

α=scale parameter

ε = location perameter

x= variant

5.4 LOG-PEARSON TYPE-III DISTRIBUTION:

The log-Pearson type-iii distribution was suggested by the US water resource council in 1967. This distribution is use for flood frequency analysis in USA and AUSTRALIA.

Here, flood magnitude is determined by the relation

$$v_n = e^{\mu+(k_n.\sigma)}$$

Where, v_n = flood magnitude

k_n = frequency factor, obtained from data sheet

The coefficient of skewness is given by the relation:

$$\sigma' = \left\{\frac{n.\sum_{i=1}^{n}\{lnQ_i - \mu\}^3}{(n-1)(n-2)\sigma^3}\right\}$$

σ' = coefficient of skewness

Q_i= i^th^ discharge

μ= mean of all discharge

n= number of observations

σ= standard deviation

The probability distribution function, f(x) is given by:

$$f(x) = |\beta|[\beta(ln|x| - \varepsilon)]^{\alpha-1} \frac{e^{-\beta(ln|x|-\varepsilon)}}{\Gamma(\alpha)}$$

Where, β=shape parameter

α=scale parameter

$\varepsilon = \text{location perameter}$

x= variant

5.5 DATA USED:

Here, the observed and predicted annual maximum discharge from the year 2000 to 2100 has been used as the input data. From 2000 to 2010 observed maximum annual stream flow data has been used while from 2011 to 2100 predicted maximum annual stream flow data has been used.

5.6 RESULT ANALYSIS:

For each of the distribution, three graphs are plotted showing the relation between actual and calculated discharge, the relation between flood magnitude and its recurrence interval and the probability distribution respectively

5.6.1 GUMBEL DISTRIBUTION:

In fig.15 the discharge calculated by Gumbel distribution is compared wit the predicted values obtain in the present work in article 4.7. The comparison sows good aggriment with the two set of results.

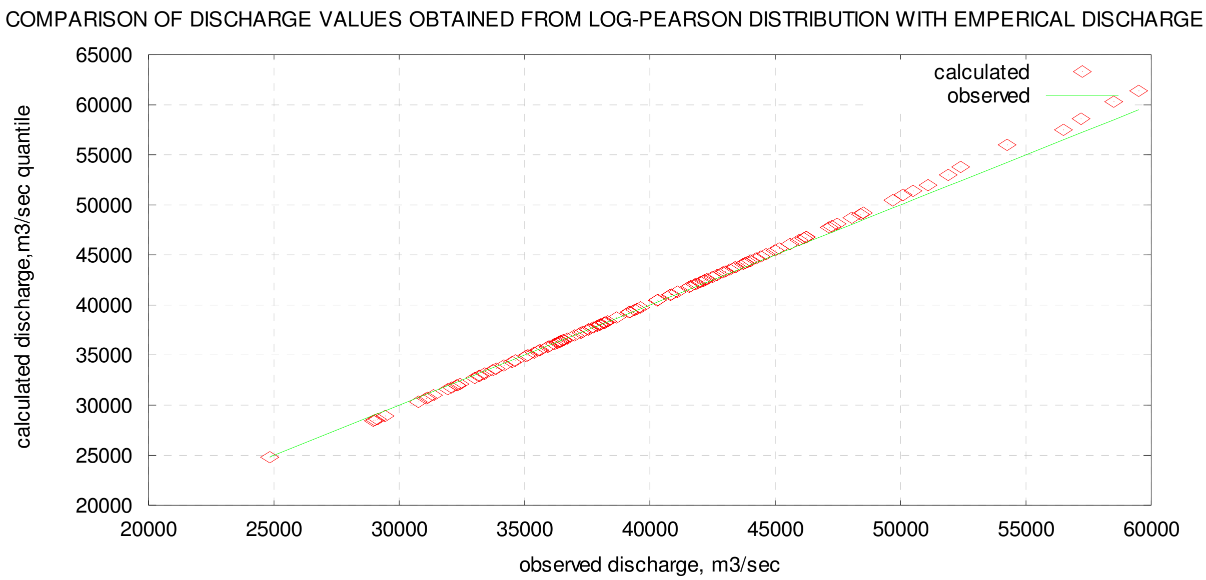

Fig.15: comparison of discharge values calculated from Gumbel distribution and predicted maximum discharge values from 2000-2100

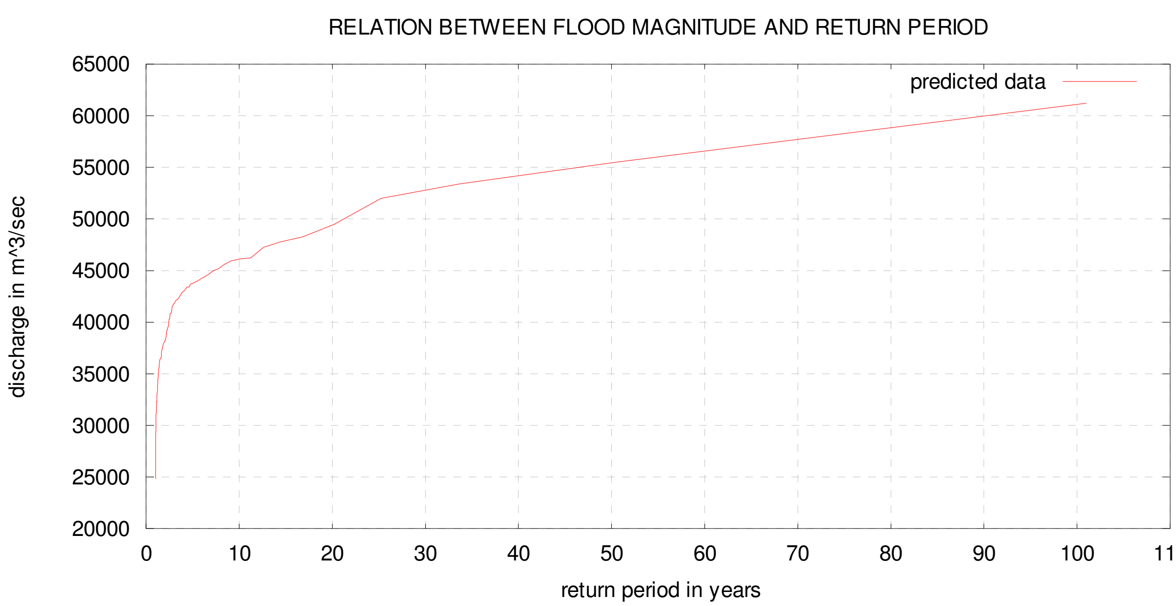

Fig.16 Relation between Flood Magnitude, calculated by Gumbel distribution, and its return period

In fig.17 discharge calculated by Gumbel distribution v/s probability density has been plotted. It is observed that floods of magnitude near about 4000m^3/sec has the maximum density than floods of any other magnitude.

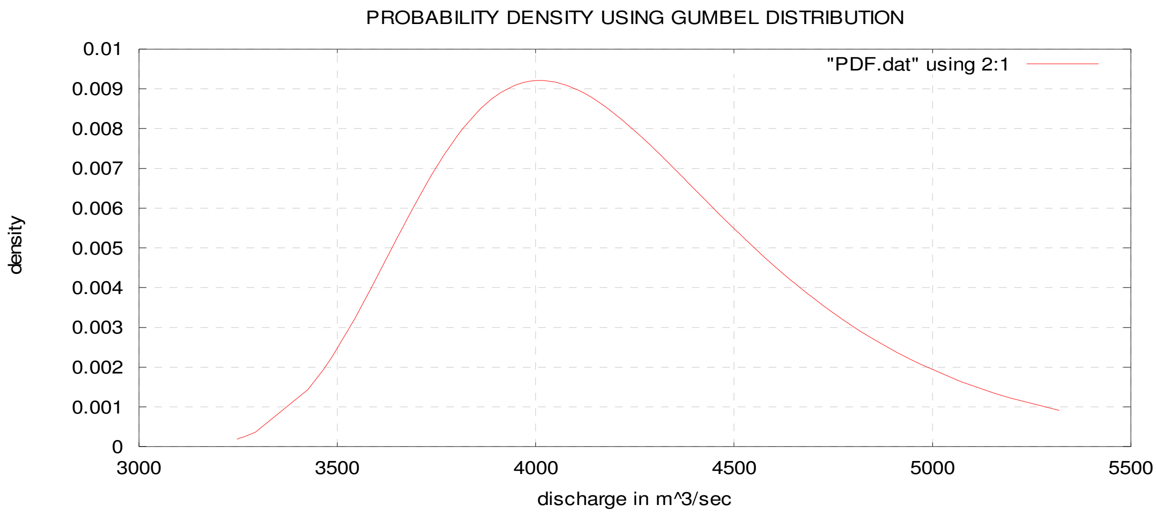

Fig.17: probability density of discharge calculated by Gumbel distribution

5.6.2 LOG-NORMAL DISTRIBUTION:

In fig.18 the discharge calculated by Log-Normal distribution is compared wit the predicted values obtain in the present work in article 4.7.

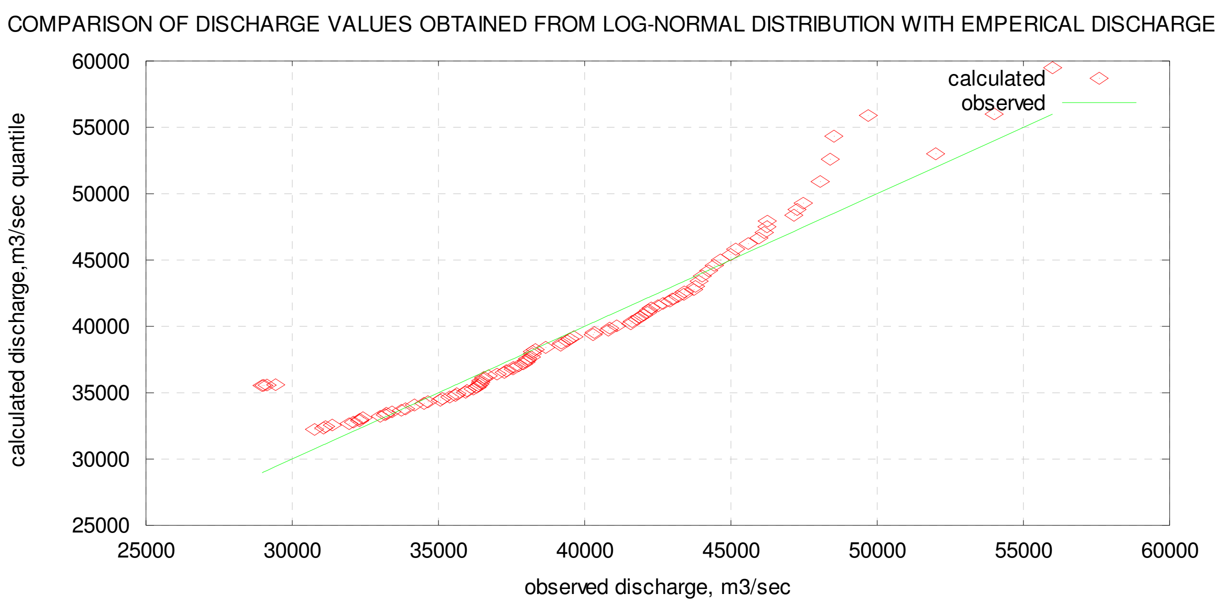

Fig.18: comparison of discharge values calculated from Log-Normal distribution and predicted maximum discharge values from 2000-2100

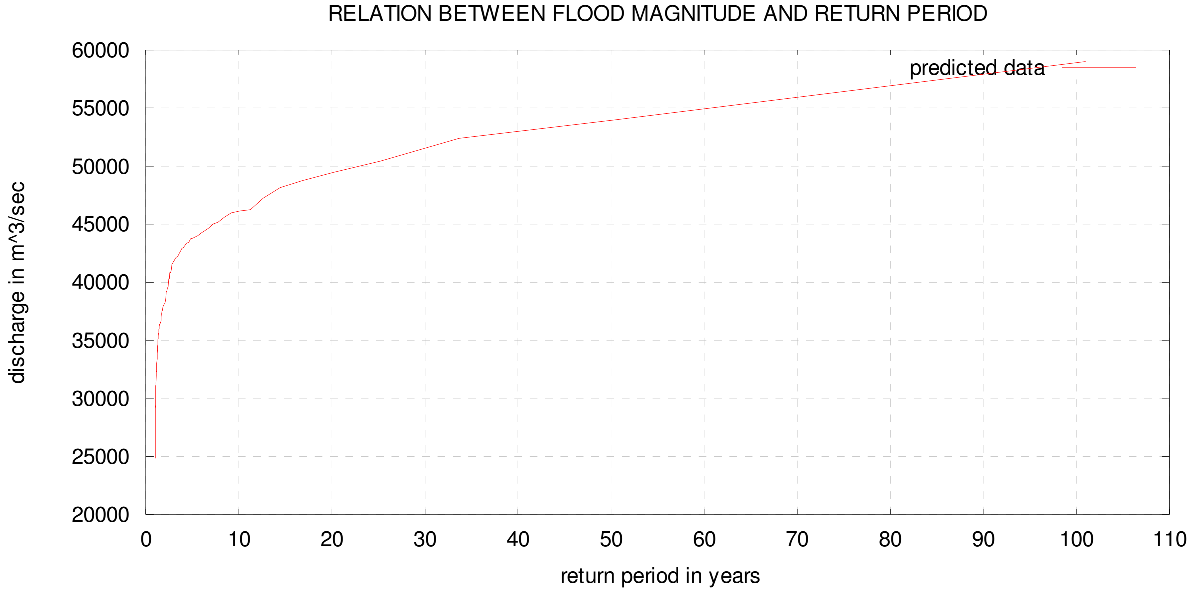

Fig.19 Relation between Flood Magnitude, calculated by Log-Normal distribution, and its return period

In fig.20 discharge calculated by Log-Normal distribution v/s probability density has been plotted. It is observed that floods of magnitude near about 4100m^3/sec has the maximum density than floods of any other magnitude.

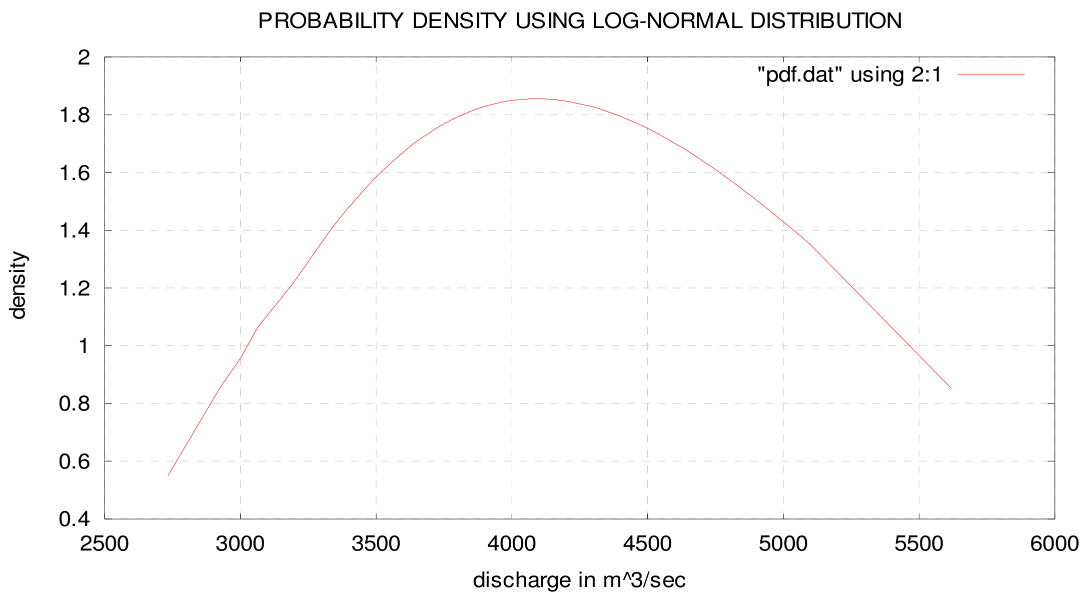

Fig.20: probability density of discharge calculated by Log-Normal distribution

5.6.3 PEARSON:

In fig.21 the discharge calculated by Pearson distribution is compared wit the predicted values obtain in the present work in article 4.7.

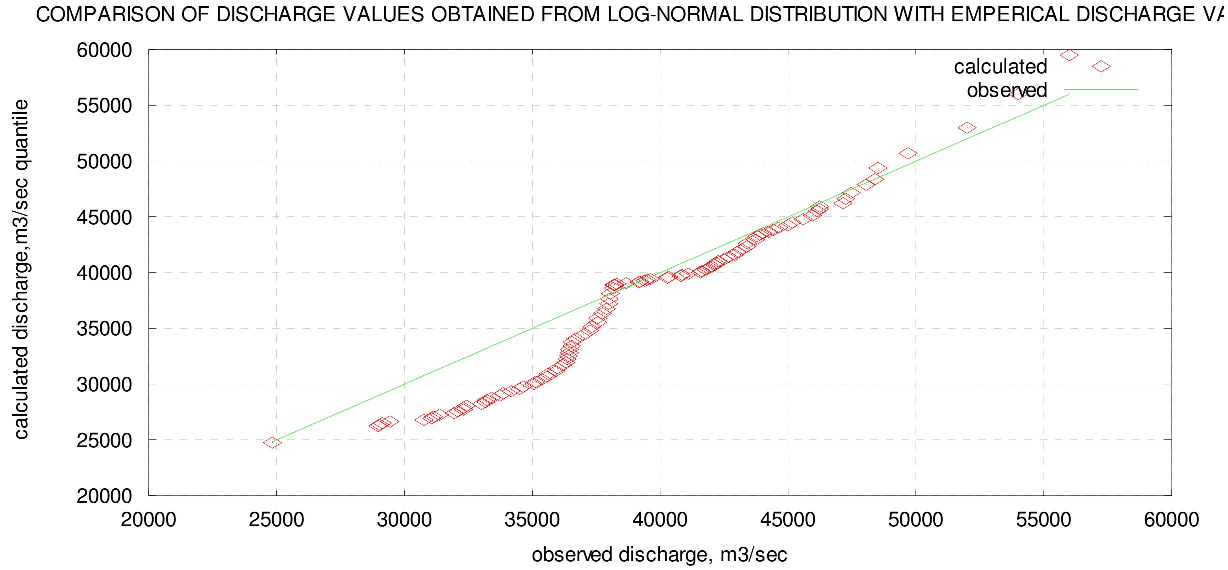

Fig.21: comparison of discharge values calculated from Pearson distribution and predicted maximum discharge values from 2000-2100

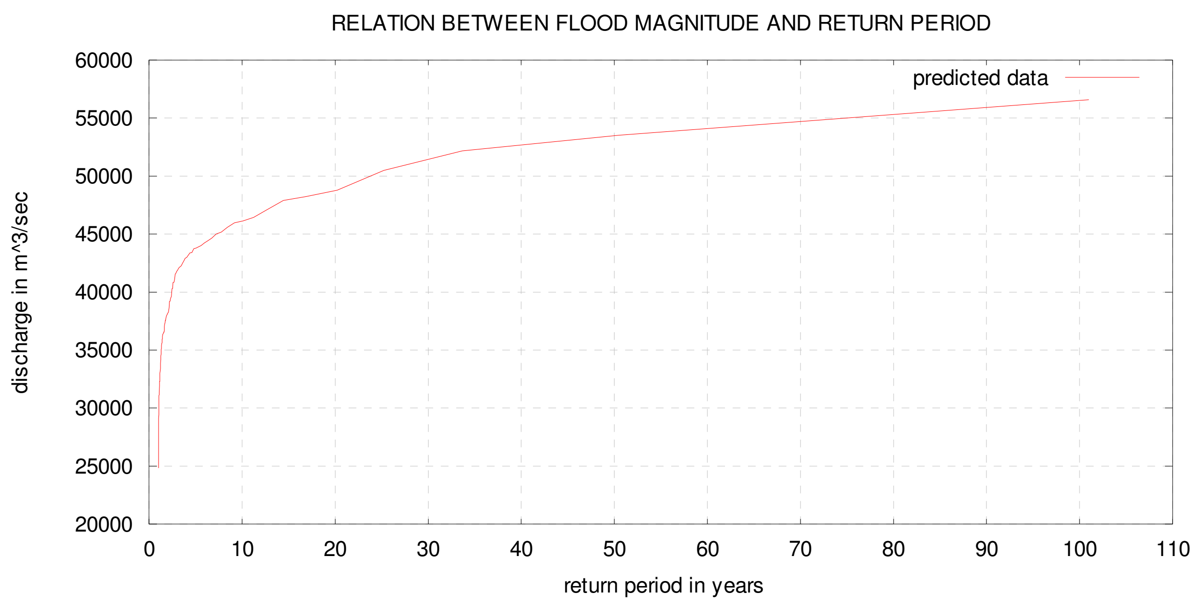

Fig.22 Relation between Flood Magnitude, calculated by Pearson distribution, and its return period

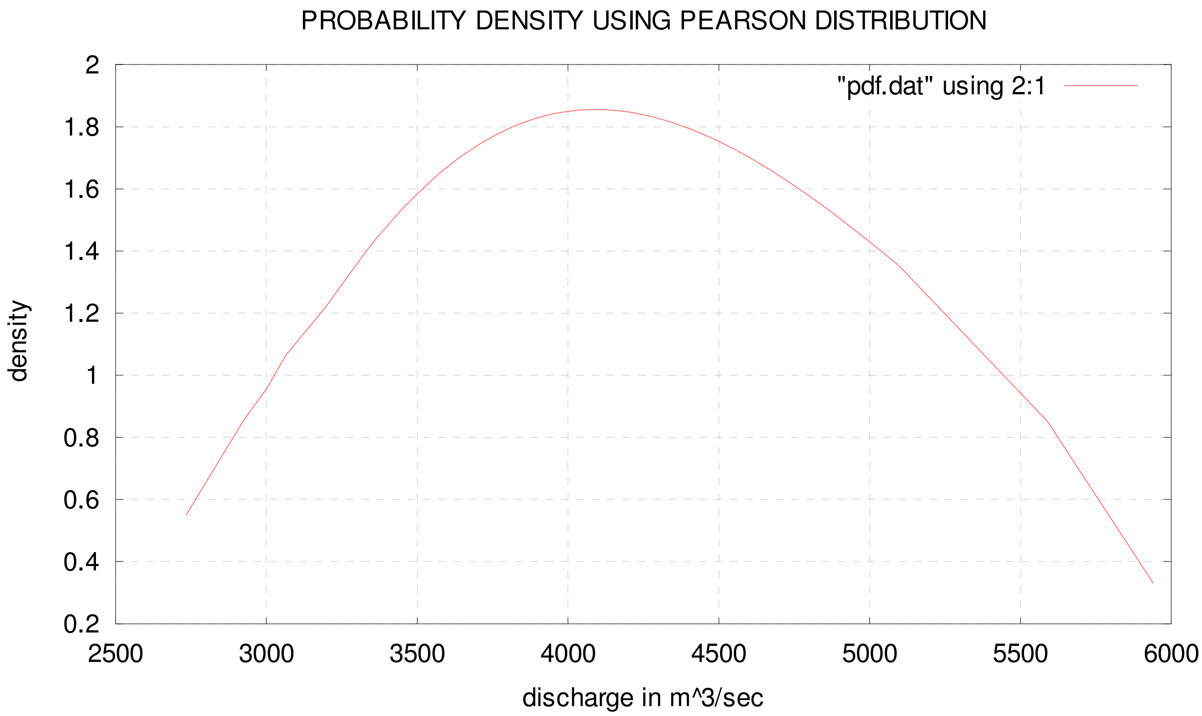

Fig.23: probability density of discharge calculated by Pearson distribution

In fig.23 discharge calculated by Pearson distribution v/s probability density has been plotted. It is observed that floods of magnitude near about 4200m^3/sec has the maximum density than floods of any other magnitude.

5.6.4 LOG-PEARSON:

In fig.24 the discharge calculated by Gumbel distribution is compared wit the predicted values obtain in the present work in article 4.7.

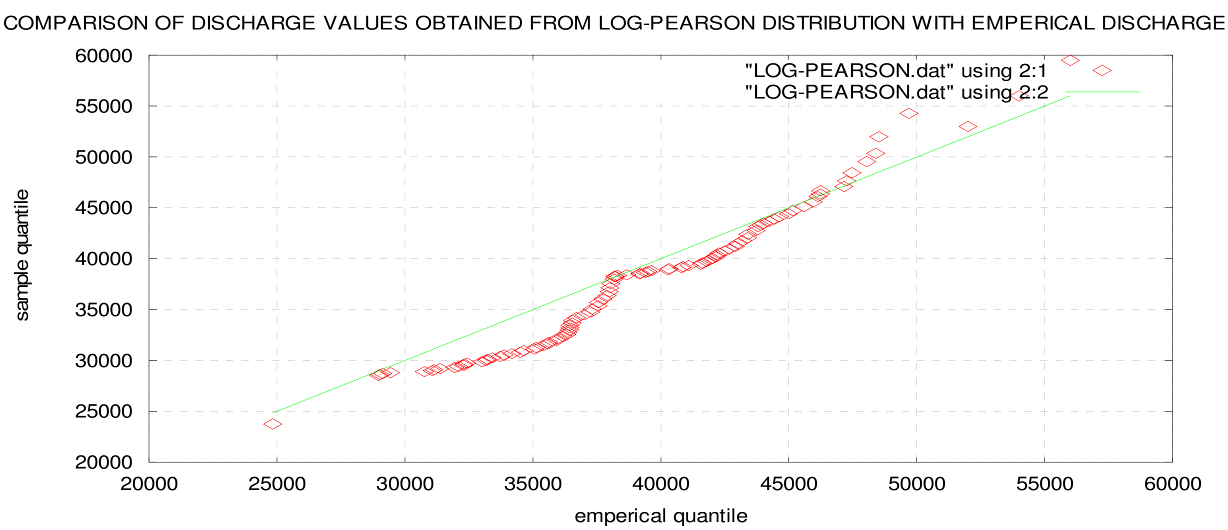

Fig.24: comparison of discharge values calculated from Log-Pearson distribution and predicted maximum discharge values from 2000-2100

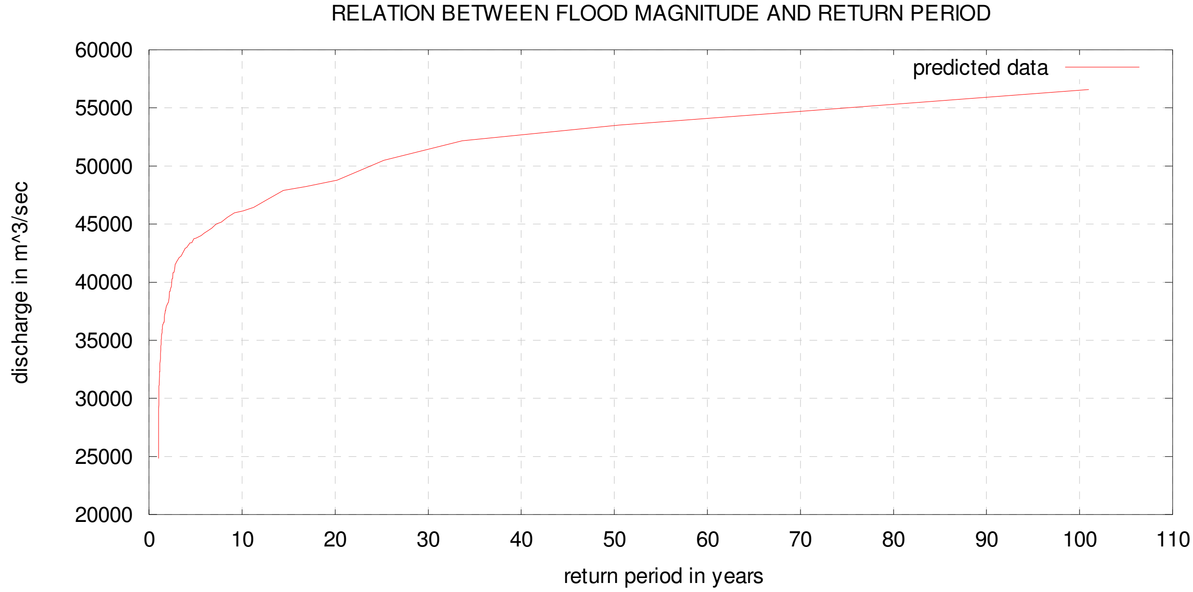

Fig.25 Relation between Flood Magnitude, calculated by Log-Pearson distribution, and its return period

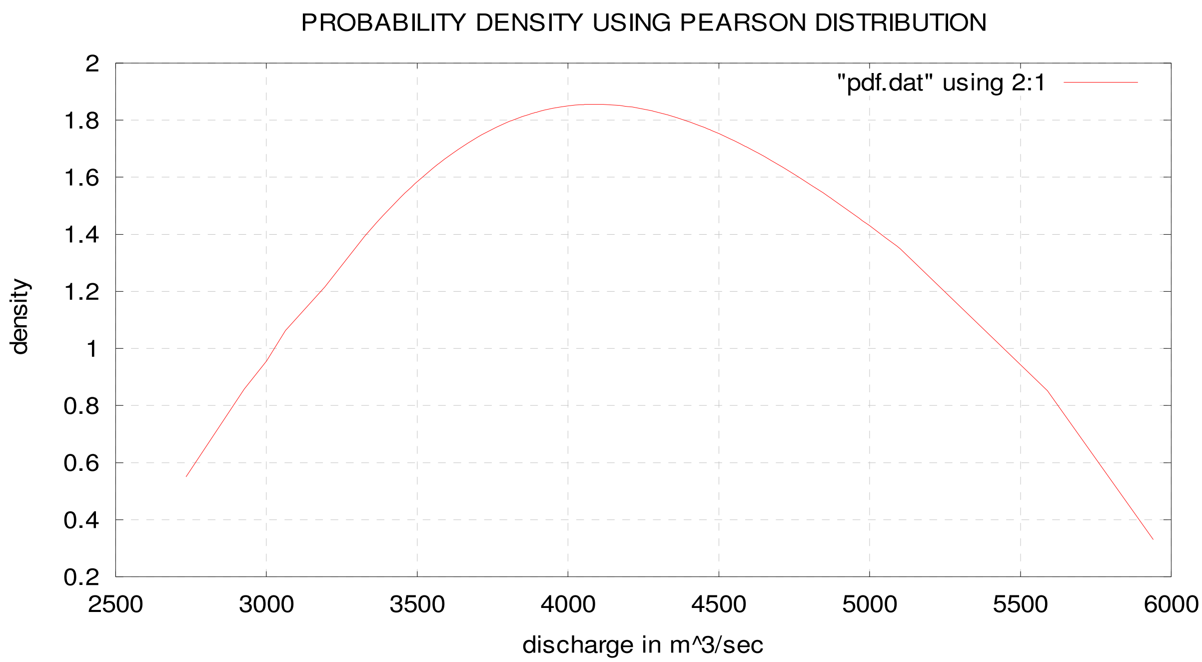

Fig.26: probability density of discharge calculated by Log-Pearson distribution

In fig.26 discharge calculated by Log-Pearson distribution v/s probability density has been plotted. It is observed that floods of magnitude near about 4200m^3/sec has the maximum density than floods of any other magnitude

5.7 COMPARISION:

The output data from each of the distribution was compared graphically. From the graphs below it was observed that Gumbel and log-Pearson has better fitting than the other two distributions.

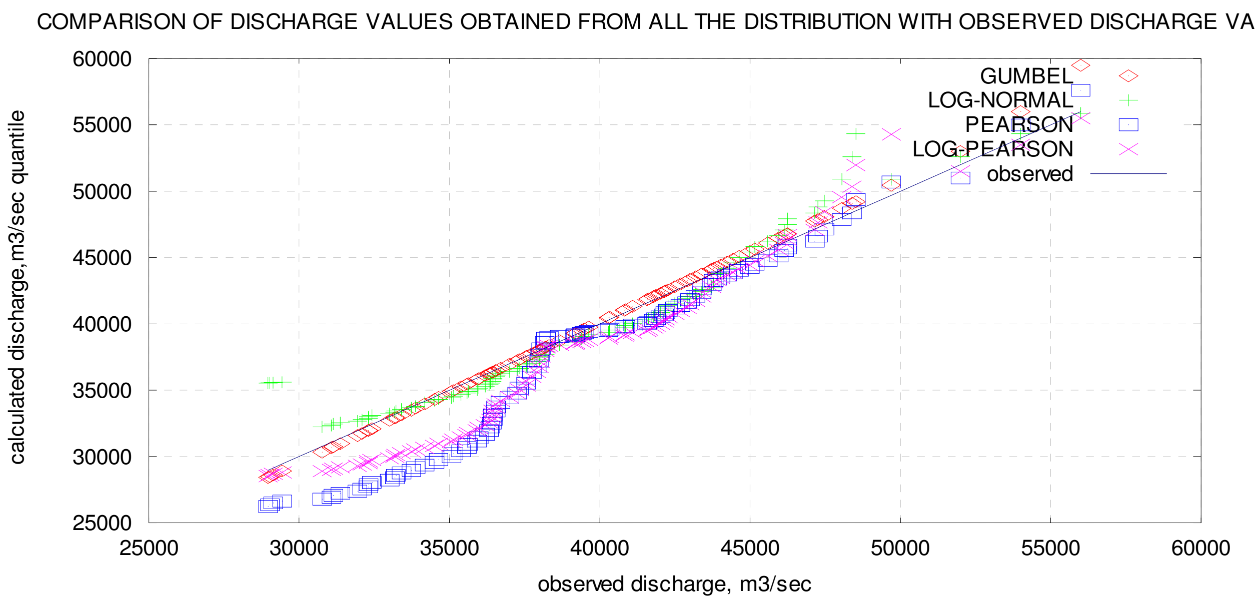

Fig.27: comparison of calculated discharge values and predicted maximum discharge values from 2000-2100 for all the distributions

5.8 COMPARISON OF FLOOD MAGNITUDE AND RETURN PERIOD:

The relation between the flood magnitude and return period for all the four distributions namely: Gumbel, Log-Normal type-iii, Pearson type-iii, Log-Pearson type-iii has been tabulated below for both observed stream flow and predicted stream flow.

Table.2: Comparison of flood magnitude and return period by using predicted stream flow

Return Period in Years	Discharge in m^3/sec			
	Gumbel	Log-normal	Pearson	Log-Pearson
10	49107.4	46103	45071.2	46693.5
25	52339.9	50143	49171.4	49088.5
50	56174.5	54088.5	52392.1	51980.7
75	58905.8	56497.1	54080.3	54870.3
100	61568.1	59487.5	57647.3	58700.1

Table.3: Comparison of flood magnitude and return period by using observed stream flow

Return Period in Years	Discharge in m³/sec			
	Gumbel	Log-normal	Pearson	Log-Pearson
10	41273.4	39544.5	38795.7	38893.3
25	45933.6	42709.7	42013.8	42353.9
50	49387.9	45568.1	44208.3	44917
75	51395.7	46562.8	45364	45708.5
100	52816.7	47830.5	46302.7	47479.5

Table.3: Comparison of flood magnitude and return period by using observed stream flow data

5.9 COMPARISION OF FLOOD MAGNITUDE AND RETURN PERIOD BY GUMBEL DISTRIBUTION:

Comparison of flood magnitude and return period by using observed and predicted stream flow data by GUMBEL distribution is shown in table 4 and in fig. 8. The comparison shows satisfactory results.

Table.4: Comparison of flood magnitude and return period by using observed and predicted stream flow data by GUMBEL distribution

Return Period in yeras	Discharge in m³/sec	
	Observed	Predicted
10	41273.4	49107.4
25	45933.6	52339.9
50	49387.9	56174.5
75	51395.7	58905.8
100	52816.7	61568.1

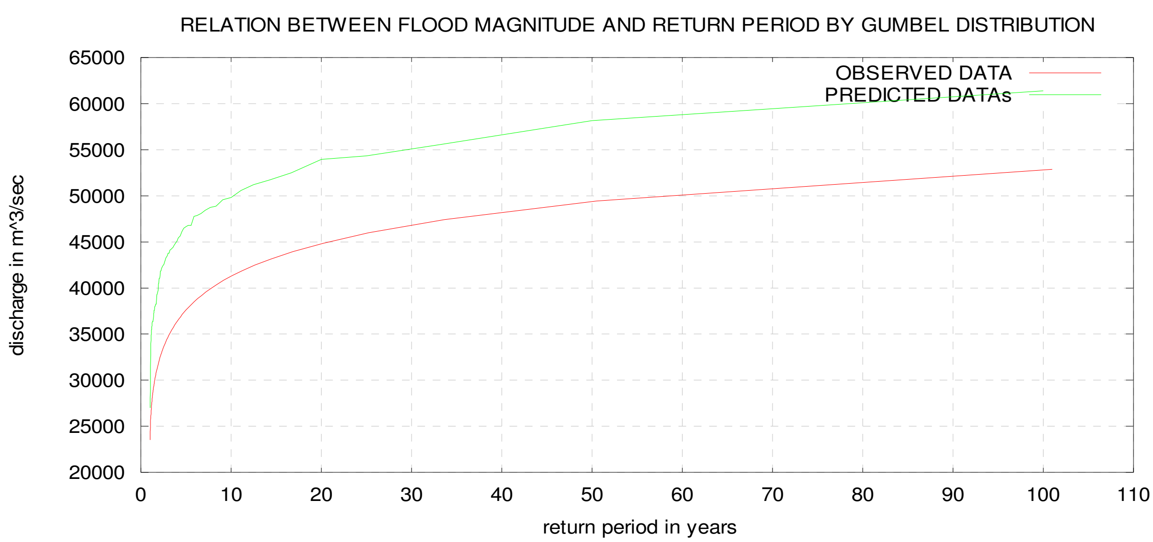

Fig.28: Graphical Comparison of flood magnitude and return period by Gumbel Distribution

5.10 SUMMARY:

In this chapter, by using different probability model namely, Gunbel, Log-Normal type-iii, Pearson type-iii, Log-Pearson type-iii the relation between flood magnitude and its return period is obtained. Here, the predicted future stream flow data has been use for the operation. Furthermore the different distribution models were compared, from which it was found that Gumbel and Log-Normal has better fitting than the other two.

6. CONCLUSION
AND FUTURE STUDY

6.1 CONCLUSION:

This study has been done in the Pandughat station. It was an important commercial port before the construction of the Saraigat Bridge and still now it is use for transportation. Therefore the stream flow behavior of the river Brahmaputra at this station has an important role. However, due to the changing climate the stream flow behavior is also changing. The following works have been done in this study:

- A downscaling model has been prepared for projecting the large scale variables to local hydrological variables.
- The method of statistical regression has been use for the downscaling.
- From the predicted observations it was found that from 2011-2050 the stream flow increases by 16.61% and from 2011-2100 the stream flow increases by 37.58%.
- The predicted maximum annual stream flow data were use for the flood frequency analysis.
- Four probability distributions were use for the study namely, Gumbel, log-Normal, log-Pearson and Pearson distribution.
- The results obtained from each of the distribution were compared to obtain the best fitted curve.

6.2 FUTURE STUDY:

From the above study it was observed that the stream flow of the river Brahmaputra increases considerably. This may lead to several problems including large scale floods unbalancing the nearby ecosystem. Furthermore, it was observed that the maximum annual discharge change from July to August which indicated the change in monsoon timing. With changed water scenario these problems may get aggravated and thus need detail study for developing strategic adaptation policy.

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