OPERATIONAL STRATEGY FOR BHAKRA RESERVOIR UNDER CHANGING CLIMATE

Thesis

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Abstract

Flourishment of civilization and survival of living species on earth is heavily dependent on availability of water resources. Since the inception of civilization, human beings have shown an inclination to settle near rivers due to guaranteed availability of water. Due to global warming, there is a rise in the temperature of the earth's atmosphere and oceans resulting in significant changes in the hydrology of a region. There is considerable evidence to suggest that anthropogenic activities are largely responsible for the rise in temperature around the world. Intergovernmental panel on climate change (IPCC) in their fifth assessment report show an increase in global temperature of around 1.5˚C between 2030-2050 when compared to preindustrial temperatures. Many aspects of water resource systems are anticipated to experience significant changes due to climate region.

The Satluj river originates from Himalayan region and is a critical source of water in northern region. A major dam in the basin is Bhakra dam with a storage capacity of 9621 million m^3. The Himalayan region is considered most sensitive to global warming. Due to changes in the precipitation pattern, considerable impact is likely on the stream flows. Changes in the streamflow magnitude and timings pose a serious challenge to water management, particularly at Bhakra. Due to rapid urbanization and high rate of population growth water resource system are stressed and climate change creates an additional stress. Design and operation of hydrological systems, including reservoirs have traditionally been carried out on the assumption of stationarity of hydro-meteorological data, but under the impacts of changing climatic conditions the assumption of stationarity of hydro-meteorological data is not valid. Therefore, to make water resources more reliable, in their management i.e. in their design and operation the effects of climate change should be considered. For efficient operation of Bhakra reservoir, the forecast of inflows that are representative of future climatic conditions is crucial.

Due to the continued widening of gap between water demand and supply, rigorous planning and management of water resource is required for sustainable development. Due to ever increasing demand and the difficulties associated with planning and building new water resource systems, more efficient operation of the existing systems becomes imperative. The main objective of the present research is to comprehensively review the existing strategies used in reservoir operations at Bhakra dam and suggest improvements while taking into account the impact of climate change in the Satluj River basin. To put the work carried out in this research, an extensive review of literature related to climate change impacts has been carried out. To evaluate the impact of climate change in the basin, an analysis of hydro meteorological data has been carried out in this research. The historical climate data at 56 nodes in the Satluj basin has been obtained from the Climate Research Unit (CRU) of the University of East Anglia, United Kingdom, thus creating a valuable dataset that could be utilized to understand the hydro meteorological trend. The RCP based projections of climate variables at 8 different locations in the Satluj river basin has also been obtained for several combinations of GCMs and RCPs from the Climate Change Knowledge Portal of the World Bank, thus enabling an analysis of the impacts of climate change in the basin for two future duration, namely 2020-2039 and 2040-2059.

An inflow calculator based on python code has been developed in this research , which would facilitate policy makers and engineers to estimate the available storage in the dam based on measured water level and release made from the reservoir. Real time inflow forecast is essential in order to develop optimal reservoir operating policy. In the present research, Long Short Term Memory (LSTM) – a machine learning technique has been developed and applied for the forecast of inflows at Bhakra. The LSTM model is trained using historical inflow data for 20 years from 1999-2018 at Bhakra Dam. For preparation of model two-third of data set is used for training and rest of the data for testing the model. Within the training set data 10 percent of data is used for validation. The performance of the model is measured on the basis of Root Mean Square Error (RMSE) and coefficient of determination R^{2} . Once trained, the model was used to forecast inflows for different time horizons ranging from one day to one year. The LSTM model overcomes the shortcomings of other approaches by using forget gates, which helps it to capture very long temporal relationships. The Thomas-Fiering model has also been used in this research to forecast inflows at Bhakra. A comparison of the monthly inflow forecasts and daily inflow forecasts made using Thomas-Fiering model and LSTM model clearly indicate the superiority of the LSTM model. Use of LSTM to forecast daily inflow provides undisputed results and real time inflow can be successfully used to decide optimal operation policy. With the use of LSTM model floods and droughts can be predicted more accurately. LSTM results shall be used to detect flood or drought by comparing model inflow results compared with observed, if anomaly persist it indicates flood or drought. LSTM being a powerful temporal sequence detector therefore can be used to analyze any stochastic nature of hydro meteorological data and climate change.

A major contribution of the present research includes the development of an LSTM model that can be utilized by the policy makers and engineers in the basin to improve the operation of Bhakra reservoir. At present, the reservoir managers use 10-daily forecasts to determine daily releases from the reservoir. With the model developed in the present research, the daily forecasts that are significantly reliable can be used to operate the reservoir in an efficient manner. For future research, the RCP data may be obtained for a greater number of models and stations than is presently done. Further research could be carried out to explore if the model trained on a particular location could be used to forecast inflows at another location or basins. An improvement in LSTM model could be made by considering a greater number of layers and neurons.

Declaration

I, **Asha Devi Singh**, student of Ph.D. hereby declare that the thesis titled "**Operational Strategy for Bhakra Reservoir Under Changing Climate"** which is submitted by me to the Faculty of Engineering and Technology/Department of Civil Engineering, Jamia Millia Islamia, New Delhi in partial fulfilment of the requirement for the award of the degree of Doctor of Philosophy has not previously formed the basis for the award of any Degree, Diploma, Associate ship, Fellowship or other similar title or recognition. This is to declare further that I have also fulfilled the requirements of para 11 ((a) to 11 (l)) of the Ph.D and that there is no plagiarism.

New Delhi   Asha Devi Singh

18th March 2020

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Certificate

On the basis of declaration submitted by **Asha Devi Singh,** student of Ph.D., we hereby certify that the thesis titled "**Operational Strategy for Bhakra Reservoir Under Changing Climate "** which is submitted to the Faculty of Engineering and Technology / Department of Civil Engineering, Jamia Millia Islamia, New Delhi in partial fulfilment of the requirement for the award of the degree of Doctor of Philosophy, is an original contribution with existing knowledge and faithful record of research carried out by him under our guidance and supervision.

To the best of our knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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1 INTRODUCTION

1.1 General

The climate conditions of a region play a significant role in the spatial and temporal distribution of water, which highly varies from region to region. The main cause of global warming is anthropogenic activities which cause changes in climate system such as an increase in temperature, change in precipitation, and rise in sea level among others. The risks associated with global warming are a function of magnitude greenhouse gas emissions, rate of global warming across the globe, the geographic location i.e. effects at the sea level will be different from the effects at the high altitudes. The levels of development and vulnerability play a significant role in determining the adverse effects of global warming, and also on the choices and implementation of adaptation and mitigation options. The global temperature record represents an average increase in temperature over the entire surface of the planet. Due to change in temperature, the precipitation pattern changes and often results in the variation in stream flow.

It is quite obvious that the rise in global warming and changing temperatures i.e. climate change is a cause of an additional stress on water resource systems in India as these are already facing remarkable pressure due to rapid urbanization and high rate of population growth. Design of the hydrological system, including reservoirs has traditionally been carried out on the assumption of stationarity of hydro–meteorological data. Under the impacts of changing climatic conditions the assumption of stationarity of hydro-meteorological data is not valid. Design of hydrological systems will be more reliable if potential impacts of climate change on hydro-meteorological variables are considered.

It is always desired to use available water judiciously by following scientific planning. Disputes are always observed between countries, state and inter sectoral regarding sharing of water. Water resource management projects often involve multiple stakeholders, are often multidisciplinary. However, despite the scale of these projects and complexities being taken into account, the projects are often planned and implemented in fragmented manner without any concerns about the optimum utilization, environment sustainability and holistic benefits to the people. Considering these conditions of availability of water and its mismatch with demand, limited water resources are to be efficiently managed in an optimal and effective way by finding solution to conflicting demands. The temporal and spatial variation in availability of surface water may increase significantly due to the combination of the impact of climate change and incidences of water related disasters like floods, increased erosion and frequency of droughts. To exploit the potential of the river, it is mandatory to estimate the inflow of river, taking into consideration climatic changes in order to have an optimum utilization of water.

Among the various multipurpose projects in India, the Bhakra Beas project is one of the largest. It consist of two major project one is Bhakra Nangal Project on the river Satluj and another is the Beas Project on the River Beas. The construction of the Bhakra Nangal Project started in 1948 and completed in 1963. The Beas Project started in 1961 and was completed in 1983. Bhakra Nangal Project comprises of Bhakra Dam and Nangal Dam. Nangal dam is a balancing reservoir which diverts its water into two separate channels.

The Himalayan region is house to several glaciers and most of north Indian gigantic plane rivers originate from it. Therefore, it serves as an critical source of water for Satluj river and this region is also considered one of the most sensitive areas of global warming. Changes in timing, with or without changes in magnitude of stream flow pose a serious implication for water management. Bhakra Dam is the mainstay of the economy of northern India as it supplies water to the states of Punjab, Haryana, Uttar Pradesh, Delhi and Rajasthan. Bhakra Dam is a multipurpose dam with an installed capacity of 1343 MW. According to the Indus water treaty signed by India and Pakistan in 1960, the water of rivers Ravi, Beas and Satluj comes under the exclusive share of India. The operating rules for large reservoir such as Bhakra which control the flow to several irrigation system needs revision considering climate change.

This chapter is further divided into five sections. Section 1.2 presents the background of the current state of research in the field of optimal operational strategies for large dam like Bhakra. Section 1.3 outlines the motivation to carry out this research. Section 1.4 lists out the objectives of this research. Likely contributions of this research are outlined in section 1.5. Section 1.6 provides organization of this research.

1.2 Background

Water resource system are nonlinear and stochastic in nature. The planning and operation of reservoir systems is a complex process. Development of water resource system are done considering potential benefits and risk associated with the operation. Operation of reservoir is done without reducing reliability and maximum benefits are obtained thus makes the system complicated. Obtaining maximum economic benefits from the water resource is involves design of a ideal system with large number of variables involved. This makes the system complicated and the problem is still an open area of research. It is well known that the inflow characteristics are stochastic in nature, and several other uncertainties involved, this causes water resource system to have non linear system dynamics. Benefits derived from the releases are always to be achieved without sacrificing the reliability. Hence the concept of reliability is one of the important aspects to be considered while making meaningful decisions regarding the reservoir storage and release strategies .The problem of trade-off renders the whole process even more complex. These complications can be overcome by the reservoir optimization models by allowing researchers to establish relationship between the inflow characteristics, reservoir storage capacity, reservoir releases and reliability of reservoir operations subject to other constraints.

Many optimization techniques have been developed in the past four decades to take decisions regarding reservoir planning, management and operations. Recent development in computer technology has helped the researchers develop more advanced and comprehensive models which will incorporate large complexities and uncertainties present in reservoir planning, operation and management. Optimization techniques in reservoir planning mainly involve search of large decision space for optimal decision sets to fulfil the intended objective subjected to various constraints. Many techniques are not capable of searching the large decision space and ends up in producing a near optimal solution or no solution. The limitations of the optimization techniques have motivated the researchers to search new methods, resulting in numerous new technologies in the field of reservoir operation.

Most of the optimization techniques are based on mathematical programming. The traditional techniques used are linear programming (LP), nonlinear programming (NLP), and dynamic programming (DP). The works (Bellman 1957; Bellman and Dreyfus 1962) have recognized DP as a novel approach in optimizing water resource systems. The design of dynamic programming as a paradigm can handle non linearity, non convexity and discontinuity in an objective function because it treats the objective maximization as a shortest path problem in a directed acyclic graph (DAGs). Recent addition to these conventional procedures are meta-heuristic procedures which are also graphical structures. In addition, they also have a learning objective associated with them that helps in optimization. The few standard structures in neural networks are such as Feed forward Neural Networks / Artificial Neural Networks (ANN), Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM). RNNs and LSTM have ability to capture temporal sequence which can solve multiple tasks which previous learning algorithms had failed to solve. LSTM provide a sufficiently good solution to an optimization problem.

1.3 Motivation for Work

Optimisation of the reservoir operations has been increasingly important over the last four decades to meet the objectives of the reservoirs to the maximum extent possible with the available water recourses. The problem is complex due to the stochastic nature of inflows, the nonlinearity of the system dynamics, and multiple constraints. No standard algorithms are available which can be applied to all the reservoir for deciding operational strategies. Each reservoir has its unique physical and operating characteristics (Yeh 1985) therefore it becomes a complicated task to decide an optimal operating policy. Many optimisation techniques have been developed, but each one of them has their own limitations. The reservoir systems have several variables upon which their function depends. This makes the optimisation of reservoir systems a problem in high dimensions and complex objective function constraints.

The major objective of this research is to a formulate methodology for optimal operation of the Bhakra reservoir under the impact of changing climate. At present, reservoir operation comprises of controlled release of water downstream of the dam so as to fulfil the designed requirement of the project. Due to climate change the temperature of the region is expected to rise by 1.5 ˚C according to IPCC report 2018. A warmer climate leads to change in the hydrological cycle. Due to climate change significant changes in precipitation are evident. This uncertainty with precipitation increases probability of extreme events resulting in large variations in inflow of river. The flow in the river may not fulfil the demand as inflow varies throughout the year. Construction of the reservoir is done to store surplus water and the same is utilized during lean periods when the availability of water is scarce. Therefore, there is large scope for improvement in the operating policies of the reservoir. Looking at the grim water stress situation of the region, it is of paramount importance to utilize the available water resources in an efficient manner.

1.4 Research Objectives

The major objective of the present research is to develop operational strategies for Gobindsagar reservoir formed by the Bhakra Dam considering climate change in the Satluj river basin. The intent of the present research is to provide guidelines for the reservoir managers for the development of comprehensive planning and operation of water resource system in the basin. Recently a lot of success has been observed with the use of machine learning techniques. The Long Short-Term Memory network (LSTM) is a machine learning technique which is capable of successfully training very large architectures. The LSTM model shall be used to forecast daily inflow into the Bhakra Dam and thereafter suggested best fit strategy for reservoir operation.

Specific research objectives envisaged are:

- To analyze the hydro-meteorological data for the Satluj River basin.
- To identify trends from hydro-meteorological data using Mann Kendall non parametric test.
- To apply Thomas -Fiering model for the generation of synthetic inflows at Bhakra Dam.
- To develop an LSTM model for daily inflow determination at Bhakra.
- To propose revised operational strategies for Bhakra Dam considering daily the impact of climate change.

1.5 Thesis Contribution

An extensive literature review related to analysis of hydro meteorological data and inflow forecasting techniques has been presented. The CRU data of for the Satluj Basin was retrieved and analyzed to evaluate the response of the basin to global warming. To achieve this, investigation of temperature trend at 56 nodes in the basis for the data spanning 113 years has been carried out. A spatio-temporal analysis of Representative Concentration Pathways (RCPs) based projections of surface air temperatures under different combinations of Global Circulation Models (GCMs) and RCPs for future 2020 -2099 has been carried out. The projections of temperature anomalies for several meteorological stations in the basin using 16 different combinations of emission scenarios and global climate models (GCMs) clearly indicate an increase in temperature for all RCPs for all durations.

Monthly synthetic inflows for the duration 2018 to 2037, and daily inflows for the duration 1stMay 2018 to 30thApril, 2019 have been generated using Thomas- Fiering model. A calculator to calculate volume of water available in the reservoir and corresponding level has also been developed to facilitate better management of water resources in the basin. LSTM model has been developed for daily inflow forecast. This daily inflow forecast is used for formulating optimal operational strategies at Bhakra Dam. The performance of LSTM model when compared to observed daily inflow of 20 years from 1999-2018 gives Root Mean Square Error (RMSE) of 3.0% and a coefficient of determination of 0.9389. This model has very high accuracy when compared to present strategies for inflow determination followed at Bhakra Dam. The model has better accuracy compared to the Thomas-Fiering model also. The results obtained using LSTM network reveals that the model is satisfactorily able to stimulate non stationary and non- linear inflow trends in the streamflow data.

1.6 Thesis Organisation

The rest of the thesis is organised in seven Chapters and four appendices.

Chapter 2 provides a comprehensive review of literature of various techniques used in the optimal reservoir operation. The chapter also includes various models used to forecast inflow in the reservoir.

Chapter 3 describes the Satluj river basin – the study area of the present research. The hydrological characteristics of the basin, and the salient features of the Bhakra Dam have been described in this chapter. The existing operational strategies at the Bhakra dam have also been described.

Chapter 4 describes the analysis of Climate Research Unit historical data using Mann-Kendall non-parametric test for 113 years at 56 nodes of the Satluj river basin. An analysis of Representative Concentration Pathways (RCPs) based projections of surface air temperatures under different combinations of Global Circulation Models (GCMs) and RCPs for two future durations, namely 2020 -2039 and 2040 to 2059 has been presented in chapter 4.

Chapter 5 describes the discharge facilities, storage utilization, methods of early flood warning system and flood disposal, and prevailing reservoir operation and regulation plan followed at Bhakra Dam.

Chapter 6 describes the forecasting techniques used for inflow determination in the reservoir. The Python Code developed for implementing Thomas -Fiering Model has been presented in chapter 6. The LSTM model used to forecast daily inflow and its use in deciding reservoir operation has also been described in this chapter.

Chapter 7 provides the conclusion of the research. This chapter lists the achievement of the research. Pointers for further application of LSTM to water resource fields are also stated at the end of the chapter.

2 LITERATURE REVIEW

2.1 General

This chapter describes the review of literature on the impact of climate change, methods to predict inflow in the river at the dam site and thereafter reservoir operation strategies. Extensive literature is available due to the vast amount of research that has been carried out in this field in the last four decades. A large number of techniques and operation methodologies have been developed in the recent past in the field of water resource planning and its management. The research in this field is largely motivated by the availability of high speed computers and the need for optimisation of available water resources. This chapter reviews the various techniques used in the field of water resource management.

2.2 Mathematical Programming Techniques

Optimization models use algorithms based on mathematical programming techniques. For optimal reservoir operation successful applications of these techniques have been reported in the literature, but no generic technique exists which is capable of handling all the problems of water resources management. To obtain alternative sequential operating policies stochastic mathematical programming models which incorporate first order Markov chains are used. Inflow into reservoirs are serially correlated random quantities wherein other parameters such as the reservoir capacity, storage and release targets are assumed fixed. To model continuously varying time, the volume and flow are approximated by discrete units. Operation of reservoir largely depends upon the current storage and inflow.

Linear programming is an optimisation method applicable when the objective function and constraints are linear functions of decision variables. Linear Programming is considered as a optimization program that solves for inequalities which are optimization constraints in objective function for complex water resource management problems. Linear equation may be in the form of equalities or inequalities. Linear programming was first formulated by George B Dantzig during world war II to allocate resources. Linear programming is successfully used in water resources for reservoir operation, reservoir capacity determination, irrigation scheduling, screening of alternatives in river basin development and resource allocation. Louoks and Falkson (1970) applied linear programming to arrive at optimal solutions for reservoir operations. Linear programming is elegant and handy tool to solve problems. Generally, a linear decision rule is chosen for unknown reservoir release targets, or storage volume targets and their maximum probabilities of failure is estimated.

2.3 Linear Programming

Linear programming is most suited to optimisation problem where the objective function and constraints are linear. Due to simplicity and adaptability LP technique finds wide application in the optimisation of reservoir management.

General form of LP model is

Linear objective function f(X) is linear function of X, whereas linear constraints c(X) are also linear function of X – the vector of decision variables. All the decision variables are physical variables and in general non negative, that is $X>0$. Linear programming can be used when all the above conditions are satisfied.

Dorfman, R (1962), in their work have demonstrated a three version model, all of the models had different i.e. increasing levels of complexity added to them by introducing more constraints to demonstrate application of linear programming for water resource management.

The central theme of their work had their objective function rooted in the maximization of economic benefits derived from the water resource. Storage capacity and target release were taken as decision variables in all the three versions. In their first version they solve a simplified problem for river basin planning using fewer inequalities. The second version of LP was used to analyse the river basin with critical hydrology, whereas the third version was used when stochastic inflows were considered.

Shane and Gilbert (1982)and Gilbert and Shane (1982) developed HYDROSIM an interactive model to simulate the Tennessee Valley Authority reservoir operation data of 42 years. The LP model used forecast reservoir storages, releases and hydropower generation for each week at the beginning of year. Alternate series of historical stream inflows were also considered in the forecasting of reservoir operation policy. Palmer and Holmes (1988) developed LP model to aid in drought decisions for Seattle water department, Washington. The region suffered extreme drought. The model determines system yield and optimal operating policies.

Randall, et al. (1990) developed a multi-objective linear program to analyse the operation of a water supply system during drought. The case study was conducted on Indianapolis Water Company. The main aim was to maximise reservoir storage the minimum flows in the river. Randall et al. (1997) formulated a simulation model using linear program which is used for water supply, having monthly time step. The model has been implemented effectively for Alameda County Water District (California) staff for its long-range, integrated planning. Model also reflects inherent weaknesses of mathematical programming and mixed integer linear programming. Model has successfully overcome these weaknesses. Anwar and Clarke (2001) formulated a mixed-integer LP model for scheduling canal irrigation water among a group of users. Users raise demand regarding the duration of flow of each outlet and a target start time. Two LP models developed were based on minimised demands at the head of the canal, target start time for subsequent irrigation period. The proposed models will help in scheduling release of water in irrigation schemes based on demands of user. Crawley and Dandy (1993) developed a linear program with a goal to develop a optimum monthly operating policies for Adelaide headworks system in South Australia, Australia. The main objective was aimed at minimising pumping cost, achieving maximum yield and also maintaining satisfactory level of reliability. Application of model for Adelaide system resulted in savings of 5% to 10% of total pumping cost.

Martin (1995) used linear-programming technique to determine the hourly generation schedule for Lower Colorado River Authority (LCRA) of Texas. The LCRA supplies water and energy to central Texas. To improve power generation an alternative operating procedure is adopted which will enhance the winter hydroelectric power generation. Main objective behind using this technique is to maximise power generation. Similarly Daniel P. Loucks (1981)developed linear programming technique which is used in optimising various aspects of water resource management, such as sizing of reservoir capacities. Pattewar et.al, (2013); Dahe and Srivastava (2002) developed a linear programming model for estimating the yield of reservoir. The yield model is applied to Narmada River in India which consists of eight reservoirs in the upper basin of river. The major objective of yield model is to achieve desired reliabilities for irrigation and energy generation and also incorporate an allowable deficit in the annual irrigation target. Needham et al.(2000) used linear programming for deciding flood control measures at Coralville Reservoir, US. Vedula et al. (2005) developed a mathematical model to achieve an optimal conjunctive use policy for irrigation of multiple crops in a reservoir-canal-aquifer system. The model was found to be useful in conjunctive use planning.

Linear programming is an elegant tool for obtaining optimal solution to a problem. However, it can handle only linear objective function and constraints. To overcome non linearity of water resource problem alternate techniques such as sequential linear programming can be used. Grygier and Stedinger(1985) and Hiew (1987) illustrated application of sequential linear programming and also described many other techniques to optimize reservoir problem. Reznicek and Simonovic (1990)developed a new algorithm using successive linear programming for management of energy. The objective was to optimise the hydropower system operation since the power is not linearly related to release. The algorithm was tested for Manitoba Hydro system in Canada, a single reservoir system. A Taylors series was used for linearization of power function. On many occasions, linearization may not produce optimal results.

2.4 Non-linear Programming

Nonlinear programming (NLP) is adopted to solve optimization in cases where objective function has non-linearity or constraints have non-linear characteristics. Non linear programming is a subclass of convex optimization problems whereas then on -linear function are concave or convex function. When the objective function is concave it is maximization problem maxima can be determined and in convex nature of objective function minima can be determined. Usually convexity and concavity of an optimization problem is interchangeable. A general NLP problem can be formula.

Minimize $$F = f(x_1, x_2, ..., x_n) \quad (2.1)$$

Maximize $$F = -f(x_1, x_2, ..., x_n) \quad (2.2)$$

subject to $$g_i(x) = 0 \quad i = 1, m \quad (2.3)$$

Where $$\underline{x}_j \le x_j \le \overline{x}_j \quad j = 1, n \quad (2.4)$$

in which F is to be minimised or maximised subject to *the* constraints expressed by equations

(2.3) and (2.4). Due to computational complexity the non-linear programming does not have much application to solve multi reservoir system optimization problem. Lee and Waziruddin (1970) used non-linear programming to obtain optimal operating policy for multipurpose reservoir system. Main aim is to maximise the non linear function for irrigation releases and storage capacity of reservoir. Simonović and Marino (1982) applied non-linear programming to develop a reliability programming model for multiple multipurpose reservoir systems. Using this model optimal solution for flood control, power generation, water supply and irrigation can be obtained. The objective function is maximising benefit and reducing risk. Rosenthal (1981)applied nonlinear network flow algorithm for maximization of benefits of power system at Tennessee Valley Authority (TVA). Guibert et al. (1990) developed a nonlinear programming model for California Central Valley Project (CVP) for monthly operation of the hydropower system. The model includes dependence of energy value and capacity factor of the generating unit for each month. Literature study indicate that in the field of power generation most of NLP applications are found. The objective function is either benefit maximisation/cost minimisation in irrigation releases, demand analysis.

Generally convex optimization procedures are also non-linear outside of the linear programming subclass. These problem classes in non linear programming are usually having polynomial run time as compared to rest of the optimization problems that are usually NP-Hard and thus computationally intractable. In general, non-linear programming optimization problems that can fall into the convex optimization subclass can be solved using the properties of convex optimization by readily available software which is standard for convex optimization problem simulation for example CVX Matlab Software. Due to computational complexity application of NLP in water resource system is not very promising. Slow in convergence of results and even stochastic nature of stream inflows are not easily implemented in the system. NLP is unable to distinguish between global optimum and local optimum and is considered as limitation in using NLP to reservoir/water management. NLP finds its application in all engineering field including reservoir operation as it allows a general mathematical formulations which is an important feature a general computer software can be developed.

The software packages in NLP which are generally used in multiple reservoir system are LINDO, INRIA, LINGO, GAMS. Many researcher have developed their own model for application of NLP and it's variants, for instance MINOS 5.5 software package for solving linear and non-linear mathematical optimization problem developed by Murtagh BA (1998).Conn et al. (1992) developed LANCELOT software which make use of first and second derivative.

2.5 Dynamic Programming

Dynamic Programming or commonly known as DP is a technique that was proposed by Richard Bellman in 1954. Dynamic Programming typically finds application in optimization problems which can be represented as multistage decision problem. The entire DP is based on Bellman's principle of optimality. According to this principle optimal policy or sequence of decision for the current state is independent of the policy adopted in the previous stages. Bellman's principal implies that given a state S_i of the system at stage *i* means at particular time one must proceed optimally till the last stage, irrespective of how one arrived at state S_i.

Optimal reservoir operation problems involve sequence of decision. These problem can be easily decomposed into series of smaller problems which can be conveniently handled using Bellman's principle of optimality. Another important characteristic of DP is non linearity and constraints can easily be considered. The dynamic behaviour of the system in DP formulation is expressed by three variables. State variable describes the state of the system. In reservoir operation it state the amount of water available at particular stage. Problem having one state at one stage is referred to as a dimensional problem. Problem can have two states at one stage it is multi dimensional problem. For optimisation of water resource system having two reservoirs will have two state variable at one stage. Stage variables defines the time at which particular event occur in the water resource system. Control variables are those decision variables which controls the state at a particular stage. For water resource system, it is the release made at each state. Set of decisions for each duration is called policy and the policy in which objective function can be optimized is stated as optimal policy. The recursive equation which finds the optimal decision for stage n, for state S_n given the optimal decisions for each state at stage (n-1)

$$f_n(\,S_n) = \frac{Max}{\{x_n\}}[r_n(x_n) + f_{n-1}\{T\,(S_n, x_n)\}] \qquad (2.5)$$

$f_n\,(S_n)$ = Cumulative return for stage n

$r_n(x_n)$ = Return for decision x_n in current state

x_n= decision variable

$T\,(S_n\,,x_n)$ = Transfer function to get the state S_{n-1} corresponding to S_n and x_n

Dynamic programming finds applications in various areas and branches of science where optimization is an important task and mainly researched as a areas and tool for problem solving by computer science researchers. Dynamic Programming in its essence is similar to divide and conquer in its approach where the problems are divided into sub-problems which can be individually solved and overall solution can be achieved using combination of solutions to those problems. Here, in dynamic programming the key word "programming" doesn't refer to a computer program but the tabular way in which solutions are obtained. The key to finding whether solutions can be formulated as an dynamic programming one are that the problem must display optimal substructure. In other words, the solution to optimal sub problems can be combined to form a optimal solution to the overall problem and secondly, the need of overlapping sub-problems can reduce the time complexity of the system.

In the problem of optimal reservoir operations several researchers have attempted to give solutions using dynamic programming approach. The question of what should be the release in an optimal operation of reservoir was attempted to be answered by Hall and Buras (1961). The optimal operation of single reservoir system using dynamic programming was modelled in the work by [Young(1967)]. Their work tried to generate a probable inflow sequence synthetically and from these sequences attempts were made to optimize for best reservoir operation policy given the synthetically generated inflow sequence. The variables upon which the operation policies are dependent regression analysis. Allen and Bridgeman (1986) used dynamic programming optimization technique for optimally scheduling of hydropower. For optimally scheduling of hydropower analysis, an operating strategy for a different time perspective is done. Optimization is done to maximise the efficiency of the system. Studies indicate dynamic programming can be successfully implemented to operate the reservoir optimally. Implementation of DP to decide reservoir operation has been reported by Collins (1977), and Opricovic and Djordjevic(1976). Extensive review of dynamic programming in deciding optimal reservoir operation policy is found in the work of William W-G. Yeh (1985) and Yakowitz (1983). Augustine O. Esogbue (1989) and more recently in Zhao et al. (2012)Stedinger et al.(2013).

Although dynamic programming is able to significantly reduce the complexity of the problems by formulating the recursive solutions and tabular or memorized dynamic programming formulations, there are few subtleties which limit the power of the dynamic programming approach as it needs its sub problem solutions to be independent of each other. For example in the longest path problems in a graph sub-problems cannot be used to combine to form solutions to larger problems. In such cases dynamic programming solutions cannot be formulated. Moreover, in some cases dynamic programming shall work but it can result in sub-optimal solutions to problems in terms of run time complexity. In other words, a DP solution may require more time to analyze every possible sub problem combination to find the solution when there is some hidden structure in the problem and the sub-problems it depends upon that can be exploited in the a greedy fashion.

The other disadvantage of dynamic programming is large requirement of computer memory and run time. System with n state variables and m levels of discretization, there exists m^n combinations for which computations are required to be carried out at each stage of analysis. The application of dynamic programming to multi reservoir system is limited by "curse of dimensionality" as reservoir operation is a function of more number of state variables and various stages. Implementation of dynamic programming to problems having more than two to three states is still a challenging task.

Dimensionality problem of DP can be solved to some extent using DP in combination with LP. Use of combined LP-DP procedure has been reported by many researchers. LP is used for stage to stage optimisation and DP is used for determining the optimal solutions at various stages. Becker and Yeh (1974) evolved a methodology by using LP-DP combination approach and its application made to optimize real time operation of reservoir and hydroelectric facility for Shasta and Trinity sub-systems of the California Central Valley Project. To minimise the loss of stored water potential energy from any release in each period in reservoir is carried out using LP. The stage wise optimisation was carried out using LP solutions in a deterministic DP. (Buyuktahtakin 2011) investigated close relationship between dynamic programming and linear programming. The LP-DP approach has also been used by Yeh, et al. (1979) to developed an hourly optimization model for the operation of the Central Valley Project, California. Model has two phases, phase 1 involves a determination of a optimal feasible policy through an iterated LP. Phase 2 uses this feasible policy as a starting policy in an incremental dynamic programming, successive approximations to derive an optimal policy. Many other researcher have also used this approach Takeuchi and Moreau (1974), Becker et al. (1976), Marino and Mohammadi (1983). The non linearities are handled using an iterative optimization technique successive linear programming (SLP). Grygier and Stedinger (1985) illustrated SLP as an optimal control algorithm.

To alleviate the curse of dimensionality associated with DP, researchers widely use Incremental DP (IDP) and Discrete Differential DP (DDDP) as DP variants. These methods are based on concept of increment of state variables. Larson (1968) initially proposed State Increment DP (SIDP). SIDP alleviate the curse of dimensionality. Later Hall et al. (1969)proposed Increment dynamic programming. Later limitations of DP formulation were systemised and referred as Discrete Differential DP (DDDP) by Heidari et al. (1971).

With the aim of obtaining good convergence, Hall et al. (1969) suggested that increments of the state variables should be small and maintained constant throughout. Strong correlation was observed between the number of iterations required for convergence and size of increment adopted for each iterations. Turgeon (1982) concluded that if same increment is used at every stage IDP may converge into non-optimal decision. The author proposed a method where if increment size is adjusted at each stage the desired results are possible. For obtaining convergence of problem or to obtain global optimum solution for a problem using DPSA, DDDP and IDP, a good initial policy or initial trajectory is critical.

2.6 Climate Change

2.6.1 Climate Research unit data analysis (CRU)

Due to rapid increase of green house gases concentration in the atmosphere, the global temperatures are expected to rise as predicted by various climate models. The Fifth Assessment Report (AR5) (IPCC) indicates a continuously rising trend of temperature over the last three decades. The earth atmosphere and ocean temperature have increased due to concentration of green house gases causing retreating of glaciers, rising of sea levels. The National Climate Data Centre (NCDC) conducted an analysis of 130 years duration regarding global annual and monthly record of ocean and land surface temperature indicate rise of 1°C above pre-industrial levels as of 2015. The CO_2 level in the atmosphere is increasing, resulting in critical changes in the hydrological cycle. IPCC special report (2018) indicates a rise in global temperature which is expected to reach 1.5˚C between 2030-2050 compared to preindustrial temperature.

Yang et al. (2003) concluded that surface air temperature is an important parameter and has impact on dynamics of atmospheric process. Jiang et al.(2007) enumerated that due to an increase in concentration of green house gases and aerosols in atmosphere, there would be a perceptible increase in temperature. It is evident that with the increase in atmospheric temperature, pattern of precipitation and runoff will alter considerably and these changes are considered important for water resource planning. Both the magnitude and frequency of extreme events is also likely to increase.

The temperature trend of eight stations of Satluj river basin using Mann-Kendall was analyzed by Hamid et al.(2014). Analysis of trends in temperature indicated predominantly increasing trend. Due to this increase in temperature water resource management in Satluj reservoir basin is likely to become more challenging as it is a snow and glacier melt contribute significantly to stream flow at Bhakra reservoir. Hamid et al (2017) estimated stream flows at Bhakra using soil and water assessment tool (SWAT). This study provides understanding of the impact of climate change in basin. Radhakrishnan et al. (2017) estimated annual and seasonal mean rainfall and temperature trend of the India for duration 1901–2014 using linear regression and Mann–Kendall test. The results indicated a negative trend in rainfall, whereas the temperature showed a positive trend.

Kothawale and Singh (2017) investigated linear trends of surface and troposphere temperature of five selected isobaric levels for the period 1971-2015 across India. The study indicated an increase in surface temperature of 0.74°C for the region with latitude greater than 22˚ N, and an increase of 0.80°C for region with latitude less than 22°N. Sharif (2015) presented a study of surface air temperature for Saudi Arabia region using Climate Wizard tool under three emissions scenarios (SRES A2, A1B, and B1). The projection of temperature anomalies were obtained using a set of four GCMs. Among the four models considered by the author, the CCSM4 model projected the maximum increase in average temperature, whereas CSIRO-Mk3.0 model projected the minimum increase.

Using Hadley Centre's high-resolution model, Kulkarni et al. (2013) predicted possible impacts of a warmer climate on the Hindukush Himalayan region. Gocic and Trajkovic (2013) used non-parametric Mann-Kendall and Sen's slope methods to analyse annual and seasonal trends for various meteorological variables for Serbia region. The authors selected twelve weather stations for duration 1980-2010. The study indicated increasing trend for temperature. Singh and Jain (2002) estimated stream flow of rivers in Himalayan region which is generated from rainfall, snow and ice. The authors concluded that the snow-covered area is contributing 59% of stream flow, mainly due to the retreat of glaciers.

2.7 Representative Concentration Pathways (RCPs)

The study of projections of temperature for different regions of the world is desired to analyse future change of climate. The projection of temperature are available on Climate change knowledge portal (CCKP) for different combinations of RCPs, Global Climate Models (GCMs), and future time periods. The climate data for the geographical locations of interest in the Satluj river basin was then retrieved from the CCKP. Models used in this study under (Coupled Model Intercomparison Project Phase 5) CMIP5 are:bcc.csm1-1, CCSM4,CISRO-MK3-6-0,and GFDL-CM3. Once the temperature anomalies have been obtained for different combinations of RCP, GCM, and future time period, the statistical analysis was conducted using R-package an open source software.

A large number of studies have been carried out to analyse the impacts of climate change. Wu et al. (2013) examined terrestrial and oceanic carbon budgets from preindustrial time to present day using Beijing Climate Centre Climate System Model (bcc.csm1-1) which is a global fully coupled climate-carbon cycle model. Gent et al. (2011) described the fourth version of the Community Climate System Model (CCSM4). The CCSM4 is a general circulation climate model consisting of atmosphere, land, ocean, sea and ice components and exchange of energy. Donner et al. (2011) extensively described the coupled general circulation model (CM3) for the earth and its atmosphere. The model is developed by Geophysical Fluid Dynamics Laboratory (GFDL).The aim of CM3 is to handle emerging issues in climate change, including aerosol–cloud interactions and to limit greenhouse gas warming.

Collier et al. (2011) developed a model CSIRO-MK3 is joint venture between the Queensland Climate Change Centre of excellence and Commonwealth Scientific Industrial Research. The stratosphere. model ensures that it had acceptable configuration for participation in climate model intercomparison project 5 (CMIP5). Panday, et al (2015) analysed outputs from different GCMs in CMIP3 and CMIP5 with the intent to investigate changes and trends in several precipitation and temperature indices for Hind Kush-Himalayan region. Rajbhandari et al. (2014) utilised projections from climate models developed by Hadley Centre, United Kingdom for the assessment of impacts due to climate change over Indus basin. Graham et al. (2007) made an estimation of impacts due to climate change on hydrology in Northern Europe using a number of RCMs and an offline hydrological model. Cannon et al. (2016) described the effect of tropical forcing on extreme winter precipitation in the western Himalayan region. Another study in Upper Indus basin made by Lutz et al.(2016) underlined the large uncertainty associated with the future availability of water.

Khattak et al. (2011)in the research analysed an increasing trend in winter maximum temperature with the trend slopes of 1.79°C, 1.66°C, and 1.20°C per 39 yr for the upper, middle, and lower regions of Indus River basin. Khattak et al. (2015) evaluated trends in stream flow data on major rivers in the Upper Indus River basin. Sharif et al. (2010)evaluated trends in extreme flow at different hydrometric stations located in Satluj River basin due to climate change. Choudhary and Dimri (2017) predicted probable changes in monsoonal precipitation in the Himalayan region for several combinations of RCPs and future time slices using the data from Coordinated Regional Climate Downscaling Experiment-South Asia (CORDEX) project. A similar study done by Dimri et al. (2018) using the CORDEX-South Asia dataset indicated an increasing trend in diurnal temperature range (DTR) with highest magnitude observed under RCP8.5. Ehsani et al.(2017)analyzed the change in precipitation patterns due to rise in surface temperature. Due to change in precipitation pattern floods and droughts frequency increased. Climate change affects the water management strategies in the Northeast United States.Baumberger et al. (2017)provided a conceptual framework for the assessment of the accuracy of models for climate change projections. The authors recommend background knowledge as an additional criterion for the evaluation of model accuracy. Nordhaus (2007) suggested that the nations should undertake extreme steps to control the damages caused due to climate change and aim at immediate reductions in greenhouse gas emissions. New et al.(2001) investigated that large scale precipitation estimates are derived from gauge station measurements and it lacks data from ocean region. Estimates derived by satellite remote sensing for precipitation are not sufficient and use of merged gauge–satellite datasets for estimation was suggested. Wang et al (2018) estimated an increase of 4° C global temperature comparative to the pre-industrial levels using the RCPs and also predicted that the impacts under RCP8.5 scenario will be devastating. New et al. (2001), Singh and Goyal (2017) investigated effect of climate change on ecosystems, and various process of earth surface. Modelling hydrological process for hilly catchments and snow fed areas is complex. A modified curve number (CN) was developed to simulate stream flow and water yield at sub-catchment for hundred years utilizing Soil and Water Assessment Tool (SWAT). Results indicate consistent increase in precipitation and water yield over Himalayan catchments. Ross et al. (2018) analysed the temperature pattern for pre-monsoon, monsoon, and post-monsoon for seven decades. The authors compared temperature of 2000s with 1950s, and found a consistent pattern of warming over North-Western and Southern India. Rahman et al. (2018)investigated effect of climate change on yield of crop in Pakistan region using 29 general circulation models (GCMs) for high and moderate representative concentration pathway (RCP) scenarios (4.5 and 8.5) and for duration (2010–2039) and mid-century (2040–2069). Result of study for all GCMs indicate increase in temperature of 1.2˚–1.8˚. Zheng et al. (2018) predicted future climate and runoff projections for the South Asia region under the RCP8.5 scenario and 42 CMIP5 GCMs. The change in runoff is driven mainly due to change in precipitation, by higher temperature and potential evaporation. The paper also investigates the uncertainties of the projection due to scaling methods and selection of GCMs.

2.8 Long Short Term Memory (LSTM)

Various approaches are used for making prediction of hydrological process. Hydrological process are intricate as it is difficult to understand the complex underlying process that generate the observed system dynamics. Thomas (1962) made use of auto regressive model to generate inflow assuming hydrological data as time series and stochastic in nature. Singhal et al. (1980) developed a mathematical model using Thomas-Fiering model wherein the inflow in any month is dependent on previous month and also depends on the inflow of the previous year of same month. Model was used for Matatila dam on river Betwa. Faruk(2010) has developed a model combining ARIMA and neural network. ARIMA model is unable to deal with non-linear relationship, whereas neural network model alone is incapable of handling linear and non-linear pattern for accurate estimation of time series data. The hybrid model was tested for 108-month observations of water quality and the results obtained were promising. Khandelwal et al.(2015)suggested a novel technique of forecasting by segregating a time series dataset into linear and non-linear parts. Thereafter the Autoregressive Integrated Moving Average (ARIMA) was used to predict linear component and Artificial Neural Network (ANN) models was used to predict non linear components. This approach used the strength of Discrete wavelet Transform, ARIMA, and ANN to improve the forecasting accuracy.

Sunet al. (2014) developed algorithm to forecast stream flow using Gaussian Process Regression (GPR). It is an effective kernel-based machine learning algorithm which is used to determine stochastic stream flow. In water resource planning and management, streamflow forecasting plays a critical role. Results obtained using GPR are more promising when compared to linear regression and artificial neural network models. Stedinger et al.(1984) have developed a stochastic dynamic programming model to forecast the current period inflow and estimated reservoir release policy. The authors enumerated the benefits of forecasting reliable inflows. Expected benefits from future operations using best inflows are also estimated. Mujumdar et al. (2007) developed an operating policy for multi-reservoir system by addressing stochastic nature of inflow. Bayeson stochastic Dynamic Programming model was developed and model performance was measured by estimating its deviation from the total firm power. This model is applied for Kalindi Hydroelectric Project Stage-1 in Karnataka state, India. Raso et al.(2017) formulated a model using Stochastic dual dynamic programming for determination of streamflow. Based on the generated streamflow reservoir operating rules were decided. Advantage of this model lies in the forecast of positive streamflow values and maintaining problem linearity. System adaption is better as it can adapt itself during high variable periods. This model is used for Menantali Reservoir located on the river Senegal, West Africa. Li et al. (2010) used dynamic programming to estimate inflow considering its uncertainty. Future inflows were estimated from the available records with the assumption that inflow forecasting error takes normal distribution. Philbrick et al.(1999) suggested that deterministic optimization can be used to decide operating policy of reservoir. When exact forecast of inflow is possible then it is possible to solve large scale problem without much simplification. Naadimuthu et.al.(1982) described the use of two nonlinear programming techniques. One is generalized reduced gradient technique and other is gradient projection technique, each was combined with Markovian decision to solve the problem of multipurpose reservoir having basically different usage of flood prevention and conservation of water. Fayaed et al.(2013) suggested that integration of stochastic dynamic programming and artificial neural network will provide better strategies for optimization of reservoir operation. Ahmad-Rashid et al.(2007) used stochastic dynamic programming to produce optimal decision for Dokan reservoir in Iraq. The authors considered storage level at the end of month as storage level for the beginning of next month when unregulated inflow persist. A simulation model was run to verify the performance of the model.

Due to large availability of hydrological data and increase of computational capacity the statistical models are developed to estimate the behaviour of observed data. Lot of seminal work involving solutions to the problems in different areas is now being powered by deep learning. For prediction of nonlinear hydrologic process Artificial Neural Network (ANN) techniques is widely used now days. Using (ANNs) for forecasting of Stream flow for short term is feasible. Castelletti et al. (2007)used Neuro-dynamic programming instead of stochastic dynamic programming for the management of multipurpose reservoir system. Various operational issues were solved using stochastic dual dynamic programming (SDDP) and neural network. Zealand, et al. (1999) tried to explore the potential of ANNs and compared the performance of ANN to conventional methods which are generally used to forecast stream flow. Coulibaly et al. (2001) conducted experiments to predict hydropower. Reservoir inflow was predicted using temporal neural networks. Three types of temporal neural networks architectures were investigated, overall recurrent neural networks (RNN) provided the best results. Duong et al.(2019) emphasized that the accurate rainfall prediction is important for assessing impacts of climate change The authors have used Long short term memory recurrent neural network technique for the determination of monthly rainfall predictions. Lin et al. (2009) suggested the use of support vector machine (SVM) to forecast reservoir inflows. Based on statistical learning theory, the SVMs are considered better than back-propagation networks (BPNs), which are generally used. SVMs have better generalization ability. SVMs can be trained more rapidly have better architectures and the weights are unique.

2.9 Bhakra Storage determination

Precise estimation of reservoir volume, inflow and release from the dam are important parameters which are used for deciding optimal reservoir operation policy. Reservoir establishes balance between inflow which is highly variable parameter with time and the quantity of water required to meet particular demands. Earlier also, several methods have been developed to estimate the availability of water. Using conventional water balance equation reservoir inflow can be estimated. Deng et al.(2015) developed an analytical method (AM) which is based on synchronized minimization of error in predicting reservoir water level and variation in inflow. and compared the results with an ensemble Kalman filter (EnKF). Evensen (2003) proposed the EnKF a recursive filter which is based on state equations and observation equations. A case study done on Gaobazhou and Danjiangkou Reservoirs in China suggest that the results obtained from AM are better compared to EnKF under various conditions.. Bharali (2015) also proposed a method to determine reservoir capacity using residual mass curve technique. This technique is successfully implemented on Dibang Multipurpose Dam on Dibang River, Arunachal Pradesh.

Amnatsan et al. (2018) proposed an analogue method (VAM) for reservoir inflow prediction, it is able to capture the peak flows as rare extreme flows. This prediction is used for appropriate management of reservoir. The approach was applied to Sirikit Dam, Thailand. On this dam monthly inflow was determined using wavelet artificial neural network (WANN) model, and the weighted mean analogue method (WMAM). Forecast of Inflow forecast using (WANN) and (WMAM) provided only satisfactory results. The VAM showed better forecasting performance as it was able to predict the extreme inflow at Sirikit Dam. Fuska et al. (2017) proposed ASC Curve based on Python script which is able to estimate current storage in reservoir. The authors used ArcPy site package. Tao (2011) proposed method to determine local inflows using the water balance equation. This technique was used in Ontario Hydro's new Energy and Resources Information System. Takal et al. (2017) proposed a technique which can successfully estimate maximum potential head and reservoir capacity. Authors used mass curve technique at Gizab multipurpose dam, Afghanistan.

Alrayess et al.(2017) proposed a model which is able to estimate the desired reservoir capacity in order to meet the demand for a given twelve-monthly inflows using mass curve. Data for annual mean flow and monthly for duration 1962 -2013 were used to estimate reservoir capacity-yield-reliability relationships for Sami Soydam Sandalcık Dam, Turkey. Furnans and Austin (2008) authors have estimated reservoir capacity of Texas reservoir using hydrographic survey. Authors made analysis of more than 100 bathymetric surveys to estimate reservoir volume and surface area corresponding to various levels. These surveys were also used to estimate sedimentation in reservoir and reduction in capacity of reservoir. Salih et al (2012) authors have successfully made use of geographic information system to investigate basin parameters. 2D and 3D models were developed for three reservoirs to retrieve information regarding maximum level, storage capacity, surface area, circumference, and shape factor. These models can be successfully used to obtain basin and reservoir information. Yilmaz (2017) prepared a spreadsheet in MS Excel to determine reservoir capacity for Gordes Dam which provides irrigation and drinking water for the city of Manisa in Turkey. For optimal operation of reservoir a volume-risk graph and monthly water budget analysis was prepared for the full, half-full, empty initial conditions. The results were consistent with Gordes Project Planning Revision report. EL-Hattab (2014) author made use of bathymetric data to calculate the depth of channel. This study will help in deciding the volume of dredging and maintenance of the channel. Model used is having 5m grid size and is in built with fastest interpolation techniques. Now-a-days remote sensing has wide application in water resource engineering it is able to predict features of earth surface, capacity of reservoir with better accuracy. Rodrigues et al. (2010) authors have estimated storage capacity of small reservoir using remote sensing data. This technique for estimation of storage capacity for small reservoir was applied to Sao Francisco, Limpopo, Bandama and Volta river basins. Khattab et al. (2017) researchers have used digital elevation model and prepared bathymetric map for Mosul Lake. To obtain hydro morphology of lakes and reservoirs bathymetric maps find applicability.

3 STUDY AREA

3.1 Description of Satluj River Basin

Mansarowar lake situated in Tibet at an elevation of 4572 m is the point of origination for Satluj river. The river extends in north direction from 30° N to 33° N latitudes and in east direction from 76°E to 83°E longitudes. River flows in South-West direction having approximate length of 1,448 km enters India from Shipkila situated in Himachal Pradesh. From Himachal Pradesh river flow south -westerly direction and reaches into plain region of Punjab where India's highest concrete dam is located. It is straight concrete gravity dam having height 225.55m (740 ft) above the deepest foundation level. Bhakra dam height above river bed is 167.64 m (550ft). The reservoir generated by Bhakra dam is having 168.35 sq km of area and gross storage capacity of 9621 million cum. Bhakra dam live storage capacity is 7191 million cum. Total catchment area of this reservoir upstream of Bhakra dam is 56,980 km^2. The reservoir formed by the Bhakra Dam is Govindsagar ,having length 96.56 km. Figure 3.1 indicates the location and DEM of Satluj River Basin. The reservoir can be depleted upto dead storage level El. 1462 (445.62 m MSL) to fulfil the demand of irrigation and power generation.

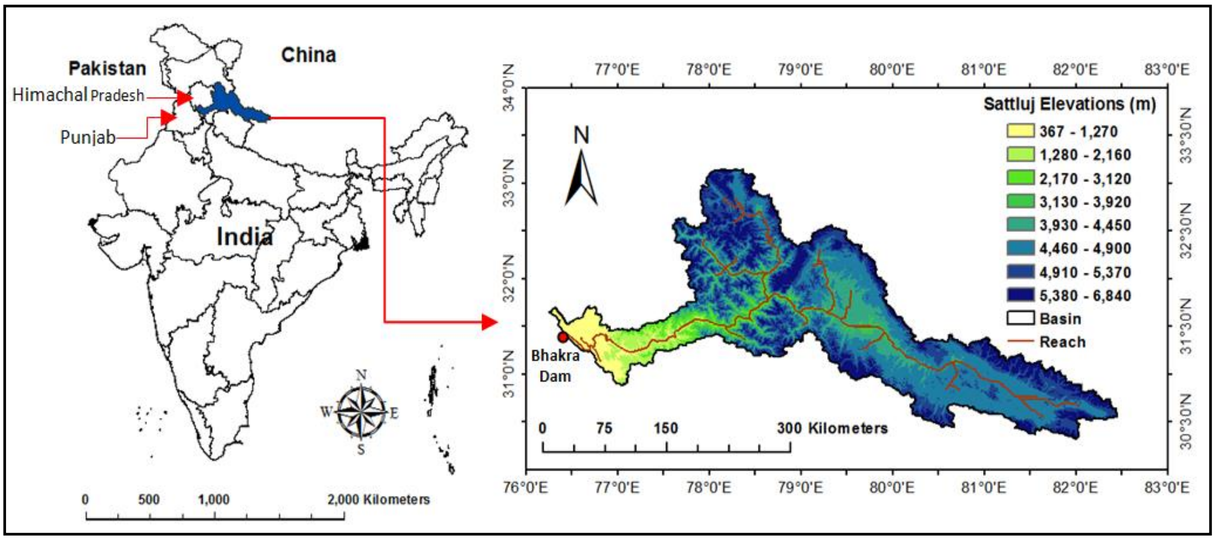


Figure 3.1 Showing location and DEM of Satluj River Basin

Bhakra dam can be filled maximum upto reservoir level of El. 1690 (515.11 m MSL) and it can be depleted upto dead storage level of El. 1462 (445.62 m MSL). Reservoir is able to store entire surplus flow of an average year with an available capacity of 6 million acre-feet. Bhakra dam is having sufficient capacity to meet the requirement of silting which is expected during the life of reservoir. Figure 3.2 and Figure 3.3 shows the location of various dams, canals and links.

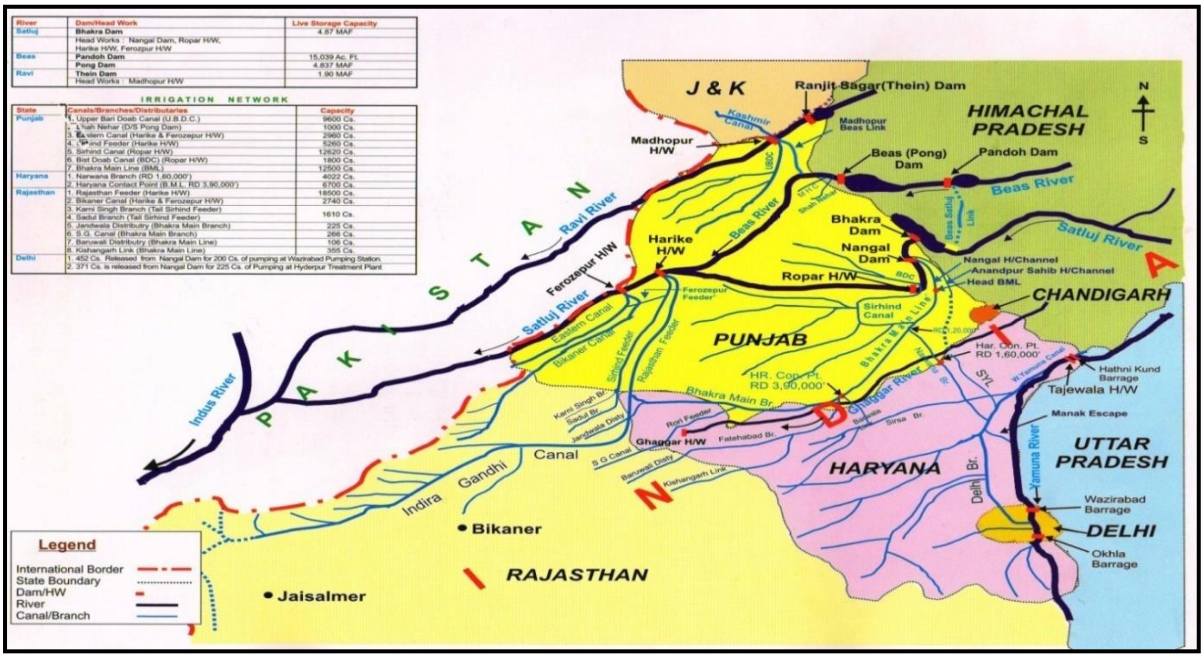


Figure 3.2 Location of Dams, headworks ,canals, rivers- Satluj, Beas and Ravi

The basin is characterized by complex hydro meteorological conditions and it is difficult to model them accurately. Large variations in the climatic conditions is experienced by the basin. Some parts of upper reaches of Satluj Basin ranges are always under snow where as sub-tropical climate is observed in the sub-mountainous areas at the foothills of the Satluj river valley.

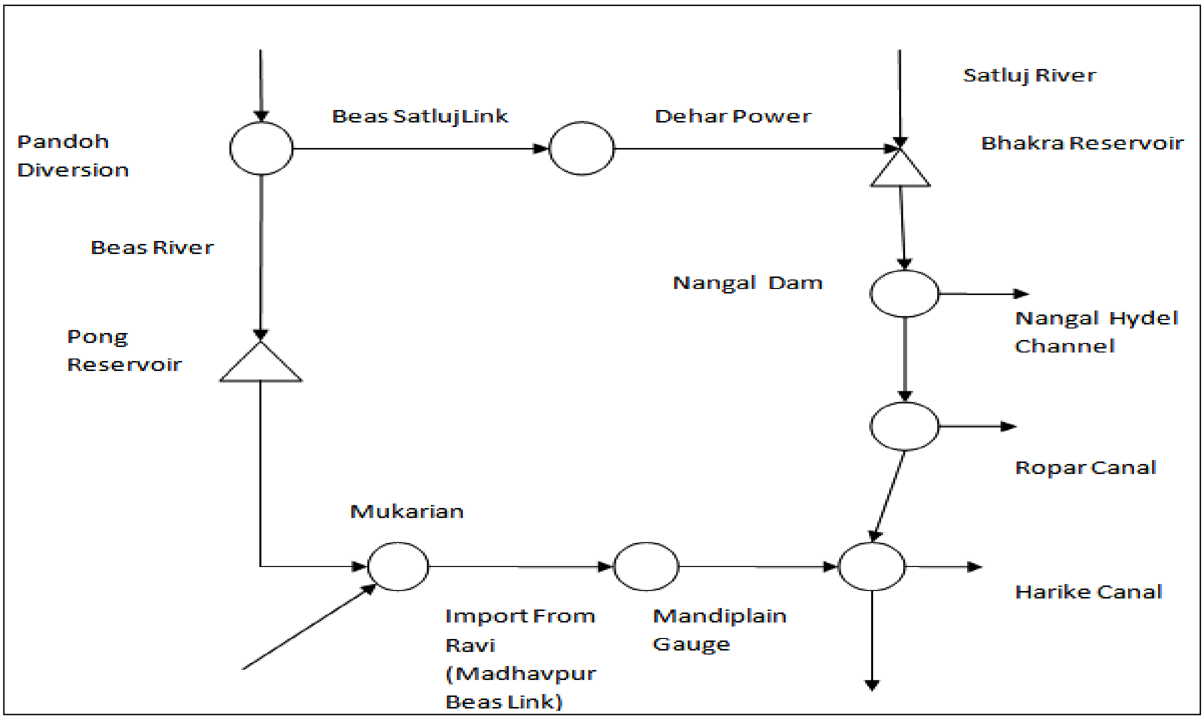


Figure 3.3 Schematic diagram showing Dam Canals and links

3.2 Spillway and Galleries

Below the top of the dam a 79.25 m long overflow spillway has been provided to pass the flood water. The discharge of the spillway is controlled by four 15.24 m long and 14.48 m high radial gates. Apart from the spillway sixteen river outlets of size 2.64 m X 2.64 m each, arranged in two tiers of eight outlets. Outlets are located in the spillway central section of the dam to release additional water from the reservoir to meet irrigation requirements. The flood gates and the river outlets can release 8212 cumecs of flood water. At the top of the dam 9.14 m wide road is provided and inside the dam galleries are provided for drainage and inspection of the dam. Length of galleries provided inside dam is 5 km.

Bhakra Dam Reservoir Table 3.1shows details of area in thousand acres and capacity of dam in million acres feet for various elevation of the dam. A software has been developed in this research which is able to calculate the reservoir level and the volume of storage available in the reservoir for given inflow and release. This code updates the status of reservoir at any given time. The elevation verses storage and area curves have been plotted and are shown in Figure

3.4 and Figure 3.5, respectively.

Table 3.1Bhakra dam elevation verses area and storage capacity data

Elevation in feet	**Area in thousand acres**	**Capacity in million acre feet**	**Elevation in feet**	**Area in thousand acres**	**Capacity in million acre feet**
1150	0	0	1460	14.5	1.94
1180	0.21	0.002	1480	15	2.255
1200	0.65	0.011	1500	17.66	2.53
1220	1.5	0.033	1520	19.35	2.95
1240	2.35	0.073	1540	21.35	3.36
1260	3.25	0.123	1560	23.35	3.8
1280	4.43	0.203	1580	25.5	4.265
1300	5.8	0.305	1600	28.15	4.83
1320	7.18	0.435	1620	30.3	5.41
1340	8.25	0.585	1640	34.06	6.05
1360	9.33	0.755	1660	37.05	6.78
1380	10.3	0.95	1680	40.15	7.575
1400	11.25	1.17	1685	41	7.8
1420	12.18	1.4	1690	41.68	8
1440	13.35	1.665	1700	43.4	8.4

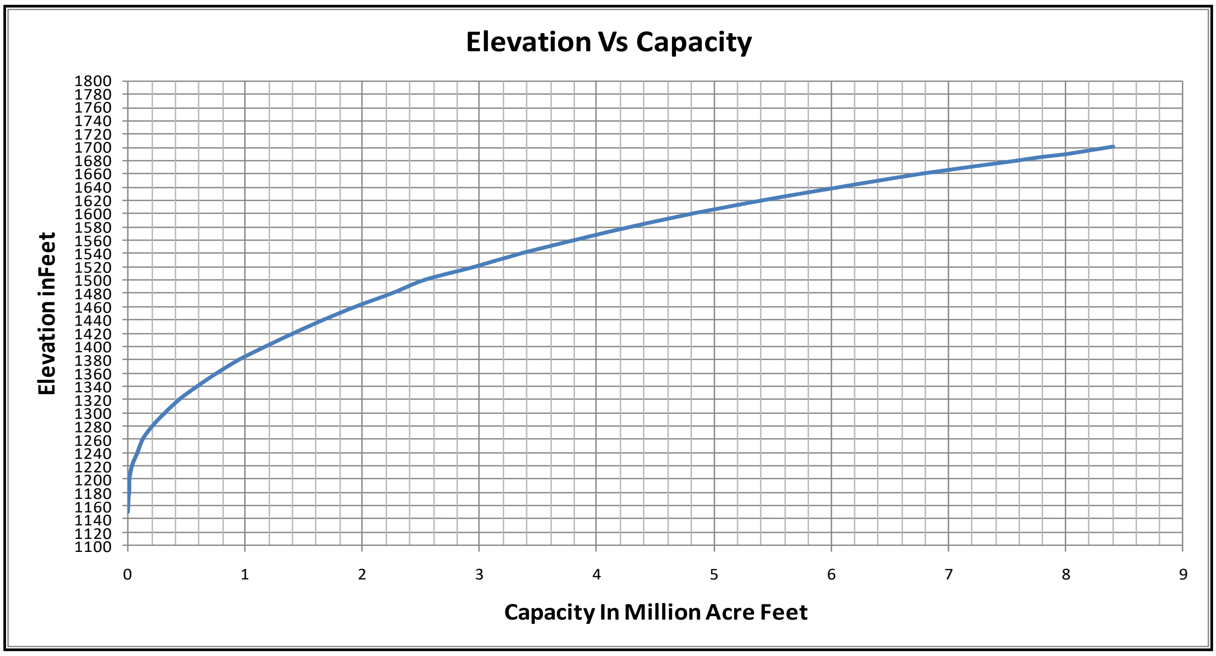


Figure 3.4 Curve Showing Elevation verses Capacity

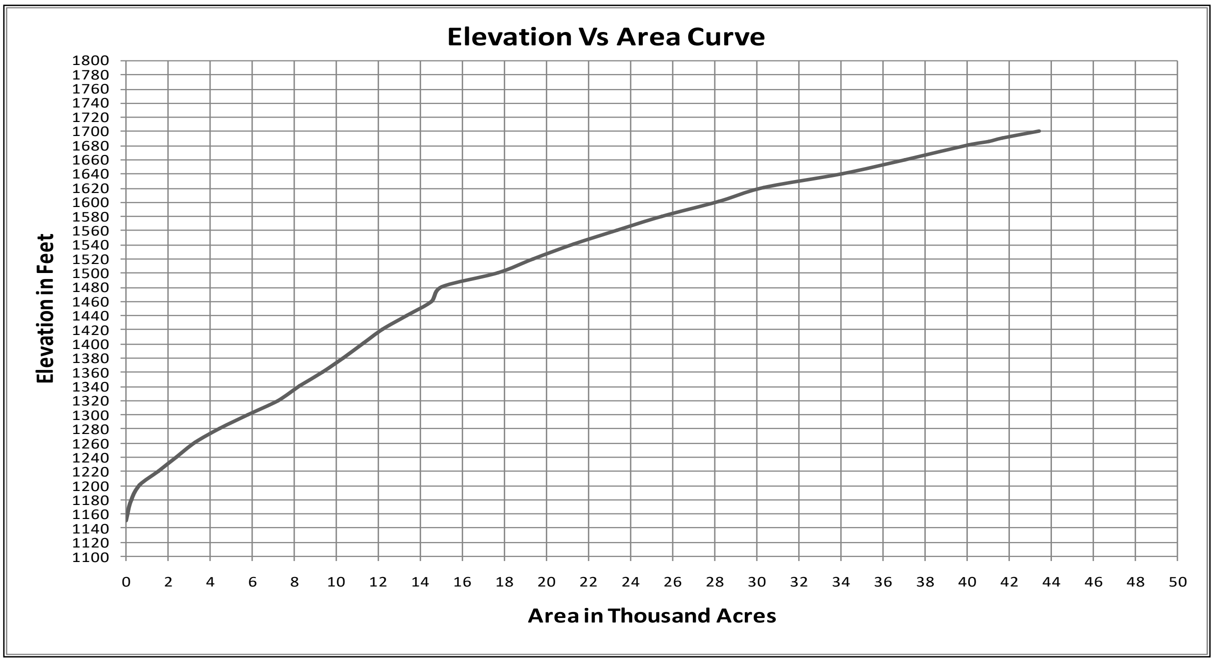


Figure 3.5 Curve Showing Elevation verses Area

3.2.1 Nangal Dam and Nangal Hydel Channel

On river Satluj Bhakra dam is located and 13 Km downstream Nangal dam is located. Nangal dam height is 29 m and comprising of 26 bays of 9.14 m length each. It can pass 9910 cumecs of flood discharge. Dam diverts 12,500 cusecs of water to Nangal Hydel Channel and 12,500 cusecs to Anandpur Sahib Hydel Channel to meet the requirements of irrigation and power generation. Nangal dam acts as a balancing reservoir and store water released from Bhakra dam and meets the requirement of Nangal Hydel Channel and Anandpur Sahib Hydel Channel. Length of Nangal Hydel Channel is 61.06 km, takes off from the left bank of Satluj river from Nangal Dam. Ganguwal and Kotla power generating units are located on Nangal Hydel Channel after power generation, water is released for irrigation purpose.

3.2.2 Beas Satluj link

Beas Satluj link connects Beas river with Satluj river. Pandoh is a diversion dam built on Beas river21 Km upstream of Mandi in Himanchal Pradesh. It is zoned earth-cum-rock fill dam of 76.20 m height. It has 5 bays having radial gates to regulate the flow of water. The Beas water from Pandoh dam is diverted to Satluj river through tunnel having diameter 7.62 m and length 13.1 Km. This concrete lined tunnel goes up to Baggi and can carry 254.85 cumecs of discharge. The balancing reservoir from Baggi to Sundernagar Beas water is taken in an 11.8 Km concrete lined open channel. Discharge capacity of Sundernagar Hydel Channel is 240.7 cumecs. The channel outfall into a balancing reservoir having storage capacity of 370 hectare meters. The balancing reservoir takes care of the supply required to meet the actual load at Dehar power plant. The length of the reservoir is 2130 m and width is 449.88 m. The water from the balancing reservoir is again passed through Sundernagar Satluj tunnel, which is 8.53 m in diameter and 12.35 Km long. The concrete lined tunnel begins from Sundernagar Balancing Reservoir and releases its water into Surge Shaft from where 3 penstock carries water to Dehar power plant. The tunnel can carry 403.53 cumecs of water. The Surge Shaft of 22.86 m diameter and 125 m height has been provided to take care of the surges in the penstock, in the event of sudden fall in the power demand or a complete shutdown of the generating units. On right bank of river Satluj upstream of Bhakra dam Dehar power plant is located. This is a power project where water is falling from a height of 320 m and generating power in the process. Dehar power plant is having six generating units each having 165 MW capacity. The water released from Dehar is utilised to augment the power potential of Bhakra.

Table 3.2 Characteristics of Bhakra Nangal Project

Dam Type	Straight Concrete Gravity Dam
Height of dam above deepest foundation	225.55 m (740 ft)
Height of dam above river bed	167.64 m (550 ft)
Length at top of the dam	518.16 m
Width at top of the dam	9.14m (30ft)
Length at bottom of the dam	99.06 m (325ft)
Base width of dam	190.5m (625 ft)
Catchment Area upstream of dam	56,980 sq km
Maximum Reservoir Elevation	1680 ft
Spillway crest level	El. 1645.211 ft
Dead storage level of dam	1462 ft
Gross reservoir capacity at El. 1685 ft.	9621 million cum.
Live storage capacity at El. 1685 ft.	7191 million cum.
No. of Penstocks	10

3.3 Rainfall In Satluj River Basin

Figure 3.6 bar chart indicates the amount of rainfall in this region received from 1983 to 2018. The average annual rainfall of this region for duration 1983 to 2018 is 1120 mm. From June to September every year maximum rainfall. Average rainfall received during this duration is 810 mm. The average rainfall received in remaining part of the year is 310 mm. Figure 3.6 indicates a decreasing trend in rainfall for duration 1983 to 2018. Rainfall trend from June to September is decreasing at the rate of 2.77 mm/year whereas for remaining part of the year also the rainfall trend is decreasing at the rate of 2.57 mm/year. Decreasing trend of rainfall is observed in Satluj river basin.

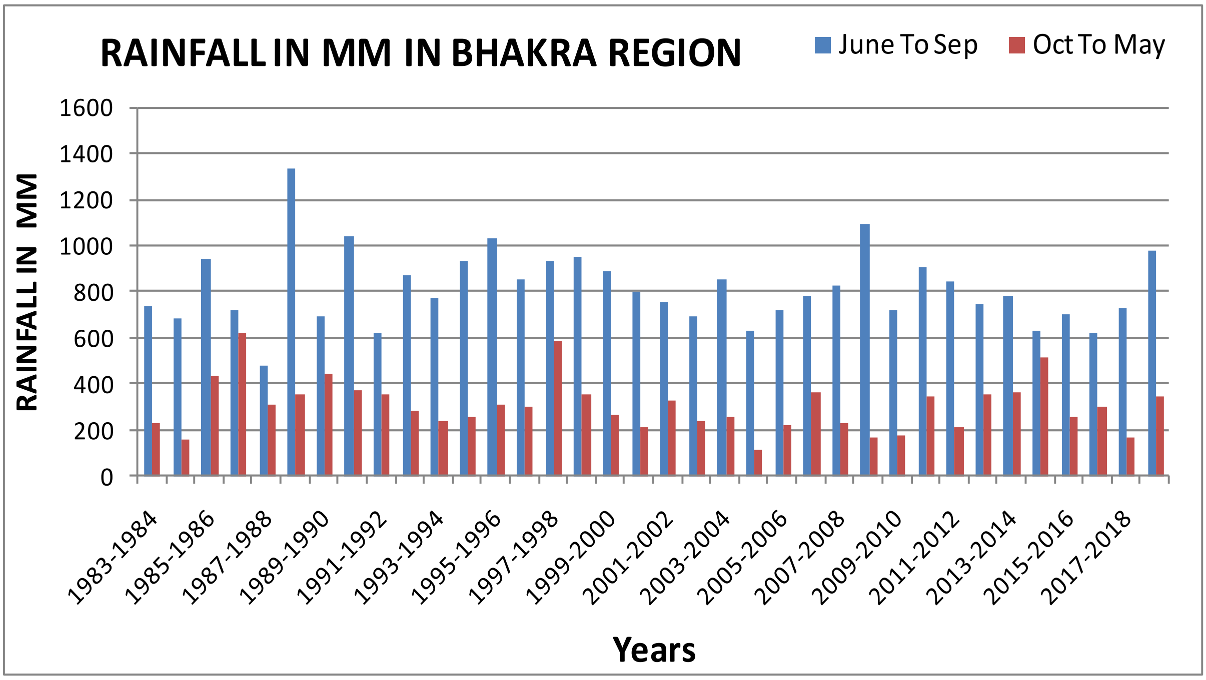


Figure 3.6 Bar chart showing rainfall from duration 1983 - 2018

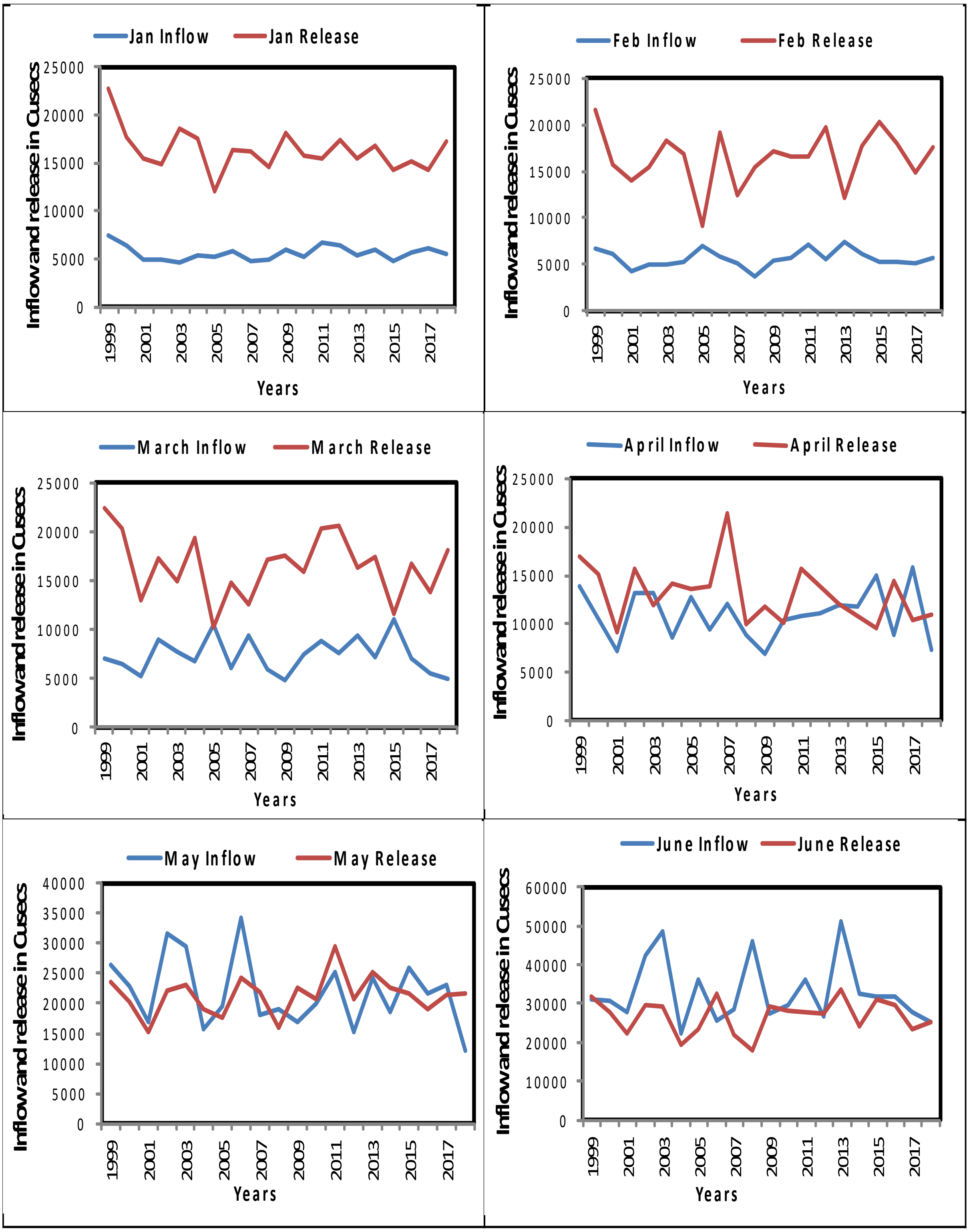


Figure 3.7 Graph showing inflow and release from January -May for duration 1999 - 2018 at Bhakra

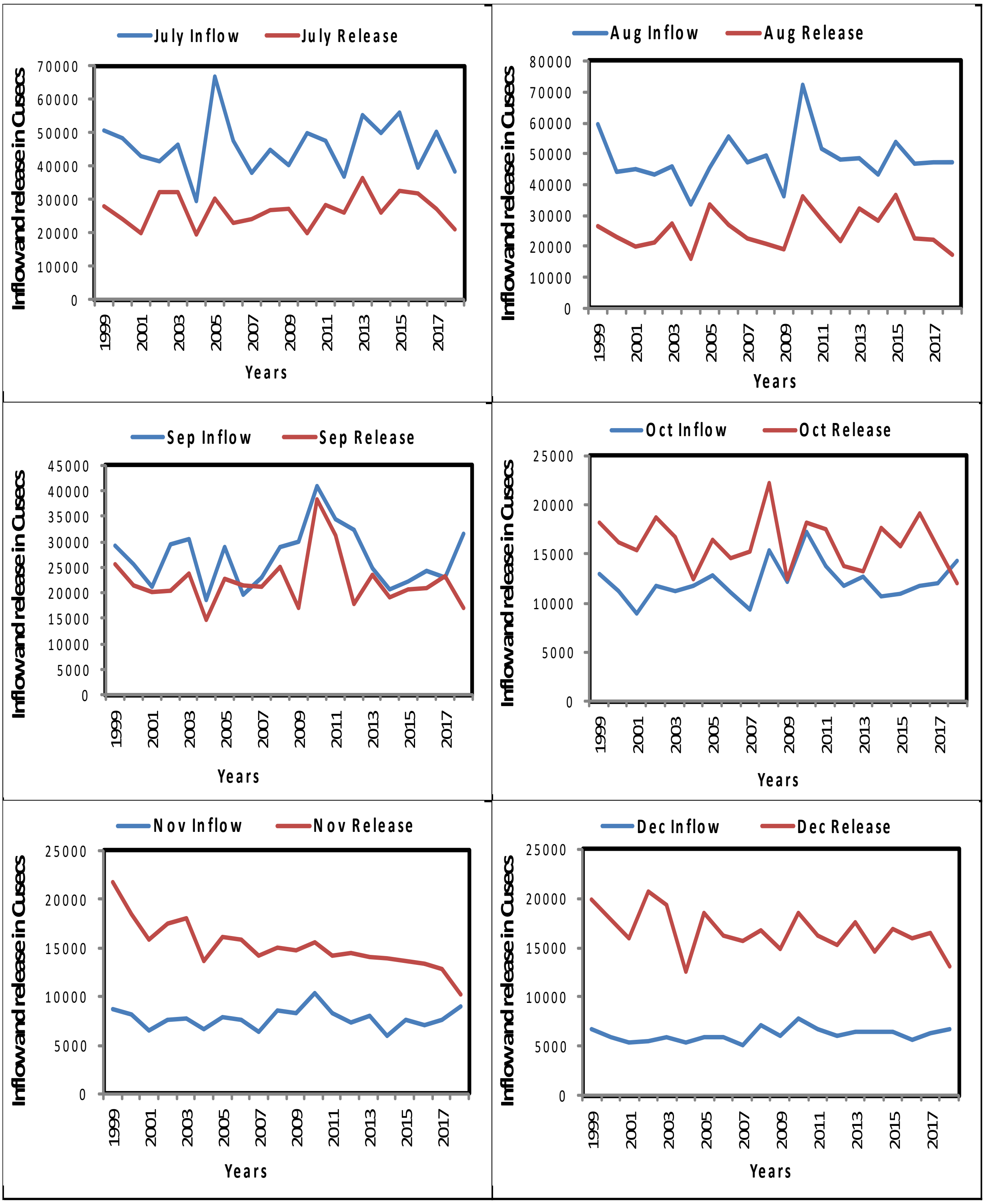


Figure 3.8 Graph showing inflow and release from June-December for duration 1999 - 2018at Bhakra

3.4 Monthly Inflow and Release for duration 1999 -2018

Monthly inflow and release from Bhakra dam for duration 1999-2018 is reflected in Table 3.3. It is evident from the Table 3.3 that inflow varies considerably in various months whereas the release depends upon the demand, available storage and inflow. It is observed from Table 3.3 that the average inflow during month of January for past 20 years is constant showing marginal decreasing trend, whereas release in this duration is higher and average release is 16268 cusecs as per demand.

Table 3.3 Average monthly Inflow and Release for Duration 1999-2018

Month	Average Inflow in Cusecs	Average Release in Cusecs
Jan	5563.655	16268.748
Feb	5622.869	16462.855
March	7412.779	16520.515
April	10994.627	13083.947
May	21847.358	21337.329
June	32920.228	26791.300
July	45904.458	26695.740
August	48152.744	25014.700
September	27006.712	22218.412
October	12181.473	16075.484
November	7717.747	15153.195
December	6218.531	16667.690

The trend of inflow in month of February, March and April shows increasing behaviour but not significant in past 20 years. In January, February and March month the average inflow is considerably low compared to monthly release in respective month. In April month the average inflow increased considerably having a value of 10994 cusecs, and release in April month is 13083 cusecs. It is observed the trend in May and June is decreasing but the inflow is more than the discharge. In July, August and September the trend of inflow is positive and it is more than the release in these month. For October, November and December month the trend is positive and the inflow reduced considerably compared to release in these respective month.

3.5 Maximum and minimum reservoir level for duration 1975-2019

Maximum and minimum yearly reservoir level in feet for duration 1975 -2019 is shown in Figure 3.9. The maximum reservoir level is restricted to El. 1680 ft and reservoir can be depleted upto dead storage level of El. 1462 ft. In order to protect downstream and mitigate flood the reservoir level in consultation with Chairman BBMB can be raised up to El. 1690 ft. Figure 3.9 indicates that the water level reaches to storage level El.1680 ft every year. Figure 3.9 it is observed every year no significant change in maximum or minimum levels from 1975 to 2019 except in few years.

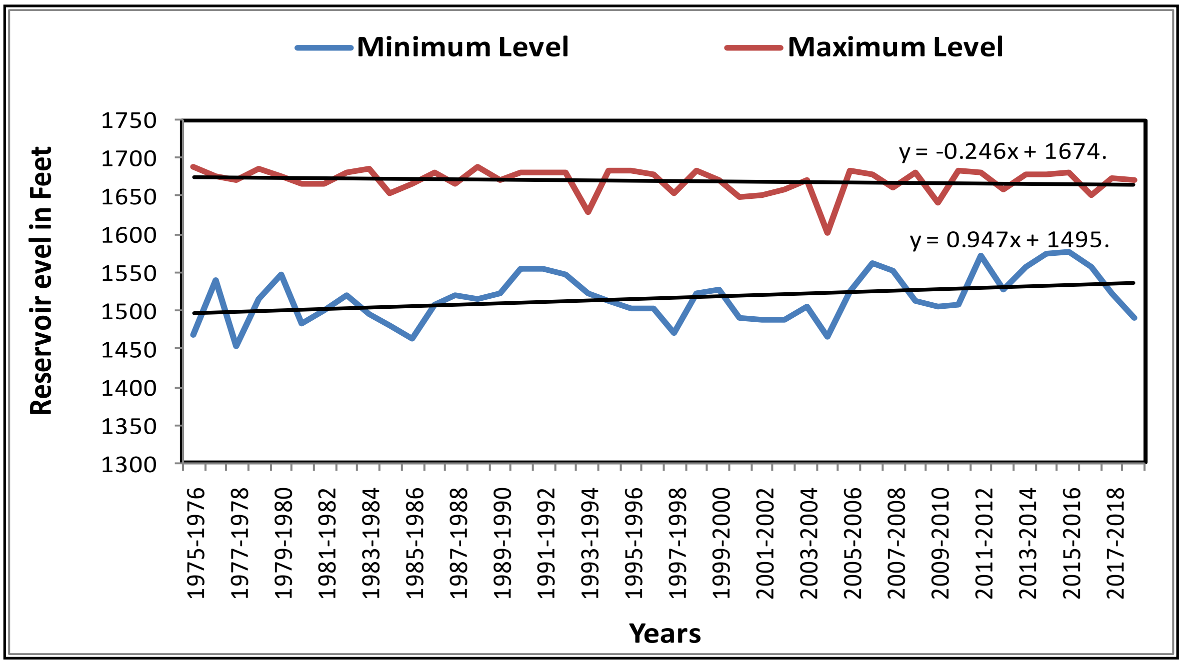


Figure 3.9 Reservoir yearly Minimum and Maximum level

4 Projections of Temperature due to Climate Change

4.1 Climate Change in Satluj Basin

Survival of living species greatly depends on water, which is an essential natural resource. Since inception of civilization, human beings have shown inclination to settle near rivers due to guaranteed availability of water. Ocean's temperature have substantial influence on the climate of a place. Due to global warming there is rise in earth's atmosphere and oceans temperature, thus the world is getting warmer. Due to rise in temperature the hydrology of a place changes. Preponderance of evidence suggests that the anthropogenic activities are responsible for rise in thermometer readings all around the world. The special report of the Intergovernmental panel on climate change (IPCC Special report,2018) indicates an increase in global temperature of 1.5˚C between 2030 and 2052 compared to preindustrial temperature. This projected increase is largely due to anthropogenic activities responsible for generation of green house gases.

Water resource system are facing an additional stress due to climate change. Global warming due to rapid urbanization and high rate of population growth is responsible for climate change. Himalayan region is most sensitive to global warming and Satluj river on which Bhakra dam is located originates from this region. Global warming is responsible for changes in temperature, precipitation pattern, and variation in stream flow. If stream flow variation occurs, it causes serious implication for water management. Bhakra dam is a large reservoir which controls the flow to several irrigation system and any changes in magnitude or timing of inflow will generate intricacies in optimal operation of reservoir. Reservoirs are designed considering stationarity of hydro meteorological data, but due to changing climatic conditions the assumption of stationarity of hydro- meteorological data is not valid. Design of reservoir will be more reliable if potential impacts of climate change on hydro-meteorological variables are considered. To exploit the potential of the Satluj river it is mandatory to estimate the inflow of river taking into consideration climate change in order to decide the releases in advance.

To meet the water demand under changing climatic scenario requires careful planning. Statistical analysis of historical hydro–meteorological data provides information regarding trend of precipitation and temperature. Historical data used for study in this research to estimate climate change is retrieved from Climate Research Unit (CRU). CRU data for maximum temperature, minimum temperature and precipitation for duration 1900 -2013 for Satluj river basin extending from latitudes 30˚N and 33˚N and longitudes 76˚E and 83˚E. The whole region is divided into 56 nodes and the coordinates of these nodes are reflected in Table 4.1. CRU data is used to evaluate the response of the basin to global warming through investigation of temperature trend. In the present research, the trend of annual surface air temperature and precipitation of 56 stations in the river basin using Mann-Kendall non-parametric test is estimated. The statistical inferences derived from this data will reflect the pattern of changes in temperature and precipitation pattern over past 113 years. Precipitation and runoff are affected by increase in temperature. It is therefore important for effective operation of water resource to forecast stream flow considering climate change. Stream flow forecasting helps decision makers to determine the amount of release from reservoirs, and subsequently, improve the operational strategies.

4.2 Climatic Research Unit

Natural anthropogenic climate changes are researched by Climatic Research Unit (CRU). The CRU is a leading institute concerned with the study of environment. It is a part of the School of Environmental Sciences at the University of East Anglia in Norwich.

The aim of this institute is to improve scientific understanding in below mentioned areas:

- Study of historical data and its impact
- The path and reasons of climate change
- Probable future forecast

Historical dataset regarding temperature and precipitation, namely CRU3.21 spanning 1900 to 1913 was downloaded from http://badc.nerc.ac.uk/browse/badc/cru. The CRU Time Series data is available in ASCII formats. The ASCII data is presented at a resolution of 0.5˚ x 0.5˚. The data is having a grid of 360 divisions along latitude x 720 divisions along longitude. For each time step it has 720 columns and 360 rows. The first row of grid provides data for 89.75 South and first column provides information for 179.75 West. For each time step the data is available for the entire globe. So, first 360 rows provide data for Jan 1900, next 360 rows provide the data for Feb 1900, next 360 rows shows data for March 1900 and so on. To extract CRU TS NetCDF data any NetCDF enabled software can be used. Code used in this study is attached at Annexure-2. The geographical limits of the Satluj basin upto Bhakra dam lies between latitudes 30˚N and 33˚N and longitudes 76˚E and 83˚E. The data is retrieved at 0.5˚Latitude x 1˚ Longitude. The whole region is divided into 56 nodes. Computed coordinates of 56 nodes in the Satluj river basin presented in Table 4.1.The precipitation, max temperatures and minimum temperature data at each node is obtained in ASCII format for duration 1901 to 2013. An R script has been developed for extracting the data using netcdf package in R (Annexure-1). Study of annual variation of precipitation in mm and variation of temperature of each month of duration 1901 -2013 is done using MS Excel add-in program called XLSTAT (Karmeshu 2012; Tesemma2009) developed by ADDINSOFT which was used to analyse trends.

4.3 Trend Analysis

Trend analysis is generally conducted on a sequence of observations over a period of time for random variables such as temperature and precipitation to evaluate decrease or increase of value in statistical terms (Helsel and Hirsch 1992). In terms of statistics, trend represents probability distribution of observations over the period of time and also describe the changes they have undergone in the central value of the distribution such as mean or median. Trend analysis results are effective in prediction with longer periods of data and helps to quantify the rate of change. The trend analysis does not give much insight into the cause/factor responsible for trend. The results obtained from trend analysis are more reliable when the period of record is significantly long.

4.3.1 Parametric test

Two test are generally used to determine trend, but it depends upon the distribution of data. A test is said to be parametric if the variability evaluated by the test can be specified in statistical terms. In parametric testing, a major assumption is that the distribution of data is normal. (Helsel and Hirsch 1992) recommended that data distribution has to be transformed to make it normal and analysis can be restricted. Parametric test are more reliable than the non parametric test as data distribution is not normal.

4.3.2 Non Parametric Mann- Kendall test

The most widely used nonparametric test for the analysis of trend is the Mann- Kendall test (Mann 1945; Kendall 1975; Gilbert 1987). This test is used to determine trend in hydro metrological variables due to climate change when the data is not normally distributed. The null hypothesis H0 for these data is that there is no trend in the series and three alternative hypotheses are there is a negative trend, null and positive trend.

$$\boldsymbol{S} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{n-1}} \sum_{\boldsymbol{j=i+1}}^{\boldsymbol{n}} \boldsymbol{Sgn}(\boldsymbol{yj} - \boldsymbol{yi}) \qquad 4.1$$

4.4

$$Var(S) = \frac{\mathrm{n}(\mathrm{n}-1)(2\mathrm{n}+1)}{18} \qquad 4.2$$

where n is the number of observations and yi(i=1…n) are the independent observations

$$\text{Zmk}=\begin{bmatrix} \frac{S-1}{\sqrt{Var(S)}} & if & S > 0 \\ \frac{S+1}{\sqrt{Var(S)}} & if & S < 0 \\ 0 & if & S = 0 \end{bmatrix} \qquad 4.3$$

The Mann-Kendall tests are based on the calculation of Kendall's tau measure of association between two samples. The S statistic is the sum of all the counting. A positive value of S indicates an increasing, whereas a negative value indicates a decreasing trend. Mann - Kendall test is used to determine trend where statistical parameters p-value and slope are determined. Lower the value of p stronger is the trend (Sen,1968). Sen's slope method projects the rate of change in the variable during the analysis period and then using the median of these slopes estimates an overall slope. A positive slope indicates an increase in hydro meteorological parameters. Negative value indicates decrease in hydro meteorological parameter.

Table 4.1 List of Latitude and Longitude and coordinates used in Satluj Basin

Node No	Latitude	Coordinate	longitude	Coordinate	Node No	Latitude	Coordinate	longitude	Coordinate
1	30˚ N	240	76˚ E	512	29		243	80˚ E	520
2		240	77˚ E	514	30		243	81˚ E	522
3		240	78˚ E	516	31		243	82˚ E	524
4		240	79˚ E	518	32		243	83˚ E	526
5		240	80˚ E	520	33	32˚ N	244	76˚ E	512
6		240	81˚ E	522	34		244	77˚ E	514
7		240	82˚ E	524	35		244	78˚ E	516
8		240	83˚ E	526	36		244	79˚ E	518
9	30˚ 30' N	241	76˚ E	512	37		244	80˚ E	520
10		241	77˚ E	514	38		244	81˚ E	522
11		241	78˚ E	516	39		244	82˚ E	524
12		241	79˚ E	518	40		244	83˚ E	526
13		241	80˚ E	520	41	32˚ 30' N	245	76˚ E	512
14		241	81˚ E	522	42		245	77˚ E	514
15		241	82˚ E	524	43		245	78˚ E	516
16		241	83˚ E	526	44		245	79˚ E	518
17	31˚ N	242	76˚ E	512	45		245	80˚ E	520
18		242	77˚ E	514	46		245	81˚ E	522
19		242	78˚ E	516	47		245	82˚ E	524
20		242	79˚ E	518	48		245	83˚ E	526
21		242	80˚ E	520	49	33˚ N	246	76˚ E	512
22		242	81˚ E	522	50		246	77˚ E	514
23		242	82˚ E	524	51		246	78˚ E	516
24		242	83˚ E	526	52		246	79˚ E	518
25	31˚ N 30'	243	76˚ E	512	53		246	80˚ E	520
26		243	77˚ E	514	54		246	81˚ E	522
27		243	78˚ E	516	55		246	82˚ E	524
28		243	79˚ E	518	56		246	83˚ E	526

4.5 Precipitation Trend in Satluj Basin

Figure 4.1shows Sen's slope estimated for precipitation for 56 nodes and decreasing trend is reflected. Figure 4.2 shows annual Precipitation trend at node 26 for duration 1901 - 2013 having latitude 31.5˚ N and longitude 77 ˚E which is approximately 65 kilometre towards East of Bhakra. To estimate value of Sen's Slope auto correlation is done using the Hamed and Rao method. The p-value at this node is less than 0.01% indicating significant trend at node 26. The value of Sen's slope estimated for node 26 is -2.229, a strong negative trend indicating decrease in precipitation.

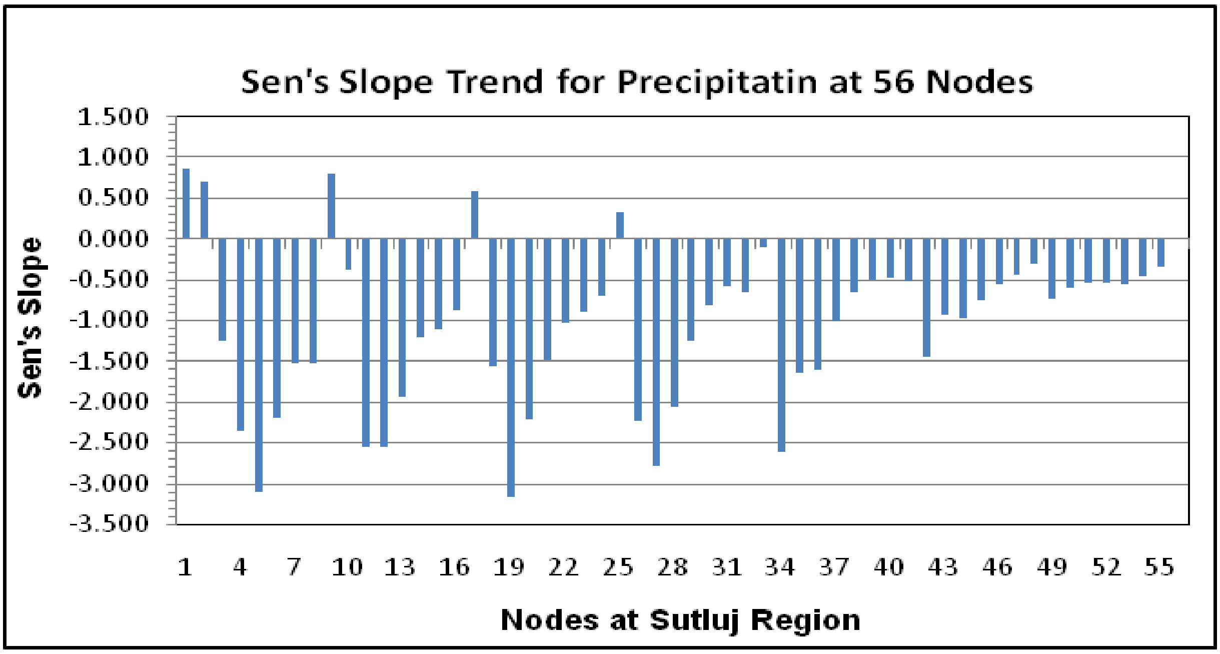


Figure 4.1Sen's Slope for Precipitation at 56 Nodes

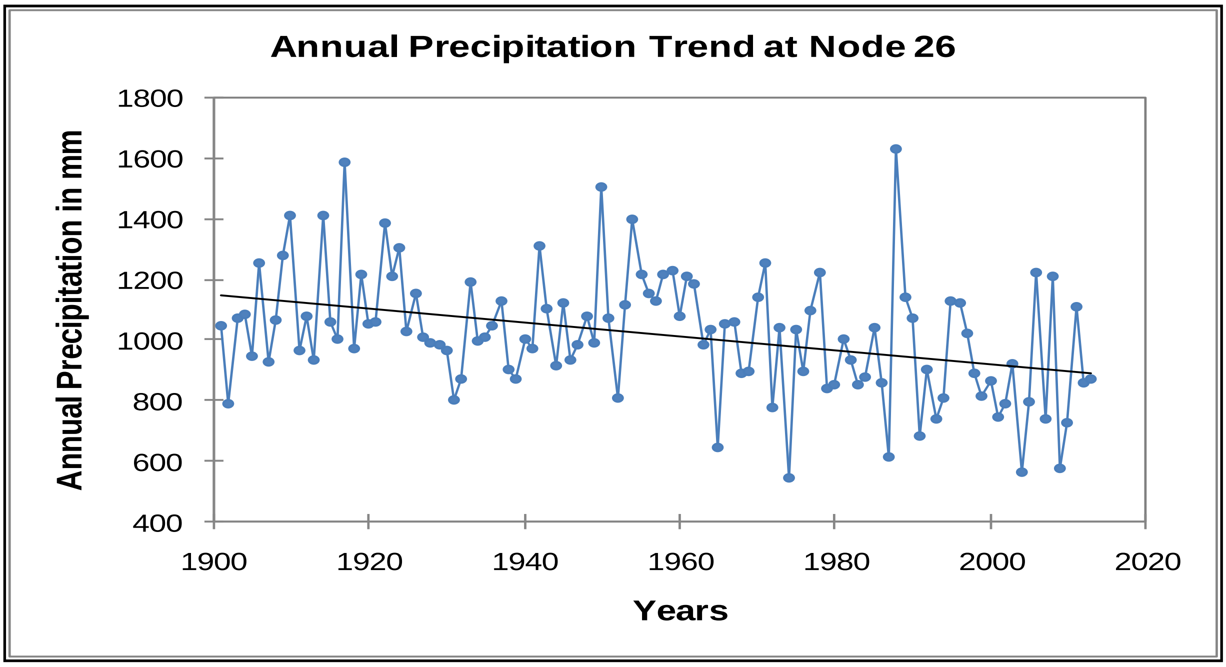


Figure 4.2 Trend of Annual Precipitation at Node 26 for Duration 1901 - 2013

4.6 Trends for Maximum Temperature

Mann-Kendall non-parametric test statistics is estimated for 56 nodes. From Figure 4.3 it is observed that Sen's Slope is +ve at 13 nodes, -ve at 26 nodes and exhibit no slope at 17 nodes in river basin. The p-value at 95% confidence at 13 stations indicate significant trend. At 90% confidence 16 stations in basin showed significant trend. Sen's Slope for maximum temperature is -0.013 a negative trend indicating decrease in maximum temperature at node 26 reflected through Figure 4.4

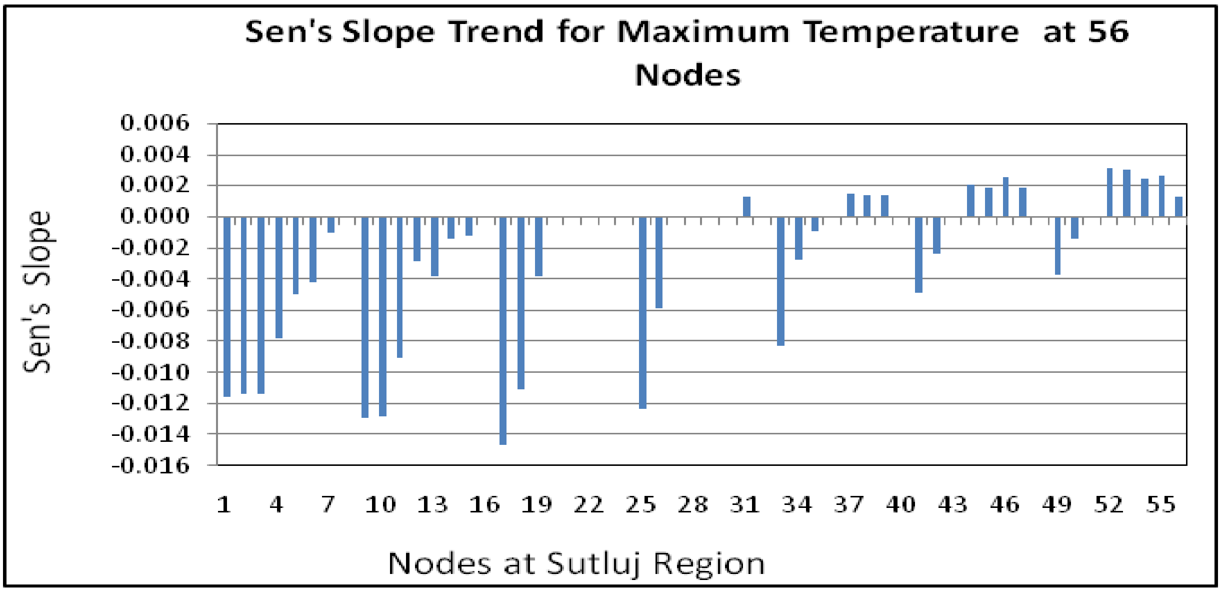


Figure 4.3 Sen's Slope for Maximum temperature at 56 Nodes

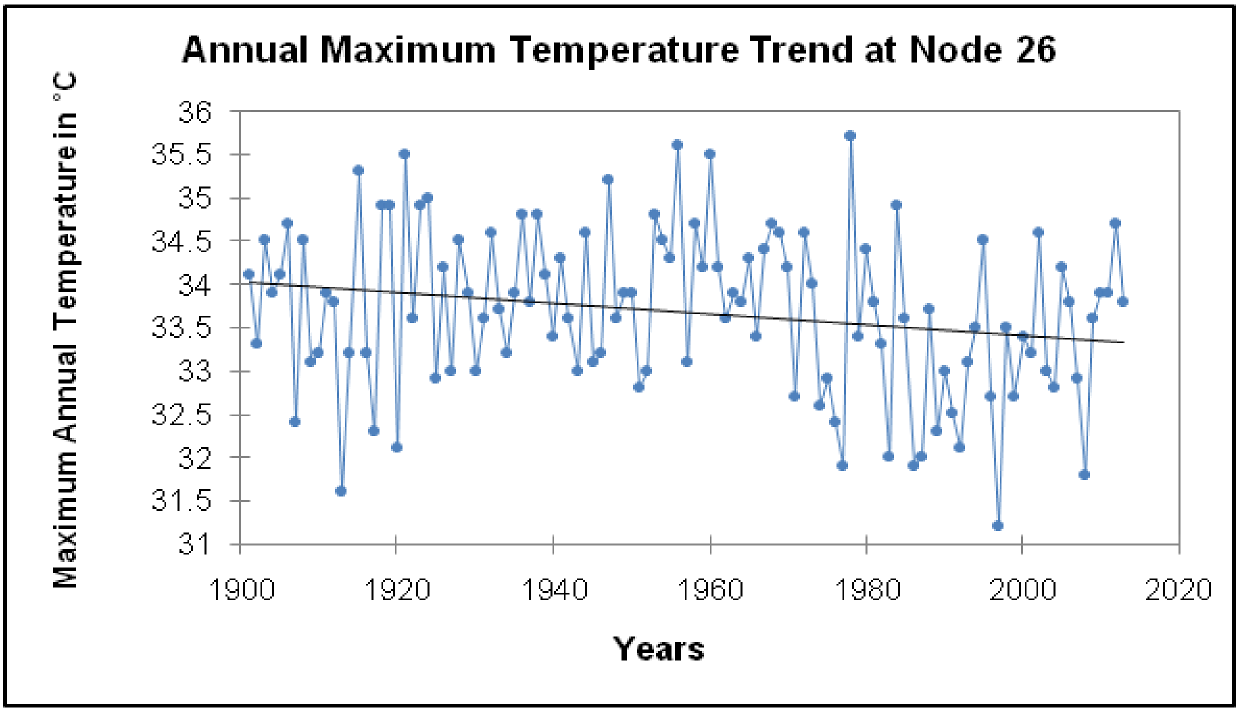


Figure 4.4 Maximum Annual Temperature Trend at node 26

4.7 Trends for Minimum Annual Temperature

The p-value at this node 26 is 76.86% which indicate no trend is observed at this node. The Sen's Slope at this node is zero, which implies that there is no change in minimum temperature for duration 1901- 2013. Figure 4.5 represent value of Sen's Slope at 56 nodes for minimum temperature which predicts increase in minimum temperature. Sen's Slope is +ve at 42 nodes, -ve at 9 nodes and exhibits no change at 5 nodes. At 26 stations, the p-value is less than 5% indicating a significant trend is shown in Figure 4.6.

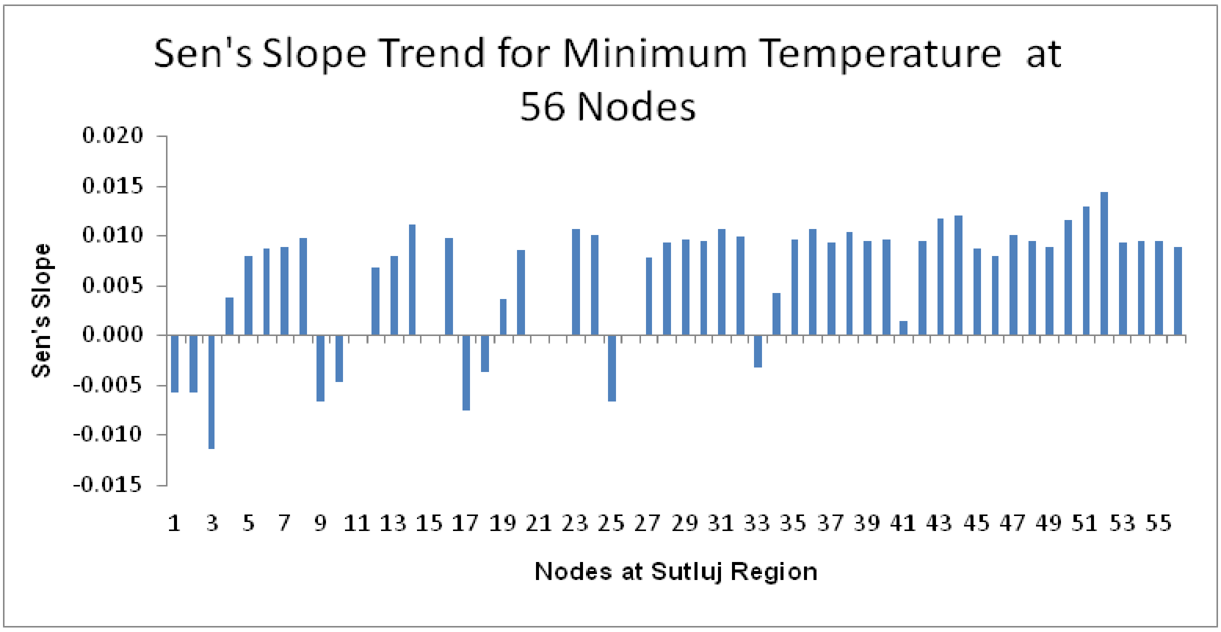


Figure 4.5 Sen's Slope for Minimum Temperature at 56 Nodes

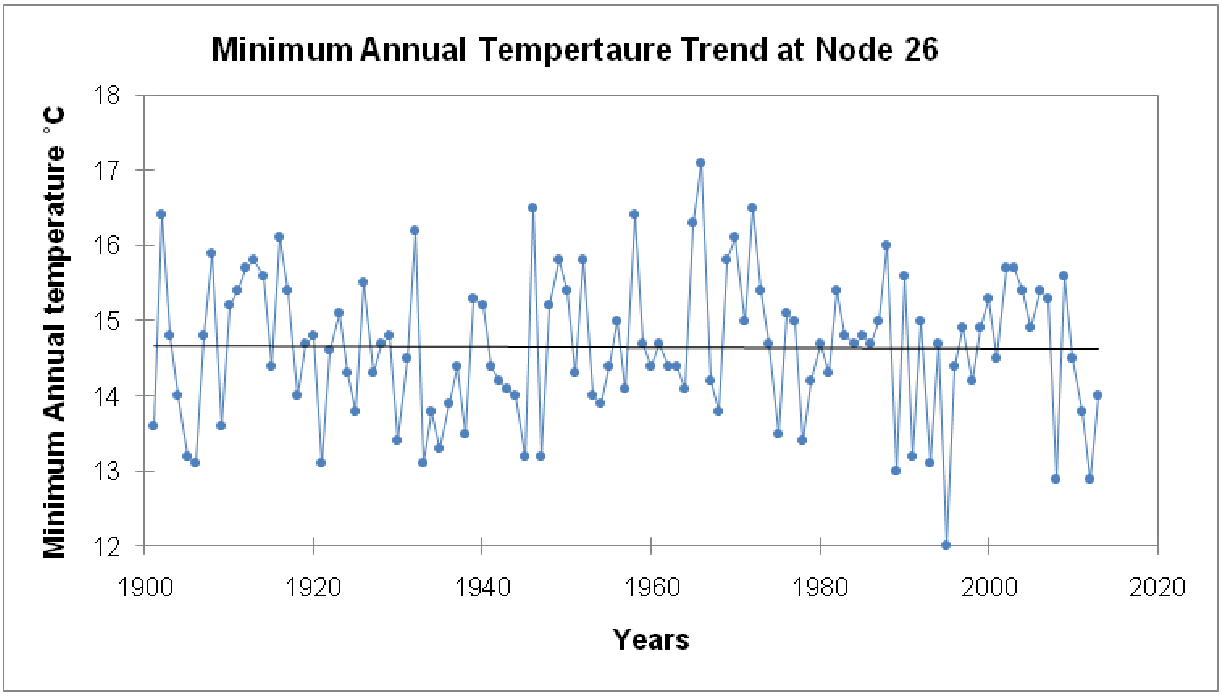


Figure 4.6 Minimum Annual Temperature Trend at Node 26

4.8 Results and Discussion

Statistical parameters p-value and Sen's slope for precipitation and temperature of Satluj river for the period 1901-2013 at 56 nodes is estimated and reflected in Table 4.2 **Error! Reference source not found.**using Mann-Kendall trend analysis. The p-value is an indicator of the trend. The lower the P value stronger is the trend. The Sen's slope method (Sen,1968) estimates the rate of change in the variable. If trend of data is positive, the slope indicates a rising trend, whereas negative slope indicates a falling trend and no slope exhibit no change in hydro-meteorological parameter. The statistical significance of the trend using Mann -Kendall test was evaluated at 5% significance level. Results of trend analysis for maximum temperature indicated negative value of Sen's slope at 26 nodes , positive value of Sen's slope at 13 nodes and a zero value of Sen's slope at 17 nodes. The maximum temperature does not exhibit any significant trend.

Table 4.2 Trends at 56 nodes in Satluj Basin for duration (1901 -2013)

Statistical Parameters	Statistics	Maximum Temperature Trend	Minimum Temperature Trend	Precipitation Trend
p-value at 5% significance	No of Nodes	13	28	47
p-value at 10% Significance	No of Nodes	16	39	49
Sen's Slope	+ve Slope	13 Nodes	42 Nodes	5 Nodes
	-ve Slope	26 Nodes	9 Nodes	51 Nodes
	No Slope	17 Nodes	5 Nodes	-

For annual minimum temperature forty two stations indicated an increasing trend, nine stations showed negative trend and five stations exhibited no trend. Mann -Kendall test was conducted at 5% significance level to determine change in annual precipitation. Sen's slope showed negative value at 51 nodes reflecting a decrease in precipitation in this region. Only 5 nodes exhibited positive values. Analysis of historical hydro meteorological data of 1901 to 2103 of this region regarding climate change trend provide critical evidence of impacts of anthropogenic activities. Expected warming in this region has created the need to consider the effect of climate change while formulating optimal operating strategies for a large dam such as Bhakra that control the flow to several irrigation systems in Northern India and is a major source of water for power generation. Inferences drawn are based on observed trends for maximum temperature, minimum temperature and precipitation at 56 nodes selected in Satluj basin. Overall, it can be concluded that the trends indicate increase in minimum temperature, decrease in precipitation and no significant change in maximum temperature.

Table 4.3 Precipitation Trend in Satluj Basin at 56 Nodes, 1901 -2013

Node no	Kendall's tau	S	Var(S)	p-value (Two-tailed)	Sen's slope	Risk to reject the null hypothesis H0	Node no	Kendall's ta	S	Var(S)	p-value (Two	alpha	Sen's slope	Risk to reject the null hypothesis H0
1	0.14096081	892	58664.69	0.000234	0.859	0.02%	29	-0.24702	-1563	113499.3	< 0.0001	0.05	-1.25114	0.0001
2	0.0897598	568	89482.69	0.058032	0.712	5.80%	30	-0.20038	-1268	129588.5	0.0004322	0.05	-0.81968	0.0004
3	-0.1513906	-958	132777.1	0.008631	-1.247	0.86%	31	-0.16104	-1019	162678.1	0.011604	0.05	-0.58095	0.0116
4	-0.2190612	-1386	243398.9	0.004996	-2.359	0.50%	32	-0.17846	-1129	44406.85	< 0.0001	0.05	-0.64706	0.0001
5	-0.2310367	-1462	217498.7	0.001732	-3.114	0.17%	33	-0.0098	-62	47089.98	0.7786313	0.05	-0.10598	0.7786
6	-0.2304046	-1458	209973.3	0.001475	-2.191	0.15%	34	-0.29475	-1865	171273.8	< 0.0001	0.05	-2.61534	0.0001
7	-0.2037139	-1289	130532.4	0.000364	-1.533	0.00%	35	-0.27781	-1758	162418.7	< 0.0001	0.05	-1.64127	0.0001
8	-0.1551833	-982	153763.5	0.012358	-1.533	1.24%	36	-0.27054	-1712	110015.5	< 0.0001	0.05	-1.59608	0.0001
9	0.11742394	743	93941.32	0.015482	0.811	1.55%	37	-0.25492	-1613	102471	< 0.0001	0.05	-1.01227	0.0001
10	-0.0464602	-294	95166.24	0.342221	-0.375	34.22%	38	-0.21839	-1382	48000.51	< 0.0001	0.05	-0.64516	0.0001
11	-0.2580798	-1633	205089.3	0.000314	-2.546	0.03%	39	-0.14349	-908	101000.2	0.0043179	0.05	-0.49354	0.0043
12	-0.2844501	-1800	230230.3	0.000177	-2.546	0.02%	40	-0.14602	-924	30560.17	< 0.0001	0.05	-0.47568	0.0001
13	-0.2436789	-1542	276496.4	0.003383	-1.938	0.34%	41	-0.0599	-379	-82.7342	1	0.05	-0.51091	1
14	-0.2166733	-1371	163905	0.000715	-1.214	0.07%	42	-0.20891	-1322	83156.59	< 0.0001	0.05	-1.44464	0.0001
15	-0.1970763	-1247	143441.7	0.001002	-1.1	0.10%	43	-0.19265	-1219	162417.7	0.002509	0.05	-0.93862	0.0025
16	-0.1749506	-1107	72467.32	< 0.0001	-0.869	0.01%	44	-0.2304	-1458	148741	0.0001582	0.05	-0.97347	0.0002
17	0.07080765	448	135699.7	0.224962	0.588	22.50%	45	-0.22443	-1420	110347.2	< 0.0001	0.05	-0.74964	0.0001
18	-0.1861568	-1178	81133.7	< 0.0001	-1.567	0.01%	46	-0.22141	-1401	60908	< 0.0001	0.05	-0.55337	0.0001
19	-0.3321745	-2102	213407.8	< 0.0001	-3.165	0.01%	47	-0.17179	-1087	140214.1	0.0037288	0.05	-0.43393	0.0037
20	-0.2977244	-1884	217473.3	< 0.0001	-2.22	0.01%	48	-0.14998	-949	107375.7	0.0038153	0.05	-0.3	0.0038
21	-0.2449431	-1550	209674.1	0.000717	-1.489	0.07%	49	-0.10383	-657	25978.55	< 0.0001	0.05	-0.72764	0.0001
22	-0.2010114	-1272	155306	0.001259	-1.034	0.13%	50	-0.11538	-730	184376.6	0.0895543	0.05	-0.59626	0.0896
23	-0.1893472	-1198	199764.4	0.007403	-0.881	0.74%	51	-0.13432	-850	162418.7	0.0351491	0.05	-0.52981	0.0351
24	-0.1751225	-1108	97138.38	0.000383	-0.69	0.04%	52	-0.13432	-850	162418.7	0.0351491	0.05	-0.52981	0.0351
25	0.03603034	228	100986	0.475027	0.328	47.50%	53	-0.20656	-1307	76886.1	< 0.0001	0.05	-0.56477	0.0001
26	-0.2452592	-1552	129823	< 0.0001	-2.229	0.01%	54	-0.21271	-1346	134340.3	0.0002429	0.05	-0.45683	0.0002
27	-0.3176861	-2010	162416.7	< 0.0001	-2.794	0.01%	55	-0.18808	-1190	123051.2	0.0007001	0.05	-0.34711	0.0007
28	-0.2876106	-1820	161181.8	< 0.0001	-2.063	0.01%	56	-0.07945	-469	213832.2	0.311506	0.05	0	0.3115
No of Nodes Sen's slope is +ve - 5					No of Nodes Sen's slope is -ve - 51					No of Nodes Sen's slope is Zero - 0				

Table 4.4 Maximum Temperature Trend in Satluj Basin at 56 Nodes, 1901 -2013

Node no	Kendall's tau	S	Var(S)	p-value (Two-tailed)	alpha	Sen's slope	Risk to reject the null hypothesis H0	Node no	Kendall's tau	S	Var(S)	p-value (Two-tailed)	alpha	Sen's slope	reject the null hypothesi
1	-0.221	-1377	144128.4	0.00029	0.05	-0.012	0.03%	29	0.001	8	227986.1	0.98830	0.05	0.00	98.83%
2	-0.212	-1325	125923.6	0.00019	0.05	-0.011	0.02%	30	0.016	97	255244.3	0.84930	0.05	0.000	84.93%
3	-0.212	-1325	125923.6	0.00019	0.05	-0.011	0.02%	31	0.061	378	230366	0.43218	0.05	0.001	43.22%
4	-0.146	-915	242216.8	0.06329	0.05	-0.008	6.33%	32	0.004	26	171111.6	0.95181	0.05	0.000	95.18%
5	-0.094	-586	162138.7	0.14627	0.05	-0.005	14.63%	33	-0.182	-1139	81037.09	< 0.0001	0.05	-0.008	0.01%
6	-0.094	-585	250635.9	0.24341	0.05	-0.004	24.34%	34	-0.078	-486	196464.2	0.27386	0.05	-0.003	27.39%
7	-0.040	-246	104793.6	0.44915	0.05	-0.001	44.92%	35	-0.057	-348	229023.7	0.46840	0.05	-9.950E-4	46.84%
8	-0.019	-119	140194.1	0.75265	0.05	0.000	75.26%	36	0.045	279	225973.8	0.55867	0.05	0.000	55.87%
9	-0.231	-1443	165464.8	0.00039	0.05	-0.013	0.04%	37	0.057	352	273654.2	0.50224	0.05	0.001	50.22%
10	-0.234	-1465	93060.57	< 0.0001	0.05	-0.013	0.01%	38	0.058	361	176812.8	0.39192	0.05	0.001	39.19%
11	-0.172	-1077	195712.4	0.01501	0.05	-0.009	1.50%	39	0.068	419	223814.7	0.37694	0.05	0.001	37.69%
12	-0.070	-435	162065	0.28100	0.05	-0.003	28.10%	40	0.045	277	220303.4	0.55651	0.05	0.000	55.65%
13	-0.064	-400	162212.7	0.32185	0.05	-0.004	32.18%	41	-0.127	-792	161991.3	0.04938	0.05	-0.005	4.94%
14	-0.053	-330	134696.7	0.37002	0.05	-0.001	37.00%	42	-0.084	-523	156404.1	0.18686	0.05	-0.002	18.69%
15	-0.051	-314	218412.7	0.50302	0.05	-0.001	50.30%	43	0.002	12	172062	0.97884	0.05	0.0	97.88%
16	0.019	116	132832.7	0.75236	0.05	0.000	75.24%	44	0.092	569	228088.6	0.23432	0.05	0.002	23.43%
17	-0.251	-1571	131614	< 0.0001	0.05	-0.015	0.01%	45	0.069	429	272049.5	0.41189	0.05	0.002	41.19%
18	-0.215	-1343	145257.4	0.00043	0.05	-0.011	0.04%	46	0.099	612	140905.1	0.10359	0.05	0.003	10.36%
19	-0.095	-592	205443.6	0.19227	0.05	-0.004	19.23%	47	0.076	471	152637.8	0.22898	0.05	0.002	22.90%
20	-0.012	-74	291216.8	0.89240	0.05	0.00	89.24%	48	0.050	308	152757.4	0.43217	0.05	0.0	43.22%
21	-0.033	-202	218747.7	0.66737	0.05	0.000	66.74%	49	-0.134	-828	217491	0.07618	0.05	-0.004	7.62%
22	-0.030	-187	108999.5	0.57318	0.05	0.000	57.32%	50	-0.064	-393	205902.7	0.38765	0.05	-0.001	38.77%
23	0.001	6	226375.2	0.99162	0.05	0.000	99.16%	51	0.032	197	166241.3	0.63072	0.05	0.0	63.07%
24	0.007	44	117374.5	0.90012	0.05	0.00	90.01%	52	0.122	755	14270.05	< 0.0001	0.05	0.003	0.01%
25	-0.222	-1391	135153	0.00016	0.05	-0.012	0.02%	53	0.105	652	162588.4	0.10642	0.05	0.003	10.64%
26	-0.143	-892	147599.6	0.02039	0.05	-0.006	2.04%	54	0.105	647	235461.1	0.18309	0.05	0.002	18.31%
27	-0.018	-110	339786.4	0.85167	0.05	0.00	85.17%	55	0.111	684	170274.2	0.09789	0.05	0.003	9.79%
28	0.027	166	130434.8	0.64777	0.05	0.00	64.78%	56	0.062	381	199138.3	0.39447	0.05	0.001	39.45%
No of Nodes Sen's slope is +ve 13						No of Nodes Sen's slope is -ve - 26					No of Nodes Sen's slope is Zero - 09				

Table 4.5 Minimum Temperature Trend in Satluj Basin at 56 Nodes, 1901 -2013

Node no	Kendall's tau	S	Var(S)	p-value (Two-tailed)	alpha	Sen's slope	Risk to reject the null hypothesis H0	Node no	Kendall's tau	S	Var(S)	p-value (Two-tailed)	alpha	Sen's slope	Risk to reject the null hypothesis H0
1	-0.145	-901	102947	0.0050	0.05	-0.006	0.50%	29	0.165	1032	324206.1	0.0702	0.05	0.01	7.02%
2	-0.145	-901	102947	0.0050	0.05	-0.006	0.50%	30	0.169	1056	384658.1	0.0889	0.05	0.009	8.89%
3	-0.212	-1325	125923.6	0.0002	0.05	-0.011	0.02%	31	0.184	1154	342616.9	0.0489	0.05	0.011	4.89%
4	0.072	449	118926.8	0.1939	0.05	0.004	19.39%	32	0.166	1036	292678.5	0.0557	0.05	0.01	5.57%
5	0.121	756	210078	0.0995	0.05	0.008	9.95%	33	-0.073	-453	90100.92	0.1321	0.05	-0.003	13.21%
6	0.149	934	383608.9	0.1320	0.05	0.009	13.20%	34	0.086	535	60174.54	0.0295	0.05	0.004	2.95%
7	0.175	1093	387212.1	0.0793	0.05	0.009	7.93%	35	0.171	1071	89547.91	0.0003	0.05	0.01	0.03%
8	0.194	1213	295983.2	0.0259	0.05	0.01	2.59%	36	0.174	1088	290234.4	0.0436	0.05	0.011	4.36%
9	-0.157	-976	147805	0.0112	0.05	-0.007	1.12%	37	0.144	899	366998.3	0.1383	0.05	0.009	13.83%
10	-0.116	-720	152975.1	0.0660	0.05	-0.005	6.60%	38	0.158	993	299954	0.0701	0.05	0.01	7.01%
11	-0.013	-80	80088.53	0.7801	0.05	0.000	78.01%	39	0.150	942	294818.1	0.0831	0.05	0.009	8.31%
12	0.128	803	90905.12	0.0078	0.05	0.007	0.78%	40	0.152	955	259872.1	0.0613	0.05	0.01	6.13%
13	0.098	616	162286.7	0.1269	0.05	0.008	12.69%	41	0.038	236	54169.94	0.3126	0.05	0.001	31.26%
14	0.192	1198	198219.8	0.0072	0.05	0.011	0.72%	42	0.149	934	74785.13	0.0006	0.05	0.009	0.06%
15	0.197	1234	300297.6	0.0244	0.05	0.0	2.44%	43	0.196	1225	129407.3	0.0007	0.05	0.012	0.07%
16	0.190	1185	302710.4	0.0314	0.05	0.01	3.14%	44	0.181	1134	325231	0.0470	0.05	0.012	4.70%
17	-0.181	-1127	203664.8	0.0126	0.05	-0.008	1.26%	45	0.127	796	281766.3	0.1342	0.05	0.009	13.42%
18	-0.081	-507	111432.1	0.1296	0.05	-0.004	12.96%	46	0.096	604	162291.3	0.1344	0.05	0.008	13.44%
19	0.080	499	61842.98	0.0452	0.05	0.004	4.52%	47	0.150	942	341870.1	0.1075	0.05	0.01	10.75%
20	0.152	954	164427.3	0.0188	0.05	0.009	1.88%	48	0.149	934	297758.5	0.0873	0.05	0.009	8.73%
21	0.029	178	168188.9	0.6660	0.05	0.000	66.60%	49	0.150	938	99236.77	0.0029	0.05	0.009	0.29%
22	0.065	394	206253.7	0.3868	0.05	0.000	38.68%	50	0.192	1203	124421.6	0.0007	0.05	0.012	0.07%
23	0.195	1222	355440.7	0.0406	0.05	0.011	4.06%	51	0.208	1302	133782.3	0.0004	0.05	0.013	0.04%
24	0.180	1127	279507.9	0.0332	0.05	0.01	3.32%	52	0.218	1364	281458.5	0.0102	0.05	0.014	1.02%
25	-0.157	-978	186227	0.0236	0.05	-0.007	2.36%	53	0.144	903	271800.6	0.0836	0.05	0.009	8.36%
26	0.014	90	91519.43	0.7686	0.05	0.000	76.86%	54	0.140	875	339988	0.1339	0.05	0.009	13.39%
27	0.146	911	72360.81	0.0007	0.05	0.008	0.07%	55	0.138	866	334292.2	0.1346	0.05	0.009	13.46%
28	0.161	1008	226104	0.0342	0.05	0.009	3.42%	56	0.137	859	399214	0.1745	0.05	0.009	17.45%
No of Nodes Sen's slope is +ve - 42						No of Nodes Sen's slope is -ve - 09						No of Nodes Sen's slope is Zero - 05			

4.9 Representative Concentration Pathways

The trajectories of greenhouse gas emissions emanating from socio- economic changes will describe how climate will change in future. Climate changes mainly depend on various factors which include socio-economic changes, technological changes, energy and land use, greenhouse gases emission and air pollutants. These factors are provided as inputs in climate models that are often employed for the evaluation of climate change impacts. Effective comparisons of model projections can only be made if common scenarios are used in various studies of model results. In 2007, the IPCC superceded the Special Report on Emission Scenarios (SRES) by Representative Concentration Pathways (RCPs). Consequently, the scenarios based on Special Report on Emission Scenarios (SRES, 2000) have been replaced by Representative Concentration Pathways (RCPs) the latest iteration of the scenario process used in the IPCC Assessment Report Five (AR5) (IPCC, 2013).

The present research describes the Spatio-Temporal analysis of projections of temperature departures under different combinations of global circulation models (GCMs) and RCPs for several meteorological stations in Satluj River Basin – a key basin in the Himalayan region. Being a mountainous basin, Satluj is considered highly vulnerable to the impacts of global warming. The intent behind the present research is to create a dataset of temperature projections under plausible scenarios of climate change in the basin. Temperature projections have been obtained for two future time scales, that is, 2020-2039 and 2040-2059 for 16 different combinations of GCMs and RCPs. The dataset of the projections of temperature, and the analysis presented herein can be potentially utilized for hydrological modelling in the basin, thus providing an impetus to climate change modelling efforts in the basin.

The Climate change knowledge portal available at (**http://sdwebx.worldbank.org/ climateportal**) is an interactive website containing historical and projected data for the climate change. The CCKP portal has been created by the World Bank in collaboration with Global Facility for Disaster

Reduction and Recovery. Girvetz et al. (2009) described how maps, graphs, and tables can be generated using CCKP. Climate related data through CCKP can be easily accessed by policy makers and development practitioners. Information regarding changing climate for various geographical locations around the globe can be easily retrieved using this tool. The raw model information is derived from the Earth System Grid distribution of CMIP 5 (Coupled Model Intercomparison Project Phase 5) as described by Taylor et al. (2012). It also evaluates how reasonable the models are in simulating the past. It also describes about the factors responsible for difference in model projections. All the models in consultation with World Bank CCKP team, use a new common (1˚ x 1˚) global grid spacing to data regarding various climatic parameters. The historical climate data of any region can be easily retrieved as it is compilation of observed data. CCKP contains data from a total of 16 most widely used GCMs as well as ensemble median of the data that provides an efficient means to improve the reliability of climate simulations obtained through multiple models. The monthly mean historical temperature dataset used as baseline (1986 -2005) have been produced by the Climatic Research Unit (CRU) of University of East Anglia (UEA).

4.10 Methodology

The projections of temperature for different regions of the world are available on CCKP for different combinations of RCPs, GCMs, and future time periods. Four RCPs for which the temperature anomalies as well as the mean data is available include RCP2.6, RCP4.5, RCP6.0, and RCP8.5. The first step in the methodology employed herein was to select a combination of climate variable, RCP, GCM, and a future time period for which the temperature anomalies are required. The next step is to select the geographical location at which the data is required. In our case, the temperature anomalies were obtained for seven different geographical locations, each corresponding to a meteorological station in the basin. The desired region is selected on CCKP portal and thereafter geographical coordinates of the region are specified along with the required GCM, RCP, and time scale. The climate data for the geographical locations of interest in the Satluj river basin was then retrieved from the CCKP.

Models used in this study under CMIP5 are:bcc.csm1-1, CCSM4,CISRO-MK3-6-0,and GFDL-CM3. The set of models used in this work have been developed by modelling centres in China, USA, Australia and Germany. Once the temperature anomalies have been obtained for different combinations of RCP, GCM, and future time period, the statistical analysis was conducted using R-package -an open source software environment for statistical computing and graphics (R Core team, 2014). The temperature anomaly data at each location of interest was obtained from the CCKP for a total of 16 different combinations of RCPs and GCMs. For each combination and each location, temperature anomalies were obtained for two future time periods; 2020-2039 and 2040-2059. Both the maximum and minimum values of projected temperature anomalies as well as the range of projections under each combination were extracted from the projected data using R-package (Annexure-3). The projected data has been presented through tables and bar plots.

4.11 RESULTS AND DISCUSSIONS

The analysis of temperature projections for duration 2020-39 and 2040-59 under RCP2.6, RCP4.5, RCP6, RCP8.5 at 7 different locations in Satluj river basin for various models is presented in the following sections. The details of the GCMS used in this research are presented in Table 4.6 and details of various stations used is presented in Table 4.7.

Table 4.6 Details of GCMs Used

S. No	Model-Name	Modelling Centre	Main Reference
1	bcc-csm1-1	Beijing Climate Centre, China	Wu et al. (2013)
2	CCSM4	National Centre for Atmospheric Research, USA	Gent et al. (2011)
3	CSIRO-Mk3-6-0	Commonwealth Scientific and Industrial Research, Australia	Rotstayn et al. (2012)
4	GFDL-CM3	Geophysical Fluid Dynamics Laboratory, USA	Donner et al. (2012)

Table 4.7 Details of stations used

S. No	Station	Latitude			Longitude		
		Degree	Minute	Second	Degree	Minute	Second
1	Bhakra	31	24	56	76	26	5
2	Berthin	31	25	11	76	38	55
3	Kasol	31	30	0	77	19	0
4	Kaza	32	13	25	78	4	11
5	Kalpa	31	32	0	78	15	0
6	Kahu	31	12	43	76	46	52
7	Rampur	31	26	24	77	37	40

4.11.1 Model bcc-csm1-1

The projections of temperature anomalies at different stations under all four RCPs for two future periods; 2020-2039 and 2040-2059. It can be seen from Table 4.8 that for RCP 2.6 and time period 2020-39, the anomalies in temperature range between 0.17˚C to 1.66˚C. For RCP2.6 and for the time period 2040-59, the temperature anomalies range from 0.29˚C to 1.47˚. For the 2040-59 time period, as expected the temperature anomalies under RCP2.6 are in general, higher than for the 2020-2039 period. It appears that the GCMs do not take into account the technological advancements and subsequent reduction in emissions that are expected to occur by the end of mid century. The projections of temperature anomalies are, therefore, on the higher side. The projected anomalies for the months of April and May were higher than for the winter season. Under RCP4.5, the anomalies in temperature varies between 0.19˚C to 1.85˚C for the 2020-39 period. For the 2040-59 period, the temperature anomalies were found to be in the range of 0.21˚ C to 2.36˚. For RCP6, the temperature anomalies for the 2020-39 period ranged from -0.3˚C to 1.46˚C. The temperature anomaly of -0.3 ˚C was shown by the model for the February and March. However, this projection may be a result of computational deficiency inherent in such models. This particular anomaly of -0.3 ˚C shall not be considered in decision making process as it is highly unlikely that the temperature trend will show a downward trend under RCP4.5, which is a moderately high emission scenario. As expected, the temperature anomalies under RCP6 for the 2040-59 period ranged from0.16˚ C to 2.79˚C. Under

RCP8.5 -the most extreme emission scenario – the temperature anomalies for the 2020-39 time period ranged from 0.52˚C to 2.1˚C. A projected increase of 2˚C can be considered to be significantly higher, and could have important implications for many aspects of the natural environment around the year 2030. The projections of temperature anomalies for the 2040-59 time period were even (1.06˚ C to 3.54˚ C) higher than the already high temperature projections for the 2020-39 period. Results clearly indicates for model bcc-csm1-1 RCP8.5 projections of temperature anomaly is higher than the rest of the scenario. It can be seen from Figure 4.7 to Figure 4.13 that the projections of temperature anomalies under RCP8.5 are the highest, whereas the lowest temperature anomalies have been projected under RCP2.6. This pattern of temperature projections is similar for both the future periods, that is, 2020-2039 and 2040-2059. These projections of temperature would be required as an input to models used for impact assessment.

4.11.2 Model CCSM4

Table 4.9 indicates under RCP2.6, the projections of temperature anomalies for the 2020-2039 period range from 0.16˚ C to 2.2˚C, whereas the corresponding values for the 2040-59 period range from 0.56˚C to 2.24˚C. There are clear indications of higher temperature anomalies for the 2040-2059 period. Under RCP4.5,theanomalies in temperature were found to vary between 0.12˚C to 2.02 ˚C, whereas the anomalies for the 2040-59 period ranged from 0.36 ˚ C to 2.31˚C. A comparison of temperature anomalies under RCP 4.5 with those projected under RCP 2.6 indicate similar magnitude of warming. The difference is the values of projected temperature anomalies obtained under these two emission scenarios was found to be negligible. Under RCP6, the projected anomalies in temperature ranged from 0.6˚C to 2.32 ˚C for the 2020-39 period. For duration 2040-59, temperature anomaly ranged from 0.4˚ C to 2.54 ˚. There was only a slight increase in the projected temperature anomalies under RCP6 for the 2040-2059 period compared to the 2020-2039 period. The negligible increase in projected temperature anomalies for the 2040-59 period indicates a level of stabilization in emissions by the year 2050 under RCP6.0. Under RCP8.5, the temperature anomalies for the 2020-39 period ranged from 0.72˚C to 2.02˚C. There was, however, some increase in temperature anomalies projections for the 2040-59 period with the lowest and highest temperature increases of 1.03˚ C to 3.22˚ C, respectively. Under RCP8.5, anomalies in the temperature for the 2020-2039 period ranged from 0.72˚C to 2.02˚C, whereas the corresponding values for the 2040-2059 period were 1.03˚C and 3.22˚C.The analysis of output from the CCSM4 model clearly indicates that the variability among the projections under different emission scenarios is not significantly large. Under RCP2.6, RCP4.5 and RCP 6, the model projected similar increases temperature for both the periods of analysis considered herein. The projections under RCP8.5 were, however, significantly higher than the other three emission scenarios Figure 4.7 to Figure 4.13 shows the temperature anomalies at various stations as projected by the CCSM4 model under different emission scenarios.

4.11.3 Model CISRO-MK3-6-0

Table 4.10 shows projections of temperatures for the 2020-39period under RCP2.6, were found to be in the range of 1.07 ˚ C to 2.24˚C. For 2040-59, the temperature anomalies were projected to vary from 1.25˚C to 3.08 ˚C. Thus, there is an increase in the maximum value of projected temperature anomalies for the 2040-2059 period compared to 2020-2039 period. Under RCP4.5, the model projects an increase of temperature of 0.9 ˚C to 2.12˚C for the 2020-2039 period, whereas the projected increase for the 2040-2059 varies from 1.95˚C to 3.33˚C. The magnitude of projections under RCP4.5 is similar to the projections under RCP2.6. Both the emission scenarios project a maximum rise of around 3 ˚C for the duration 2040-2059, thus indicating negligible differences in the magnitude of projections by the model under these scenarios. Under RCP6.0, the projected temperature anomalies for the 2020-2039 period ranged from 0.37˚C to 1.44˚C. For the 2040-2059 time period, the temperature is projected to rise by 1.2˚C to 2.2 ˚C. This is on expected lines as under all emission scenarios, the temperature projections are higher for 2040-2059 period compared to the

2020-2039 period. Under RCP 8.5, the temperature anomalies for the 2020-2039 period were found to be in the range of 1.08˚C to 1.86˚C, whereas for the 2040-59 period, the temperature anomalies ranged from 1.67˚C to 3.24˚C. The analysis of projections clearly indicated that the temperature anomalies are the highest under RCP8.5, which is the most extreme scenario. The results from Figure 4.7 to Figure 4.13 clearly indicate that the CISRO-MK3-6-0 model projects the highest increase in temperature for winter months, and not in summer months as was the case with CCSM4 model.

4.11.4 Model GFDL-CM3

The projections of temperature anomalies under different emission scenarios and for the 2020-2039 and 2040-2059 periods made by GFDL-CM3 model were also analysed Table 4.11. Relatively high temperature anomalies ranging from 0.8˚ C to 3.51˚C were projected by the model under RCP2.6 for the 2020-2039 period. For the 2040-59 period, the corresponding values of temperature projections under RCP2.6 were only slightly higher (1.02˚C to 3.93˚C) than the 2020-39 period. A similar pattern of temperature projections was observed under RCP4.5 and RCP6.0. Under RCP4.5, the projected anomalies in temperature for the 2020-39 period ranged between 0.46˚C to 3.53˚C. For the 2040-2059 period, the increase in temperature was projected to be between 0.78˚C to 3.95˚C, which is only slightly higher than that for the 2020-2039 period. Under RCP6.0, the anomalies in temperature projections for the 2020-2039 period ranged from 0.25˚C to 3.13˚C, whereas the corresponding values for the 2040-2059 period were 0.58˚C to 3.71˚C. It can be seen that the temperature anomalies under RCP6.0 for the 2040-2059 period were only slightly higher than for the 2020-2039 period. The analysis indicated that the model projected a relatively higher increase in temperature compared to other models under all emission scenarios. However, the magnitude of projections were only slightly higher for the 2040-2059 period compared to 2020-2039 period.

4.12 CONCLUSIONS

The analysis of projected temperature anomalies clearly indicate substantial warming under all the combinations of GCMs and RCPs considered in this research. There is, however, a high inter-model variability in the projections of temperature anomalies for both the periods of analysis, that is 2020-2039 and 2040-2059. But all the models considered in this study indicate positive temperature anomalies over Satluj region for both the future time period considered in this research regardless of emission scenarios, except in very few cases where temperature anomalies were found to be negative. The negative temperature anomalies in a very few cases could be attributed to modelling errors as most models project positive temperature under all combinations RCPs and future time periods. As expected RCP8.5 projections were the most extreme for both the future periods and all models, whereas the RCP2.6 projected the least warming. The other two RCPs, namely RCP4.5 and RCP6.0, projected moderate increase in temperatures. Among the models, GFDL is the most extreme model whereas the bcc_cm_1_1projections, particularly for 2020-39, were very close to change in monthly temperature compared to the reference period of 1986-2005.Expected warming of the order of 3˚C to 4˚C has necessitated the need to consider the impacts of climate change while devising operating strategies for a large dam such as Bhakra that control the flow to several irrigation systems in northern India and is a major source of water for power generation.

Table 4.8.Model bcc-csm1-1

S.No.	Station	RCPs	2020-2039		2040-2059	
			Min	Max	Min	Max
1	Bhakra	2.6	0.3	1.64	0.3	1.4
		4.5	0.19	1.52	0.21	2.31
		6	-0.3	1.26	0.16	2.79
		8.5	0.8	1.94	1.06	2.61
2	Berthin	2.6	0.29	1.63	0.3	1.24
		4.5	0.19	1.68	0.29	2.26
		6	0.22	1.29	0.22	2.71
		8.5	0.52	1.93	1.22	2.67
3	Kasol	2.6	0.22	1.66	0.31	1.47
		4.5	0.19	1.68	0.29	2.26
		6	0.22	1.3	0.22	2.71
		8.5	0.52	1.93	1.22	3.43
4	Kaza	2.6	0.17	1.66	0.31	1.46
		4.5	0.25	1.85	0.47	2.36
		6	0.13	1.46	0.32	2.7
		8.5	0.69	2.1	1.58	3.54
5	Kalpa	2.6	0.17	1.66	0.31	1.46
		4.5	0.25	1.85	0.47	2.36
		6	0.13	1.46	0.32	2.7
		8.5	0.69	2.1	1.58	3.54
6	Kahu	2.6	0.29	1.63	0.3	1.24
		4.5	0.19	1.68	0.29	2.26
		6	0.22	1.29	0.22	2.71
		8.5	0.52	1.93	1.22	2.67
7	Rampur	2.6	0.25	1.62	0.29	1.4
		4.5	0.2	1.73	0.37	2.22
		6	0.13	1.32	0.28	2.64
		8.5	0.55	1.93	1.39	3.45

Table 4.9. Model CCSM4

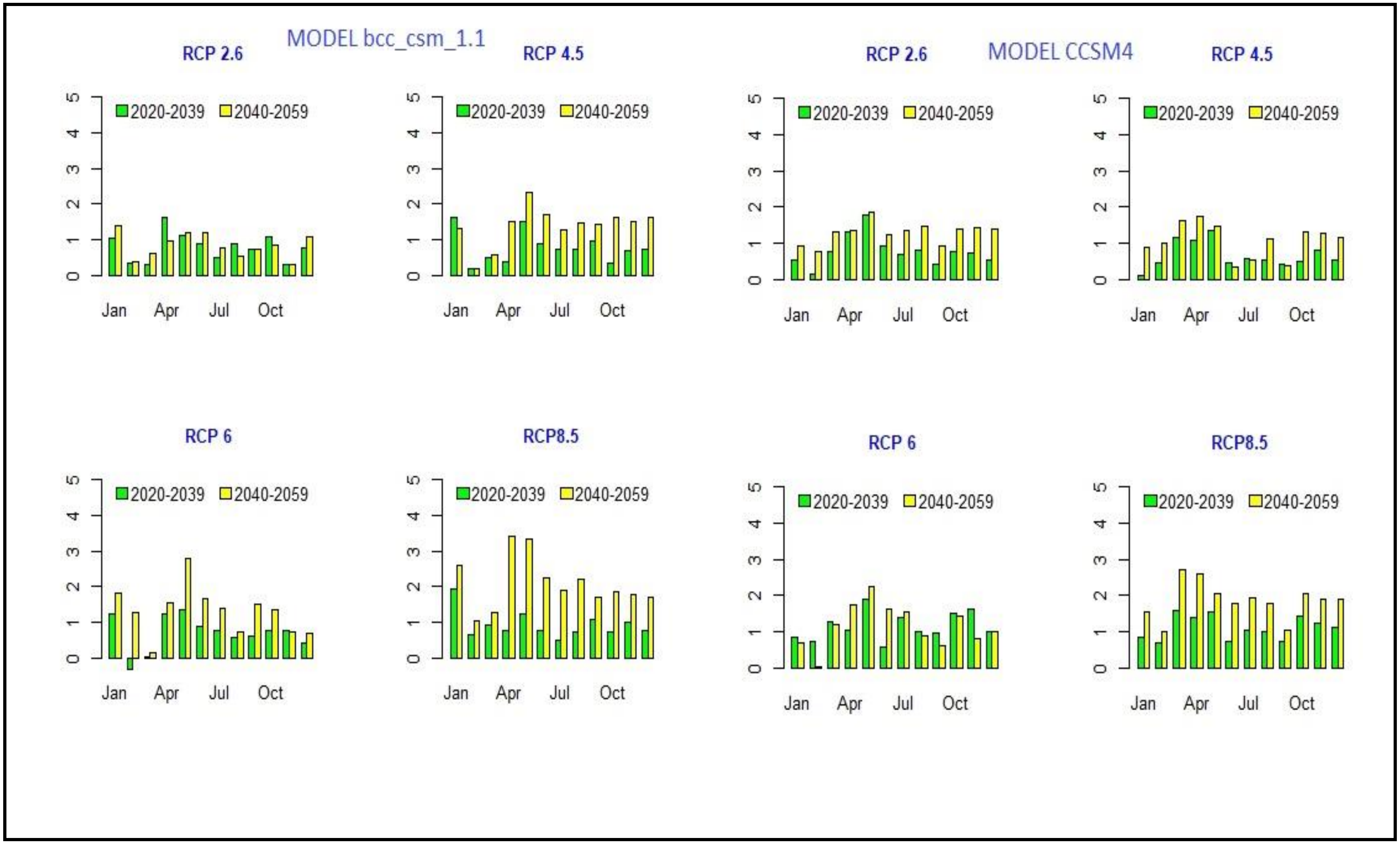
S.No.	Station	RCPs	2020-2039		2040-2059	
			Min	Max	Min	Max
1	Bhakra	2.6	0.16	1.79	0.8	1.85
		4.5	0.12	1.17	0.36	1.73
		6	0.6	1.91	0.4	2.25
		8.5	0.72	1.56	1.03	2.59
2	Berthin	2.6	0.28	1.98	0.88	2.08
		4.5	0.56	1.44	0.69	1.92
		6	0.92	2.2	0.49	2.44
		8.5	0.93	1.82	1.49	3.09
3	Kasol	2.6	0.28	1.98	0.56	1.77
		4.5	0.81	1.77	0.69	1.92
		6	0.92	2.2	0.62	2.33
		8.5	1.04	1.92	1.49	3.09
4	Kaza	2.6	0.47	2.13	0.79	2.04
		4.5	0.88	2.02	0.73	2.31
		6	0.71	1.87	0.83	2.5
		8.5	1.03	2.02	1.74	3.06
5	Kalpa	2.6	0.47	2.13	0.79	2.04
		4.5	0.88	2.02	0.73	2.31
		6	0.8	1.87	0.83	2.5
		8.5	1.03	2.02	1.74	3.06
6	Kahu	2.6	0.28	1.98	0.88	2.08
		4.5	0.56	1.44	0.69	1.92
		6	0.92	2.2	0.49	2.44
		8.5	0.93	1.82	1.49	3.09
7	Rampur	2.6	0.35	2.2	0.78	2.24
		4.5	0.77	1.72	0.98	2.22
		6	0.89	2.32	0.88	2.54
		8.5	1.12	1.85	1.73	3.22

Table 4.10 Model CISRO-MK3-6-0

S.No.	Station	RCPs	2020-2039		2040-2059	
			Min	Max	Min	Max
1	Bhakra	2.6	1.16	1.91	1.35	2.75
		4.5	0.9	1.53	2.01	2.99
		6	0.67	1.44	1.35	2.2
		8.5	1.26	1.66	1.92	3.24
2	Berthin	2.6	1.3	1.95	1.33	2.27
		4.5	0.97	1.68	2.01	3.02
		6	0.79	1.41	1.29	2.13
		8.5	1.15	1.67	1.87	3.08
3	Kasol	2.6	1.07	2.24	1.25	3.08
		4.5	0.99	2.06	1.95	3.33
		6	0.4	1.39	1.28	2.13
		8.5	1.09	1.83	1.87	3.19
4	Kaza	2.6	1.11	1.95	1.34	2.57
		4.5	1.08	2.12	2.09	3.24
		6	0.37	1.33	1.2	2.02
		8.5	1.08	1.86	1.67	3.14
5	Kalpa	2.6	1.11	1.95	1.34	2.57
		4.5	1.08	2.12	2.09	3.24
		6	0.37	1.33	1.2	2.02
		8.5	1.08	1.86	1.67	3.14
6	Kahu	2.6	1.3	1.95	1.33	2.27
		4.5	0.97	1.68	2.01	3.02
		6	0.79	1.41	1.29	2.13
		8.5	1.15	1.67	1.87	3.08
7	Rampur	2.6	1.12	1.78	1.29	2.43
		4.5	0.9	1.6	2.02	2.77
		6	0.46	1.32	1.27	1.94
		8.5	1.08	1.7	1.8	2.94

Table 4.11. Model GFDL-CM3

S.No.	Station	RCPs	2020-2039		2040-2059	
			Min	Max	Min	Max
1	Bhakra	2.6	0.8	2.13	1.02	2.66
		4.5	0.46	1.96	0.78	2.76
		6	0.25	1.76	0.58	2.73
		8.5	-0.19	1.44	1.27	4.06
2	Berthin	2.6	1.2	2.72	1.5	3.19
		4.5	1.13	2.55	1.04	2.58
		6	0.46	2.34	0.98	2.68
		8.5	0.04	2.33	2.14	3.99
3	Kasol	2.6	1.29	3.18	1.49	3.57
		4.5	1.23	3.16	0.99	3.64
		6	0.69	2.63	1.32	3.18
		8.5	0.27	2.89	2.48	4.53
4	Kaza	2.6	1.29	3.18	1.49	3.57
		4.5	1.23	3.16	0.99	3.64
		6	0.69	2.63	1.32	3.18
		8.5	0.27	2.89	2.48	4.53
5	Kalpa	2.6	1.29	3.18	1.49	3.57
		4.5	1.23	3.16	0.99	3.64
		6	0.69	2.63	1.32	3.18
		8.5	0.27	2.89	2.48	4.53
6	Kahu	2.6	1.2	2.72	1.5	3.19
		4.5	1.13	2.55	1.04	2.58
		6	0.46	2.34	0.98	2.68
		8.5	0.04	2.33	2.14	3.99
7	Rampur	2.6	1.43	3.51	1.47	3.93
		4.5	1.41	3.53	1.43	3.95
		6	0.76	3.13	1.54	3.71
		8.5	0.42	3.28	2.55	4.91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MODEL CCSM4
RCP 2.6
RCP 4.5
RCP 6
RCP8.5
2020-2039
2040-2059
Jan
Apr
Jul
Oct
0
1
2
3
4
5

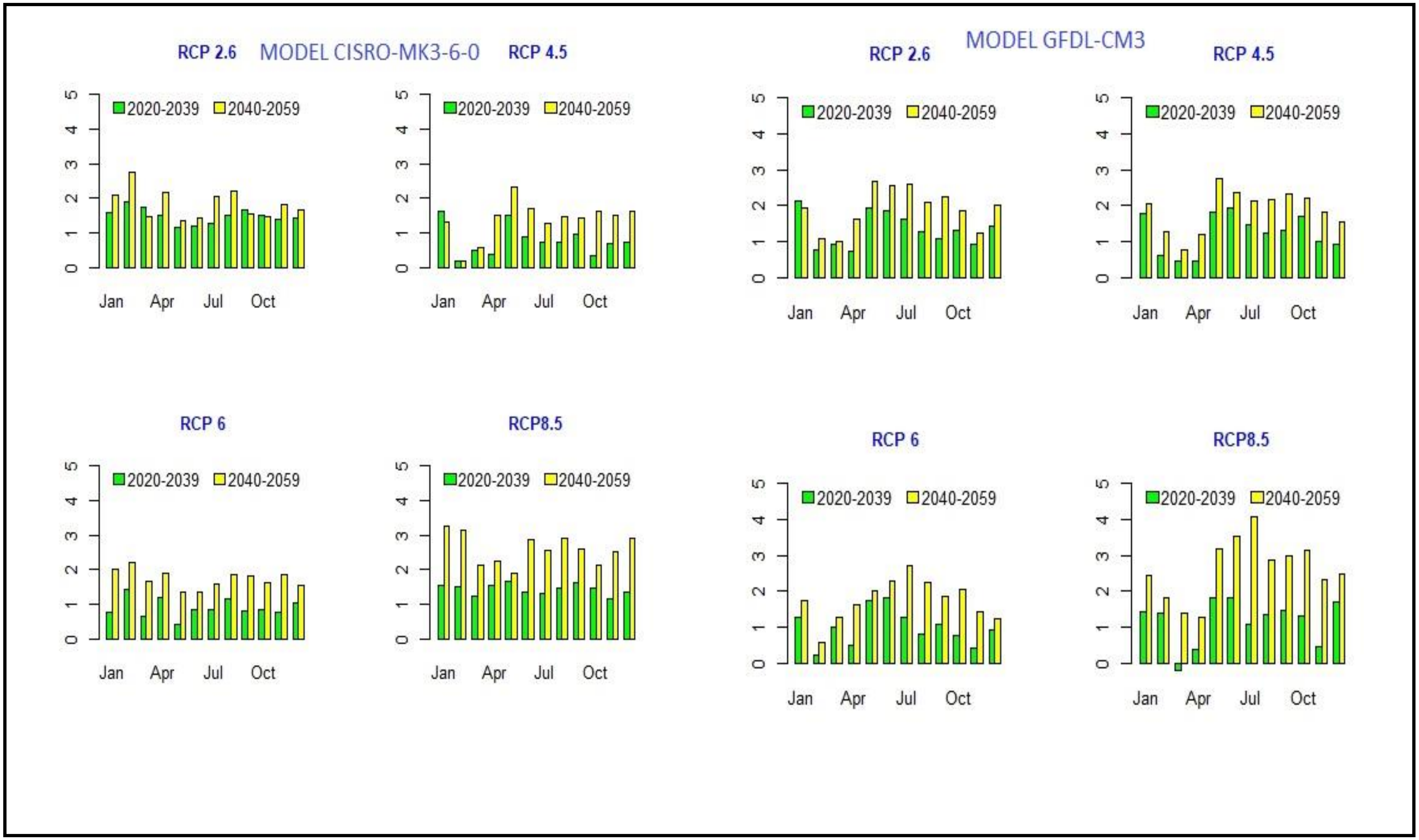
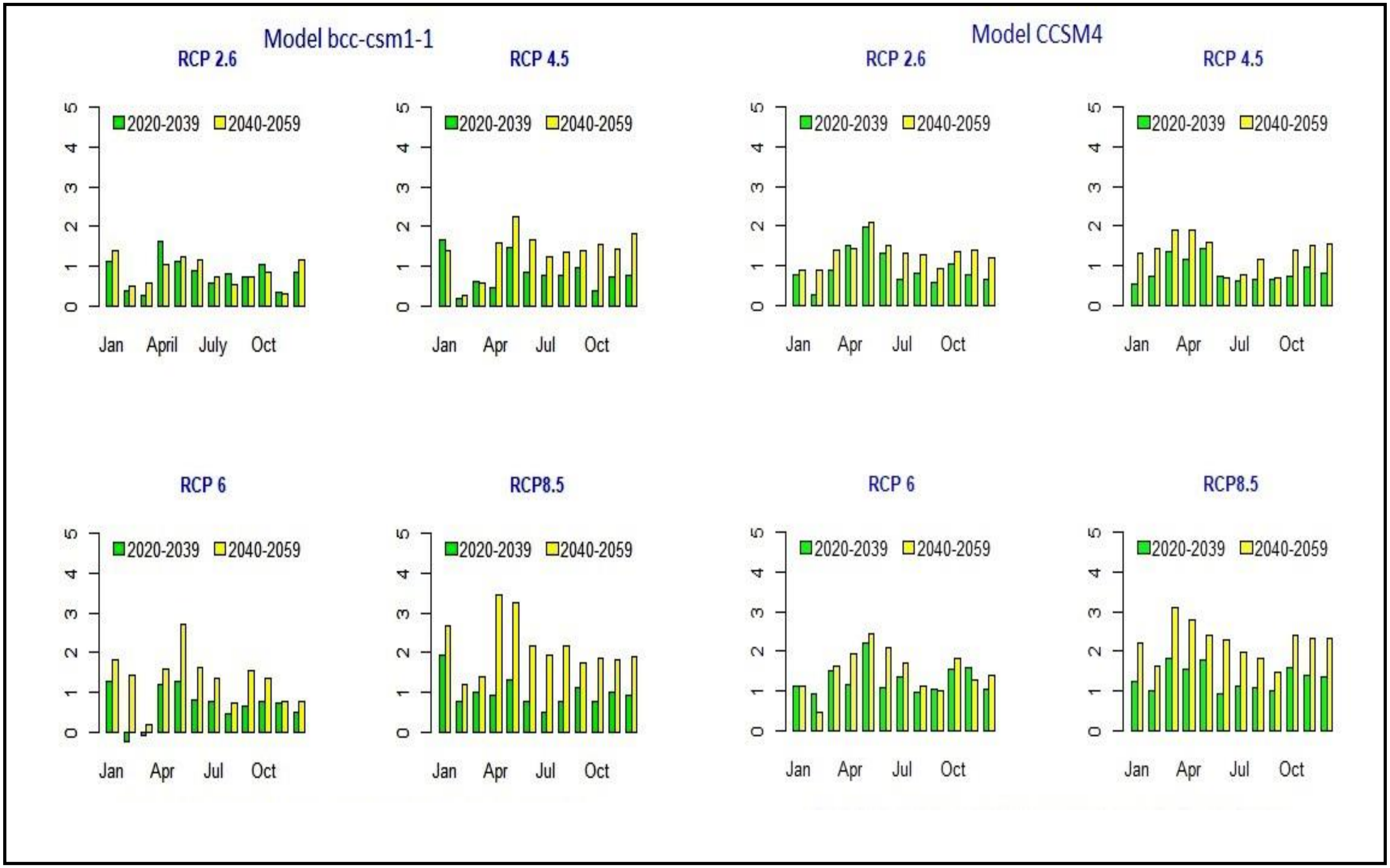


Figure 4.7 Temperature projections for various models, RCPs and duration for Bhakra Station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RCP 4.5
Model CCSM4
RCP 2.6
RCP 4.5
RCP 6
RCP8.5
RCP 6
RCP8.5
2020-2039
2040-2059
0 1 2 3 4 5
Jan April July Oct
Jan Apr Jul Oct

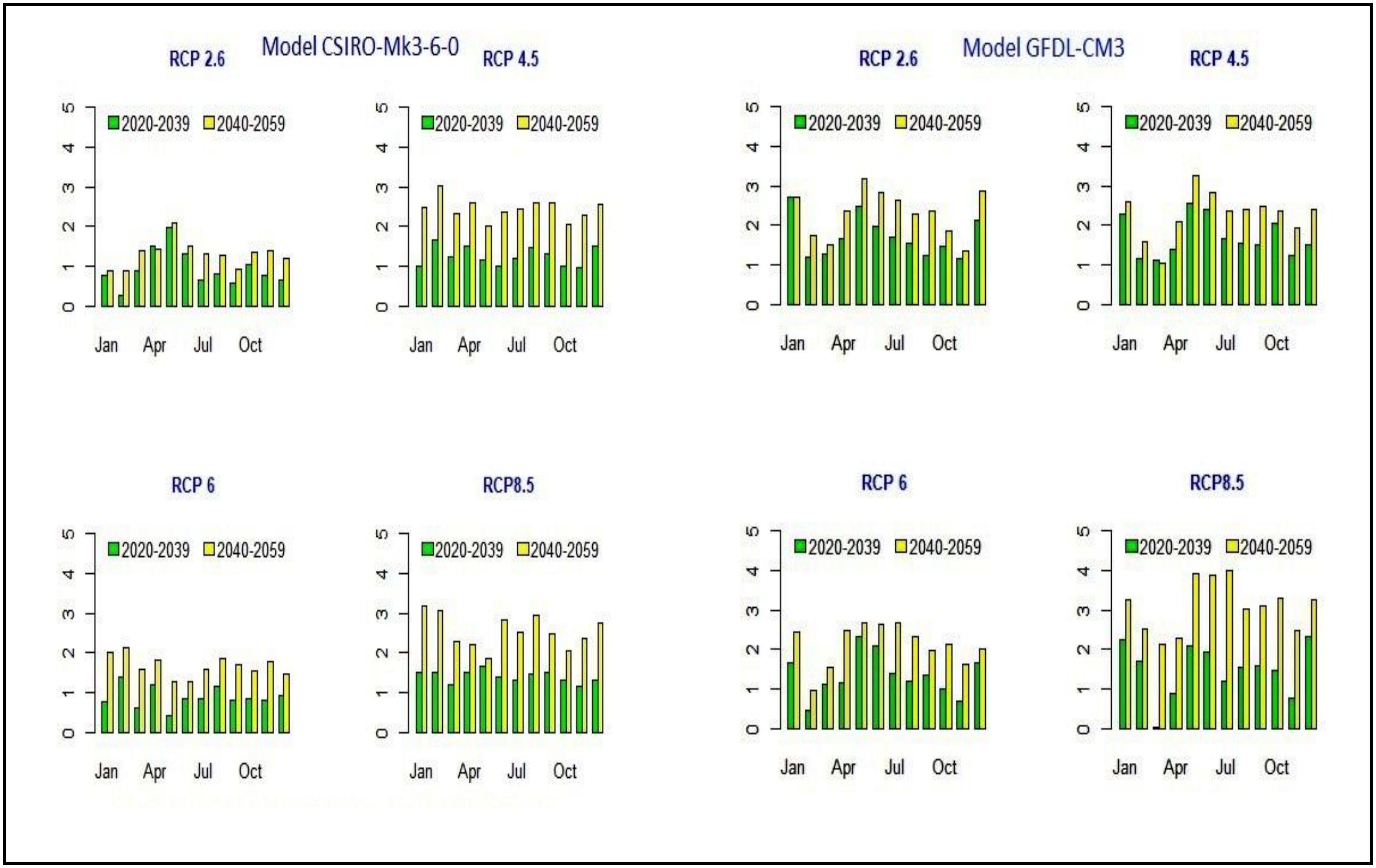
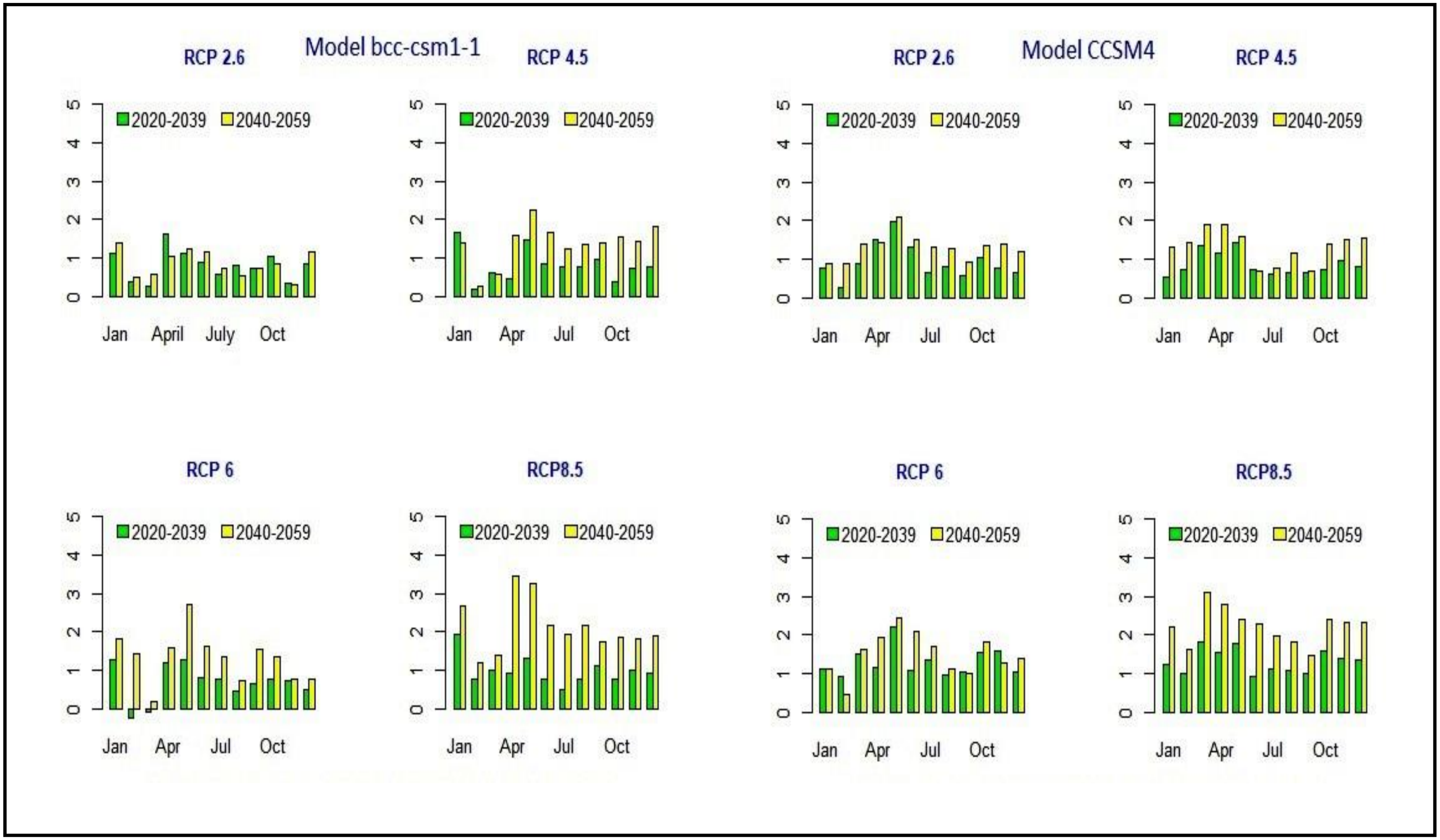


Figure 4.8 Temperature projections for various models, RCPs and duration for Berthin Station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Model CCSM4
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RCP 4.5
RCP 6
RCP8.5
2020-2039
2040-2059
Jan
April
July
Apr
Jul
Oct

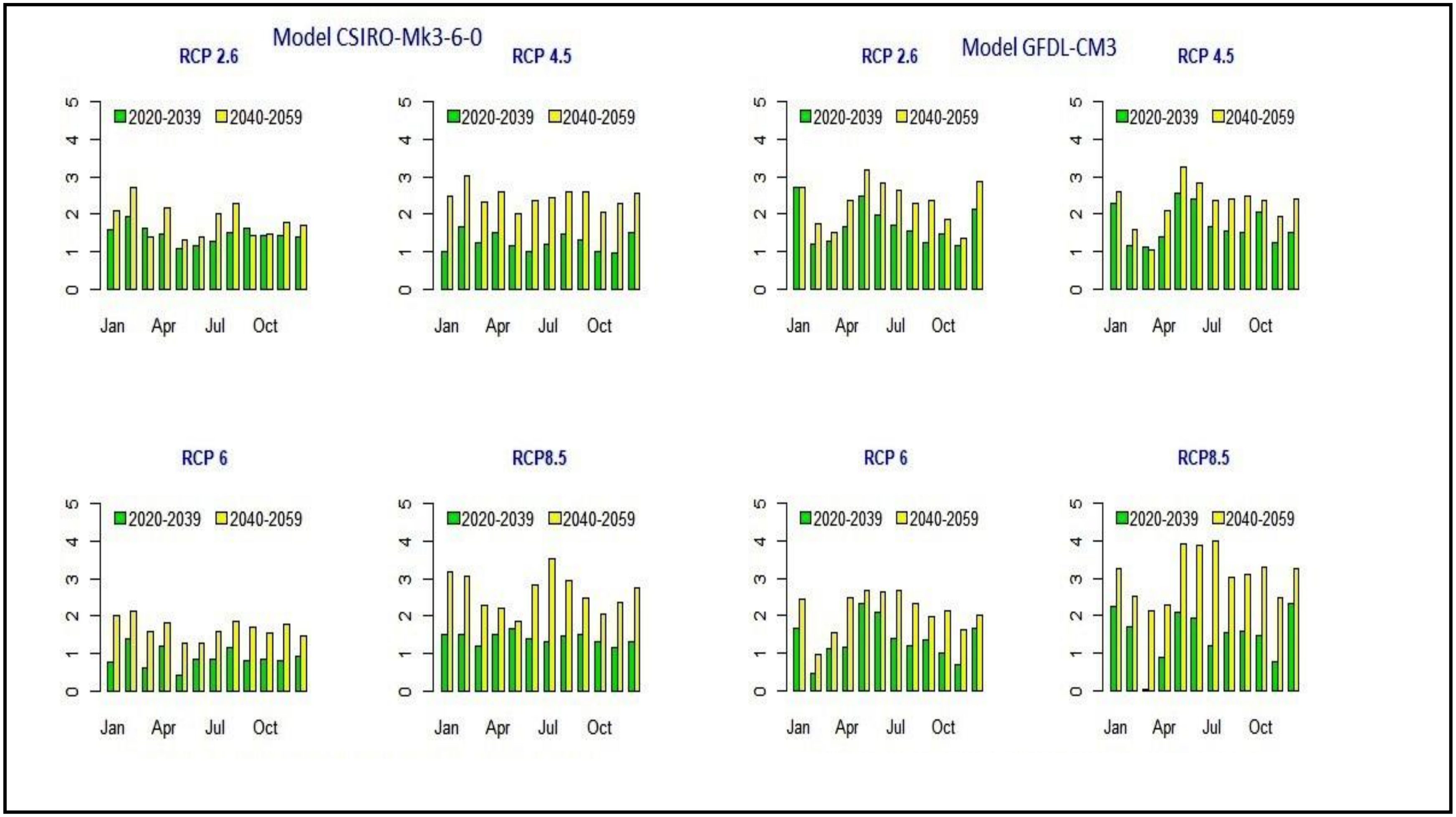
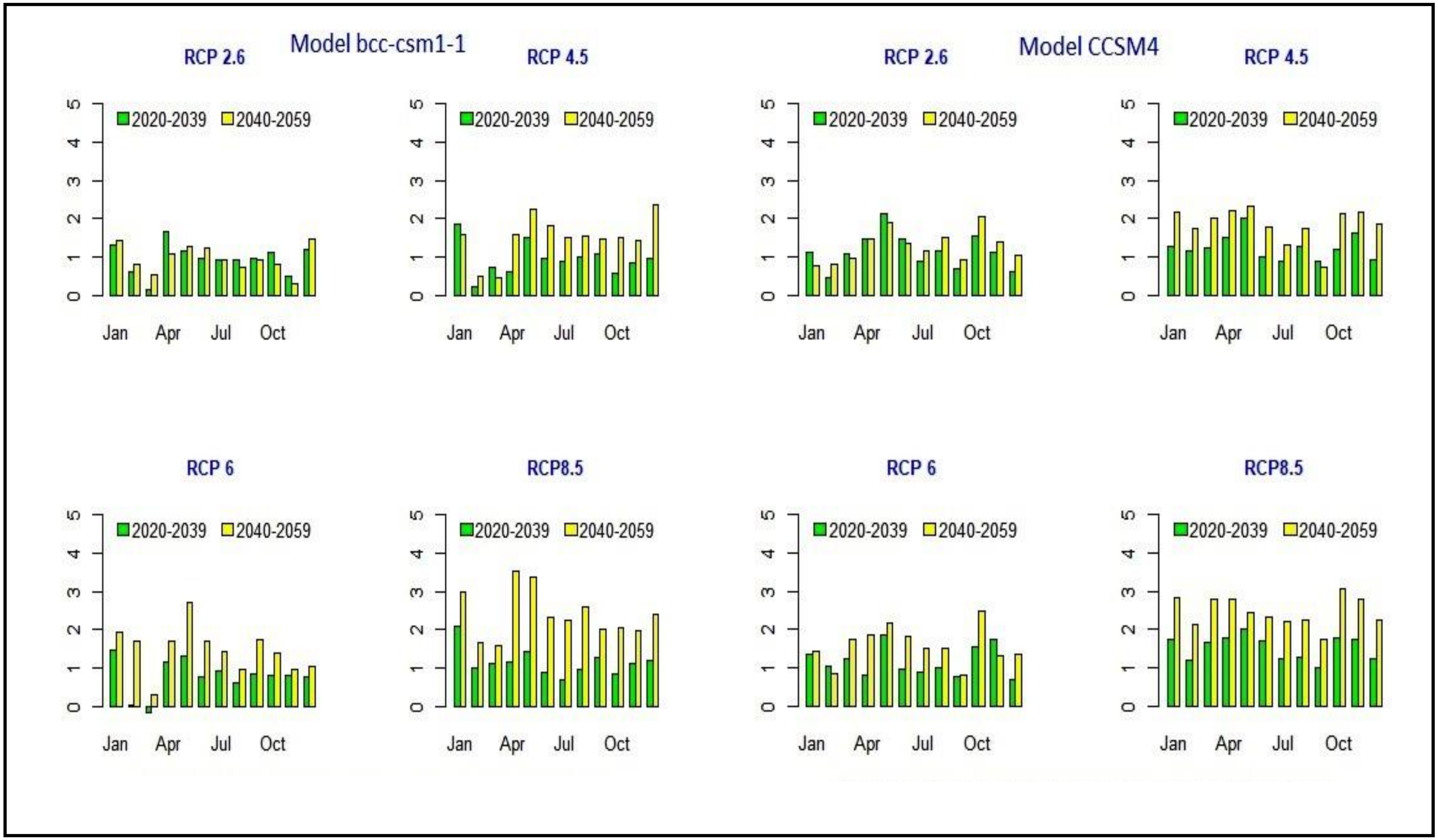


Figure 4.9 Temperature projections for various models, RCPs and duration for Kahu Station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RCP 2.6
RCP 4.5
RCP 6
RCP8.5
2020-2039
2040-2059
Jan
Apr
Jul
Oct

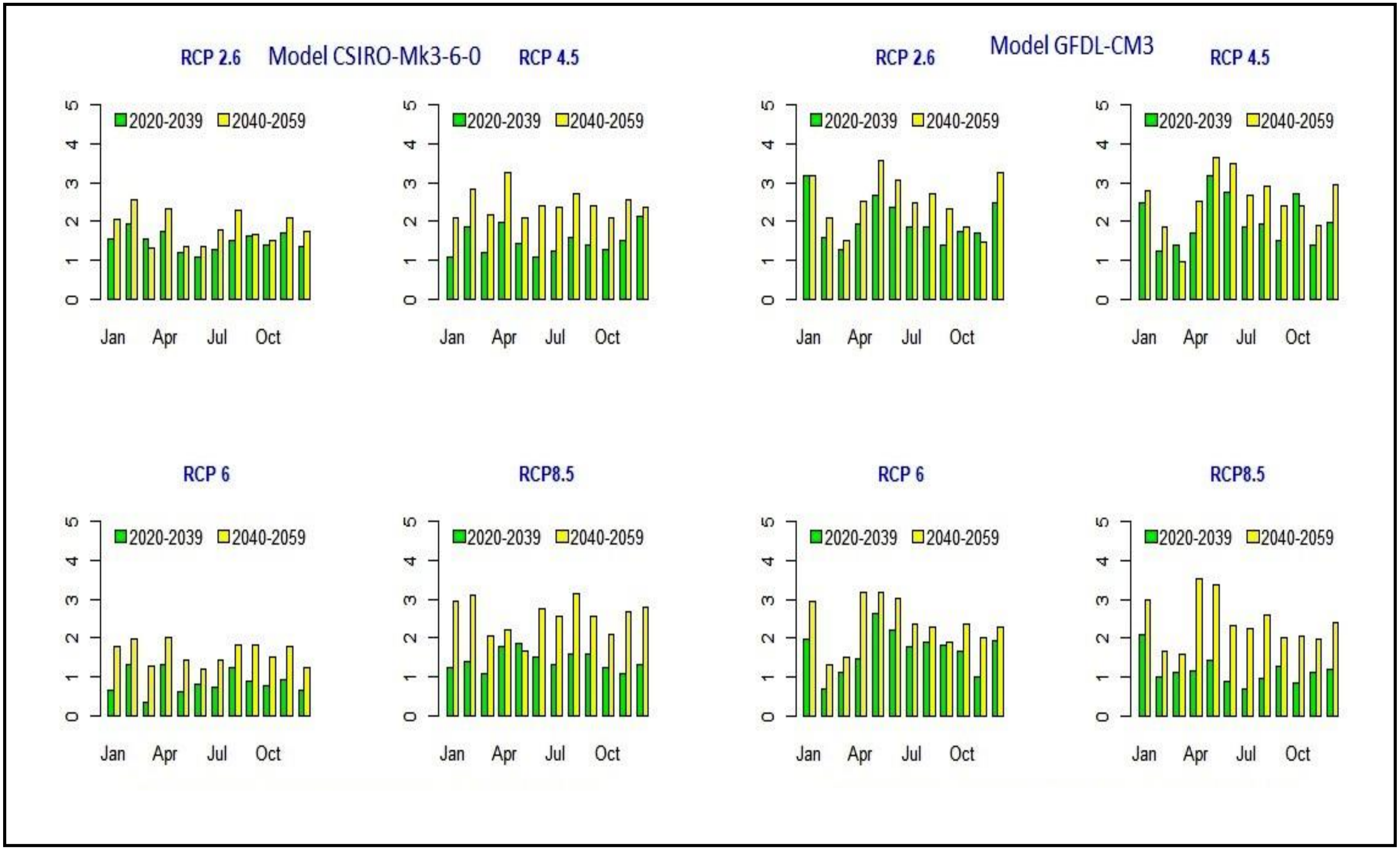
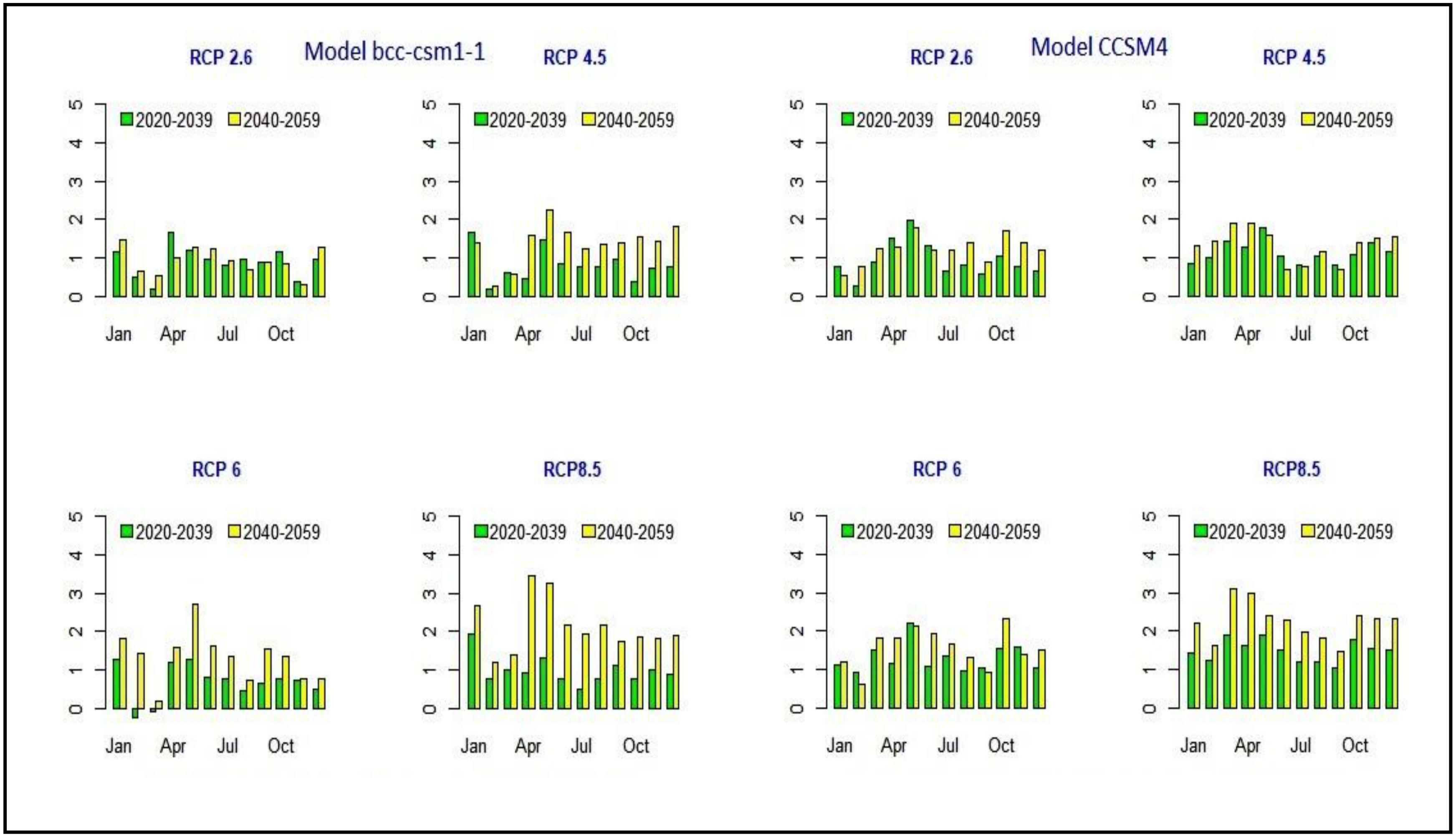


Figure 4.10 Temperature projections for various models, RCPs and duration for Kalpa Station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RCP 4.5
RCP 2.6
Model CCSM4
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RCP8.5
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2040-2059
Jan
Apr
Jul
Oct

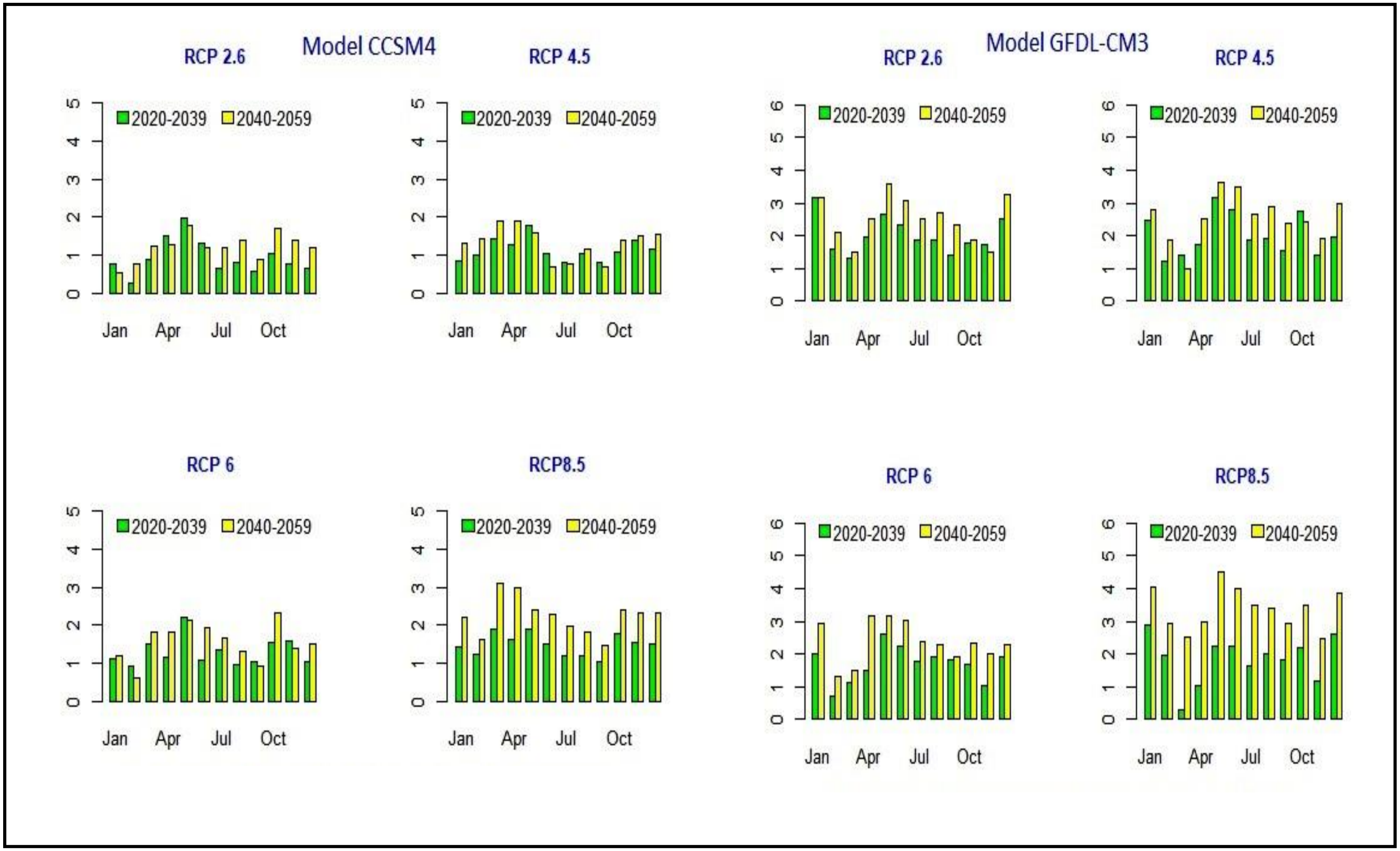
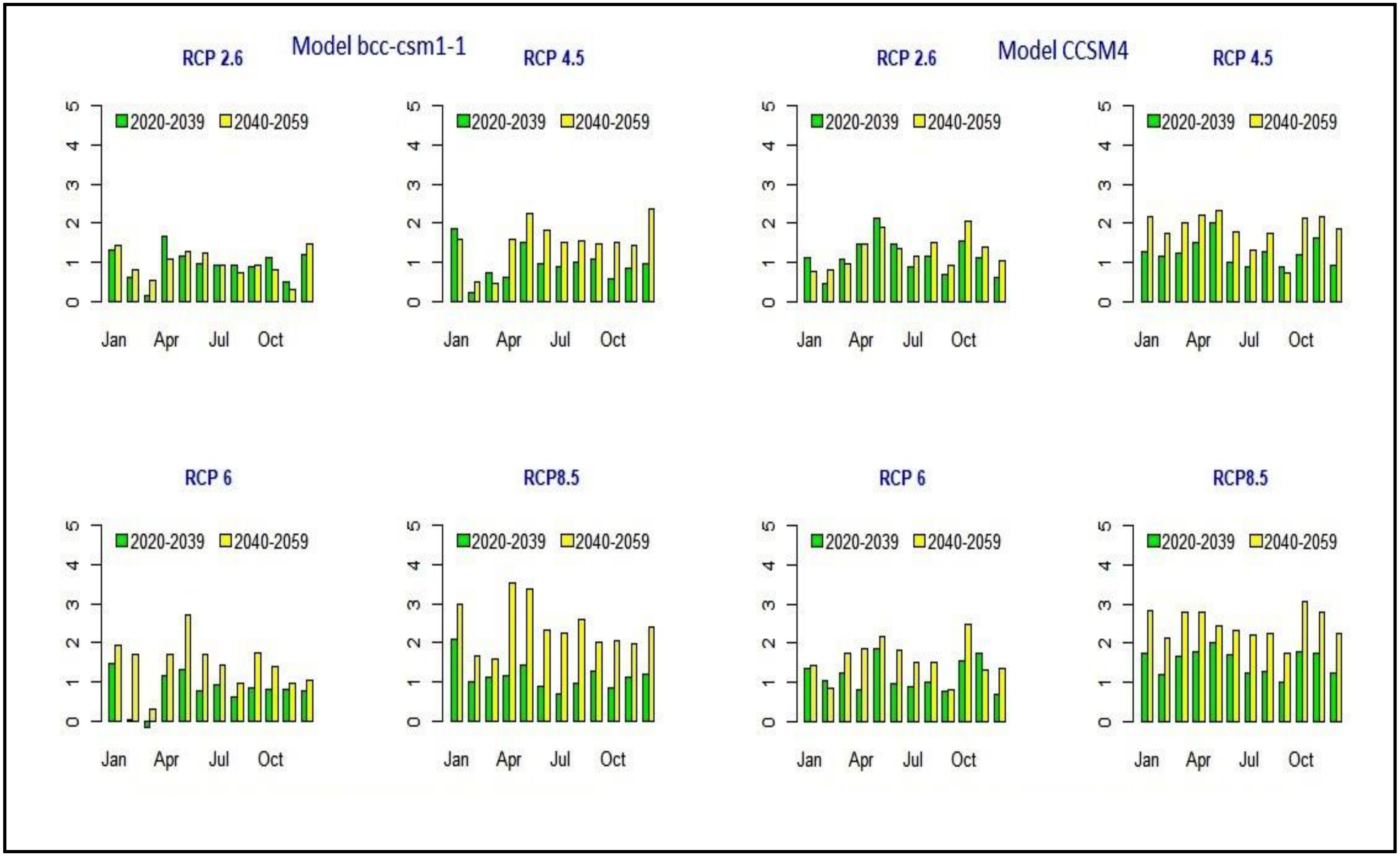


Figure 4.11 Temperature projections for various models, RCPs and duration for Kasol Station



Model bcc-csm1-1
Model CCSM4
RCP 2.6
RCP 4.5
RCP 6
RCP8.5
2020-2039
2040-2059
Jan
Apr
Jul
Oct

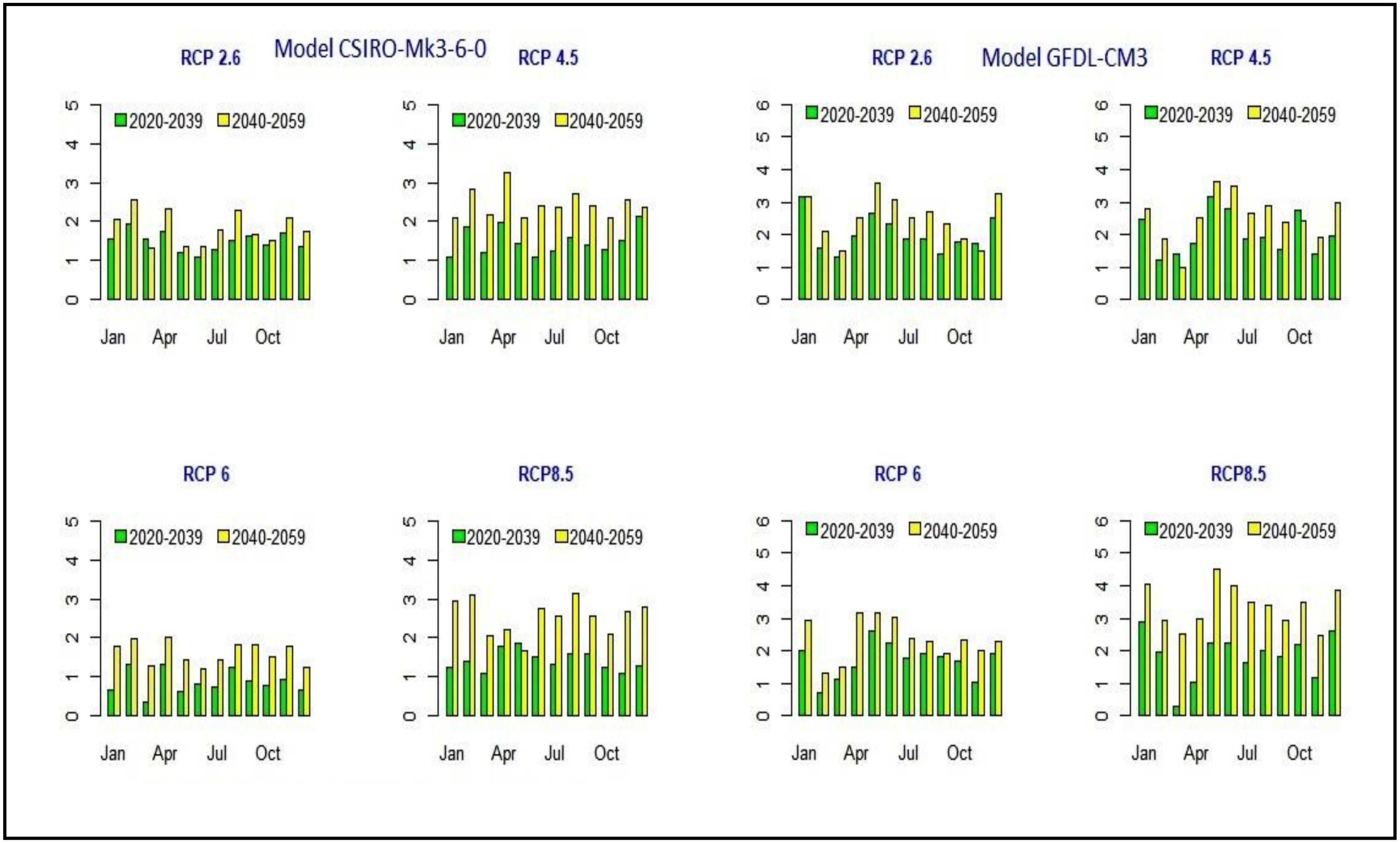


Figure 4.12 Temperature projections for various models, RCPs and duration for Kaza Station

Model bcc-csm1-1
Model CCSM4
RCP 2.6
RCP 4.5
RCP 6
RCP8.5
2020-2039
2040-2059
Jan
Apr
Jul
Oct

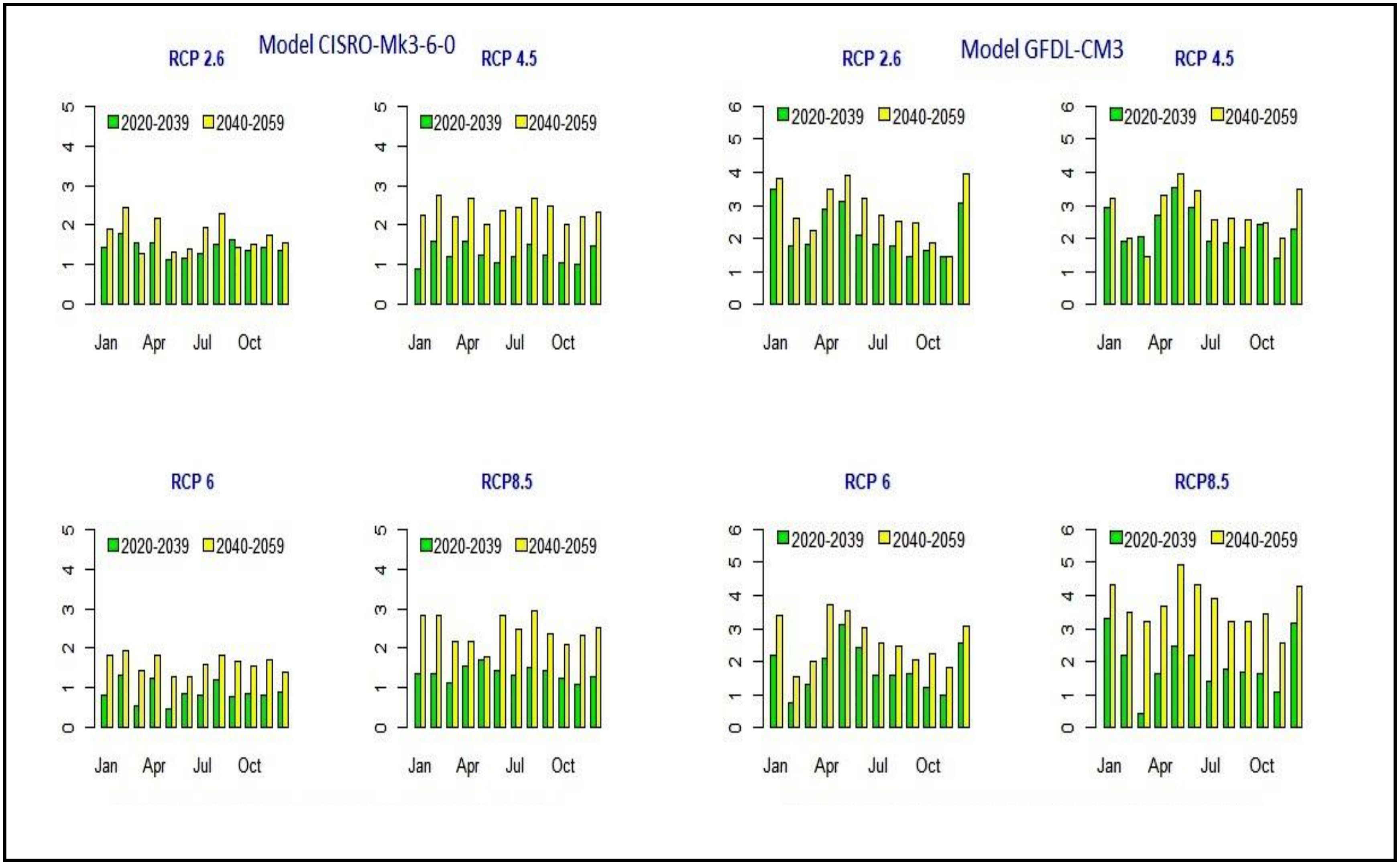


Figure 4.13 Temperature projections for various models, RCPs and duration for Rampur Station

5 Reservoir Operation Strategies

5.1 Operation Reservoir Policy at Bhakra

Reservoir operation constitutes the controlled releases of water downstream in relation to the inflow and the available storage above the dam so as to fulfil the design requirements of the project with respect to irrigation, power, flood control, and other purposes. Water is released downstream of Bhakra Dam for one or more of the following purposes:

1. To meet the day to day irrigation and power requirements
2. For safe disposal of floods and surplus flows
3. Passage of density currents

The established procedure for operation of the reservoir at Bhakra require that the reservoir level of El. 1690 ft is not exceeded during normal operation. However, the reservoir is normally operated such that the El. 1680 ft is not exceeded. However, this restriction may be removed by the competent authority in order to provide protection to the downstream areas.

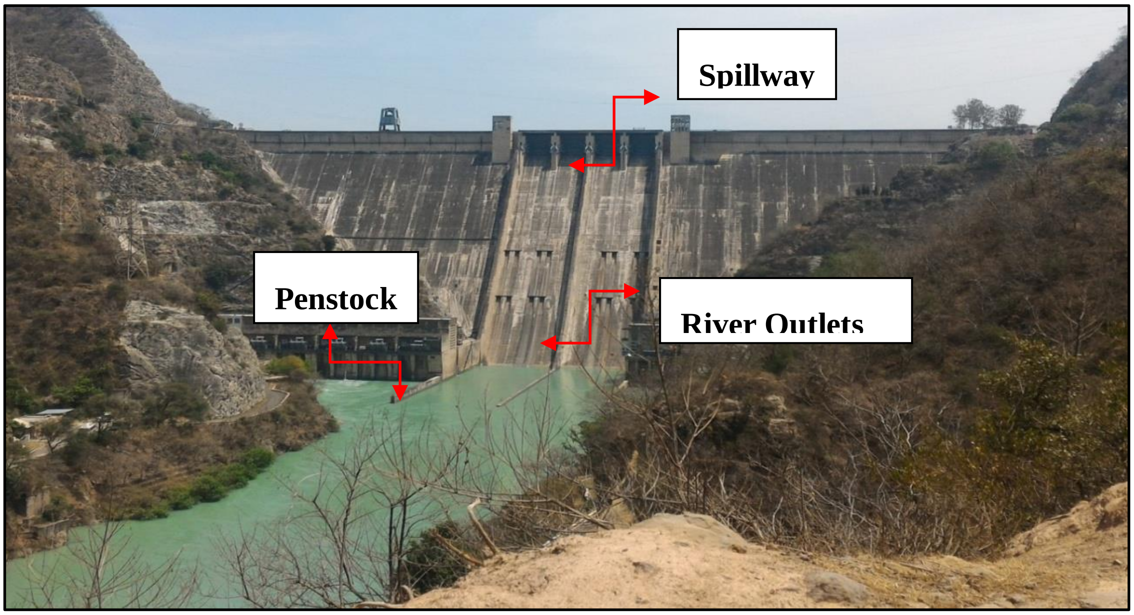


Figure 5.1 A view of Bhakra Dam

5.2 Discharge Facilities

Following facilities are available inside the Bhakra dam for discharging water to the downstream.

1. River outlets
2. Penstocks
3. Spillway

Discharge through the operating penstock depends on the requirement of the power plant. Additional requirement of water to fulfil the irrigation requirement is made through river outlets. Discharge through spillway is possible when the reservoir level reaches above spillway crest level El. 1645.211 ft. Dam is having 16 river outlets beside fulfilling the requirement of irrigation they are also used for passing the floods.

5.2.1 Penstocks

Bhakra dam have immense capacity to generate hydroelectric power. Five penstocks are located on either abutment and are numbered in increasing order 1 to 5 from spillway to abutment on the left side. On the right side left side penstock are numbered 6 to 10 increasing from spillway to abutment. Turbine wicket gates control the operation of penstock automatically Reservoir elevation and tail water elevation difference and discharge through one unit of penstock is deciding factor for power output.

5.2.2 River outlets

In the spillway portion of the dam river outlets are located in two horizontal tiers. Total number of river outlets are sixteen having size 2.64 m x 2.64 m. River outlets from one to eight are located at elevation 1420 ft another row of river outlets nine to sixteen are located at elevation. 1320 ft. The river outlets are controlled by jet flows gates operated from gate galleries El. 1333ft/El. 1433 ft inside the dam. Two emergency gate have also been provided for closure at upstream face of the dam. These gates are lowered to close any particular outlet in the event of failure of jet flow gate or for the inspection of the conduit upstream of the jet flow gate.

5.2.3 Spillway

The spillway is a structure constructed within the body of the concrete dam in order to effectively dispose of the surplus water from upstream to downstream. Spillway act as safety valve for the dam. At spillway opening is provided at elevation of 1645.211 ft. It consists of four spillway opening provided with radial gates for controlling the flow of water . In central block numbers 18, 19, 20, 21 and 22 of the dam the spillway is located. Tables are prepared which specifies for various elevation the quantity of discharge is feasible from one gate of spillway.

5.3 Gauging Facilities

For gauging the upstream reservoir level a head water gauge well of 762 mm diameter is provided in block 17 records reading automatically by the water stage recorder installed in the hoist gallery El. 1684 ft. A water stage recording gauge has also been provided near the end of the tailrace channel and one just downstream of the spillway apron on the left bank. A permanent gauging station for measuring the discharge passing downstream of the dam has been provided at Olinda about 2377 m downstream of the dam axis.

5.4 Storage Utilisation

5.4.1 Water Indents

The water released from Bhakra Dam primarily cater the water indents at Nangal Dam which is main regulating point for actual requirements of the areas covered under Bhakra Nangal Project. Thus the total water indent on Nangal Dam consists of the requirement of Nangal Hydel Channel which tails off into the Bhakra Main Line, Anandpur Sahib Hydel Channel and the requirements at Rupar Headworks with due allowances for losses or gains made in the length of river channel between Nangal and Ropar.

Normally, the water releases made for irrigation requirements would also cover the water demand for power generation purposes, but in some dry years releases from Bhakra may have to be made from power consideration, when during specific periods firm power requirements cannot be met by the releases made for irrigation purposes only. The extent to which the total water indents required at Nangal can be met from Bhakra depends upon the total available water, that is, existing storage and the expected inflow of the GovindSagar (reservoir) during an year. In case of the total available water falling short of the total requirements, the indents at Nangal generally have to be suitably reduced. Water is released from Bhakra storage according to the ruling reservoir factor. The total daily indents at Nangal, after being modified according to the existing practice, shall be met from Bhakra Dam.

The water released for irrigation and power purposes from GovindSagar is available for use at Nangal Dam. The releases from Nangal Dam shall be regulated according to the actual irrigation and power generation requirements at Nangal, whereas the releases made through penstocks at Bhakra are governed by the power demands at Bhakra. In case the demands at Nangal are not met from the release made at Bhakra, the shortfall is made up through the release through outlets at Bhakra. However, this additional release from the outlets at Bhakra cannot exceed the pondage capacity at Nangal. The capacity of Nangal Pond for post Bhakra dam operation is 25.221 million m^3. This capacity is designed to serve as balancing reservoir for smoothening the diurnal and weekly fluctuations of the Bhakra power Houses, so as to have a non fluctuating supply for irrigation and power from Nangal Power Houses, which work as base load stations.

5.4.2 Storage capacity

The reservoir can be depleted upto dead storage level El. 1462 ft to fulfil the demands for irrigation and power generation considerations. The reservoir has sufficient capacity to accommodate silting during the expected life of the reservoir. Between the maximum reservoir level at El. 1690 ft and dead storage level at El. 1462 ft, the reservoir has an available capacity of 7,400.9 million m^3 which is sufficient to store the entire surplus flow of an average year.

While depleting the reservoir the water level should never be allowed to fall below the dead storage level under any circumstances as over depletion to meet the shortage of water during any year results into acute water shortage next year if it turns out to be a dry one. The dead storage level at El. 1462 ft has been fixed after raising the initially designed dead storage level at El. 1440 ft to increase the firm generation of Bhakra units.

5.4.3 Control of reservoir

An efficient control of reservoir would fulfil the following design requirements to the best possible extent.

1. To achieve optimum amount of irrigation from water available upstream of the dam and to generate the maximum power. Minimum specified power to be ensured by extra releases in the interest of power generation whenever required.
2. To absorb and rout the floods without danger to the safety of the dam structure and appurtenant works and without causing undesirable flow conditions along the river course downstream of the dam.
3. To keep the project operative for maximum period with minimum maintenance.

Releases in the interest of irrigation as mentioned before, the water indents to be passed downstream of the dam are to be suitably modified according to the ruling reservoir factor to distribute any excess or shortage of the water over the prescribed period of the year consistent with the current practice. According to the prescribed instructions for reservoir operation, the GobindSagar is to be regulated on year to year basis.

The present procedure of meeting the water indents shall fulfil the following objectives:

1. To supply full water requirements during filling period irrespective of the type of the year (above or below average) expected to encountered .
2. Depending upon whether the year is likely to be wet or a dry one, a suitable reservoir factor is estimated for the depletion period and releases made accordingly till the

reservoir touches down the dead storage level after which only the runoff of the river is passed down to meet the indents.

For the above purposes the reservoir factor is defined as a factor by which indents are to reduced before making the releases and is equal to the ratio

$$Reservoir\ factor = \frac{Available\ storage + Total\ river\ flow\ during\ the\ remaining\ period\ of\ the\ year}{Total\ water\ indent\ during\ the\ remaining\ period\ of\ the\ year}$$

where 'available storage' allows for the reservoir losses during the remaining period of year and total river flow during the remaining period of the year also includes the effect of losses or gains in the river channel downstream. The reservoir factor is effective only when its value is 1 or less than 1.Estimating the reservoir factor according to the above definition requires estimating the likely inflow during the depletion period. The accuracy of the reservoir factor would thus depend upon the degree of accuracy to which likely inflow during the depletion period can be estimated.

5.4.4 Average year

For regulation purposes an average year consists of river flow data for a year comprising of average 10 daily discharges obtained from the discharge observations for the corresponding 10 day periods for various years for which the discharge record is available.

5.4.5 Filling-in-period

Filling -in- period is the period during which the flow of the river is more than the indented water requirements and the surplus flow is impounded to build up the storage. The period covers the monsoon season and does not include the period of high winter flows which may occur for short times. The commencement of filling -in-period is taken from a date, on which the reservoir will start building up if the flow had been according to the average year. It would be advantageous to fix this date slightly towards the later part of the year, so that before the commencement of this period when the reservoir touches down the dead storage level, improved flow condition of the river are ensured. The end of the filling -in - period is taken to be the date on which the flow of the average year falls below the indented water requirements of the corresponding period after the monsoon.

5.4.6 Depletion period

The remaining part of the year outside the filling-in-period is considered as depletion period. For operation and regulation of dam the year commences from the start of filling-in- period and ends at the end of the depletion period. Regulation is done on year to year basis the storage in the reservoir begins from the dead storage level at the beginning of the year and it comes down again to dead storage level at the end of the year in case of an average or dry year. In case of a year having total flow more than the total indent, the storage left at the end of the year would be carried over to the beginning of the next year which could be of use in case coming year turns out below average.

Commencement of the filling in period can be taken from first of June each year and beginning of the depletion period from first of October. These characteristics should be modified after every 10 years or earlier for the purposes of working out the reservoir factor to allow for any change in the pattern of inflow due to the formation of the lake and the new available flow data. The estimated reservoir losses for 10 daily periods of 'the year' are also estimated. These values would need revision after actual losses have been observed for the GovindSagar.

5.4.7 Reservoir Factor Chart

Reservoir factor chart has been prepared to facilitate working out the reservoir factor at any time of the year in the following manner. Workout 10 daily flows for the average year from the available record and this could be modified after every 10 years or earlier to account for changed pattern of flow of river. Average losses or gains between the point of release and the point where a desired indent is required are worked out. Thus, while assessing the quantity of Bhakra the losses due to evaporation and seepage, and gains due to precipitation are taken as 100 and 50 percent, respectively.

5.5 Reservoir operation

Operation of Reservoir under normal circumstances shall be done as described below.

When the reservoir level is below El. 1550ft the first set of river outlets to be operated are No. 11 and No. 14. If four river outlets are required to be operated then the next pair shall be No.12 and No.13. When the reservoir level is higher than El. 1550ft and lower than 1650ft, the river outlets No.3 and No.6 are operated to supply water for irrigation. If 4 outlets are required to be operated, the next pair shall be No.4 and No. 5.With reservoir level above El. 1650ft, releases will be through the radial gates and not by running river outlets. Operation of river outlets in conjunction with the radial gates is not considered desirable.

When only one bay is available for releasing water for reservoir level below El. 1550 ft single river outlet may be operated in individual bays such as No.11 in left bay or No.14 in right bay. In case two river outlets are required to be operated, then No. 11 and No.12 shall be operated in the left bay or No. 14 and No. 13 shall be operated in the right bay.

For reservoir level above El. 1550 ft and below El. 1650 ft single river outlet may be operated in individual bays. For example, No. 3 in left bay or No.6 in right bay. In case two river outlets are required to be operated, No. 3 and 4 shall be operated in left bay or No. 6 and No.5 shall be operated in the right bay. When the reservoir level is above El. 1650 ft water shall be released for irrigation needs through the radial gates of the bay.

Following additional instructions shall also be followed irrespective of whether one bay or two bays are available for releasing the water.

River outlets other than the central ones shall be occasionally operated to keep them in working order. In the event of central river outlets not available for operation, other outlets may be run for short duration when the maintenance and repair of the central bay is in progress. Determine the rise/fall of the reservoir level during the last half hour period according to the class of flood and work out the average rate of inflow /outflow in cusecs from the change of the storage. The levels at the beginning and end of the time interval are used to determine the volume for water in a given time interval. The water balance equation is then used to determine the inflow into the reservoir for the given time interval. While observing discharges at Olinda due care should be taken regarding transient effect of opening/closing of any discharge facility. The discharge estimation at Olinda and reservoir gauge observation should be made simultaneously.

5.6 Flood Disposal

Surplus river flows and floods may be disposed of with the help of the following facilities.

- River outlets
- Spillway

The spillway has been designed for a net over all discharge of 8,212 cumecs and discharge including the flow contributed by the river outlets and the peak inflow of 11,327 cumecs can be catered to corresponding to the pattern and duration of maximum 1947 flood. In addition to the considerations mentioned for the release of water through river outlets, the following procedures shall be followed to dispose surplus river flows and floods downstream of Bhakra Dam through the spillway:

- Build up the reservoir to the full reservoir level of 1680 ft /1690 ft as permitted.
- When the reservoir is full , the procedure for the disposal of floods and surplus inflows shall be as follows:

If the flow is more than the normal irrigation and power demand, open the requisite number of additional parts of river outlets of the upper tier at an elevation of 1420 ft so as to keep the reservoir steady at elevation of 1680 ft to 1690 ft. Alternatively, regulation may be done by radial gates if that is found smoother and less injurious to spillway surface.

If the rise in the reservoir level persists and there is an anticipated medium or high flood, operate the spillway by raising all the four radial gates simultaneously and open all river outlets of EL. 1420 (432.82 m MSL) with a view to depleting the reservoir to such an extent as considered safe. The spillway gates may be lowered progressively in the falling flood with a view to bringing back the reservoir to the maximum level.

Proper regulation at this stage will depend upon the vigilance and judgement with a aim to get rid of as much water as possible before the reservoir is hit by the peak flood, and at the same time to ensure the reservoir would be filled in the falling flood. In this connection, it shall be absolutely necessary to remain updated with the flood and rainfall recording stations in the catchment by means of wireless equipment.

Table 5.1 Maximum discharge at various water levels

Discharge Through	**Water Level in dam**		
	1680 ft	1685 ft	1690 ft
Upper tier 8 River outlet	44800 cusecs	45250 cusecs	45700 cusecs
Lower tier 8 River outlet	52700 cusecs	53100 cusecs	53500 cusecs
Spillway	157600 cusecs	197300 cusecs	239300 cusecs
Total Discharge possible through openings	255100 cusecs	295650 cusecs	338500 cusecs

Table 5.1shows the discharges which are possible through river outlets and spillways at various elevation of water level in the dam. However, the total discharge through opening is restricted to 290,000 cusecs considering the stability of the dam. The spillway has been designed to pass a total discharge of 290,000 cusecs (8,212 cumecs) corresponding to an inflow flood of 400000 cusecs (11,327 cumecs). There is a very low probability of encountering such a heavy flood, in which case the lower tier outlets should also be opened in pairs steps by step after the upper tier outlets and the four bays of spillway are unable to cope with the inflow. However, the maximum discharge intensity shall not more than 290,000 cusecs (8,212 cumecs). In such case the lower tier outlets shall be closed at the earliest opportunity after the spillway gates have been closed.

When the reservoir is filled up to an elevation of 1690 ft and the anticipated flood is such that its peak discharge is likely to be more than the combined capacity of these facilities, the reservoir should be depleted well in time to such an extent as to adequately absorb the extra inflow. The area of the anticipated flood hydrograph above the maximum discharge capacity of facilities of the dam, would give the volume of the extra inflow likely to be encountered. The depletion level corresponding to volume can be read from the curve provided for the reservoir. As soon as the peak has passed and the inflow falls within the discharging capacity of the spillway and outlets they should be progressively closed to build up the depleted storage. It is very important to estimate the minimum time period of reporting discharge at stations. This minimum time period should be more than the time required to deplete the reservoir to the desired level with the available disposal capacity.

Following steps should be considered to mitigate the peak flow:

For the design flood of 400,000 cusecs (11,327 cumecs) according to the 1947 pattern, it would be necessary to deplete the reservoir by 4 ft, that is, from an elevation of 1690 ft to an elevation of 1686 ft. This depletion at Bhakra Dam would require 20 hours. The process of depletion should start immediately on receiving the flood warning 36 hours before the arrival of the peak. It should also be noted that if the warning is delayed by just a few hours it will not be possible to deplete the reservoir in time at all.

Before the beginning of the monsoon season every year it shall be ensured that all the electrical and mechanical equipment connected with the jet flow gates and emergency gates of the river outlets and radial gates of the spillway are in perfect working order, and are ready for immediate operation at all hours. A careful inspection of all connected civil structures shall be made and recorded in writing before the onset of the monsoon each year.

A general vigilance should be maintained on the inflow conditions of the reservoir. The rate of rise of reservoir level shall be observed and peak of any inflow constituting a flood shall be recorded. During monsoon season rainfall and discharge reports from various observation station in the catchment area should be monitored regularly. Meteorological forecast and heavy rainfall warning in the catchment area for the coming 24 hours should be considered for reservoir depletion. Flood warning shall be issued to all concerned according to the instructions and in the manner prescribed from time to time for class of flood encountered whenever the inflow or outflow exceeds the prescribed limits.

Considerable judgement shall be required for depleting the reservoir below the elevation of 1680/1690ft with the help of spillway radial gates. Too early closure of these gates would need reopening in case the heavy inflow continues, whereas too much lowering of the reservoir level might result in unrecoverable loss in storage. It would be a good plan to deplete the reservoir on the higher side in the early period of monsoon season, as subsequent floods and high inflow would make up the lost storage. In the later part of the monsoon over depletion should be kept to the minimum possible extent.

5.7 Early flood warnings

The maximum reservoir elevation of the GovindSagar has been fixed at an elevation of 1690ft such that water cannot be allowed to rise above this elevation under any circumstances. For this, it is absolutely essential that accurate and timely warning of heavy inflows in the reservoir is made, such that sufficient time is available for proper assessment of flood and operation of facilities at dam.

To achieve the above objective discharge observation stations fitted with wireless facilities have to be suitably located on main streams and all important tributaries just before their entrance into the lake area. Heavy inflow in any of the sub-catchments would thus be immediately transmitted to the dam site there by giving the advance warning of the approaching heavy inflow. It may be possible that more than one station may report heavy inflows at the same time or in such sequence which may lead to the accumulation of all peak flows from various tributaries at the same time. Such a situation would lead to a high flood condition and should always be watched very carefully. The following procedure is prescribed for collecting and utilizing the early flood warning data.

5.7.1 Time period of gauging station

It would be essential to work out the period for each gauging station in which, the flow peak travels from the gauging station to the dam site. To observe this, data should be carefully compiled for occasion when an isolated heavy inflow is reported by only one gauging in the whole of the catchment. A detailed hydrograph for the flow at the gauge site with half an hour gauge observation should be obtained and a number of hydrographs of such flows plotted. The time of peak flow occurring at the site should be worked out from these hydrographs.

Corresponding to the above hydrographs, from the reservoir gauge observations and discharge data of the river at Olinda, the time of arrival of the inflow peak at Bhakra should be observed. The difference between the time of peak passing the discharge site and time of arrival at dam site would give the required ' Time period ' for the particular gauging station. Average values of a number of such observations should be worked out to arrive at a reliable figure. A record of inflow hydrograph at Bhakra as worked out above for each gauging station corresponding to various reservoir elevations should be maintained to assess the inflow pattern of each substation covered by the respective gauging station. Special efforts should be made to collect this data by arranging for the required gauging and reporting facilities at various points of the catchment and experiments conducted to establish the feasibility of the proposed method of early flood warning. Since no actual data is available the adequacy of the proposed method of early flood warning is required to be established and alternatives evolved where snags are encountered.

5.7.2 Expected flood and period of occurrence

To work out the expected peak inflow and time of its occurrence, flood warnings from all the reporting station with the help of past record in such a way that the discharge ordinates of the hydrographs are in ratio of the recorded and reported peaks. Overlap these worked out hydrographs such that their peaks fall at the time of expected arrival worked out by adding the 'Time period ' of each reporting station to the time of its reporting the peak. The hydrograph obtained by the summation of the flow ordinates of these hydrographs would give the time of the occurrence and magnitude of the peak flows expected at Bhakra. With the help of the above information, it would be possible to take precautionary measures and deplete the reservoir to receive the flood at Bhakra as described in the previous sections.

5.8 Prevailing Reservoir operation and regulation plan

5.8.1 General

Reservoir operation comprises controlled release of water downstream of the dam in relation to the inflow and the available storage above the dam so as to fulfil the designed requirements of the project. Regulation of the Bhakra reservoir is made on year to year basis which envisages that the reservoir would start from the dead storage level at El. 1462 ft at the beginning of the year from where filling period begins on 21st May and ends at 20th September in the case of an average or dry year. Some storage is kept at the end of the depletion period on 21st May to cater for the adversities of weather and delayed monsoon etc.

5.8.2 Reservoir filling

The criteria in vogue for the filling of Bhakra reservoir has been as under:

- The reservoir should not be filled beyond El.1650 ft 31st July and El. 1670 ft by 15th August.
- The reservoir upto El. 1680 ft should be filled not earlier than 31st August and filling above this elevation would be attempted after ensuring due safeguards.
- The raising/filling of reservoir above the design FRL upto the level of El. 1688 ft is subject to that filling beyond the designed FRL must be done most carefully taking all precautions in consultation with Chairman, BBMB and Member (Irrigation) very frequently and daily.

Subsequently, in the special (139th) meeting of the Bhakra Beas Management Board held on 29th August 1990, it was decided that the maximum level of the Bhakra should be kept at 1680 ft for the storage purpose. However, in case the level is allowed to rise a little higher than this value for the purpose of flood routing /absorption and to avoid synchronisation of release with operation strategies.

5.8.3 Instrumentation

In order to monitor the behaviour of the Bhakra dam and appurtenant works, a large number of instruments/devices were installed both inside and outside the body of the dam. Instruments which are embedded in the body of the dam consists of Carlson type elastic wire, strain meters , stress meters, joint meters and resistance thermometers. The other measuring instruments installed inside the dam are the plumblines, tiltmeters, settlement benchmarks, uplift pressure pipes, groundwater holes, drain holes, strong motion accelerographs and structural response recorders. Measurements of the deformation of the dam top and downstream face, rock ribs, etc. are made with the help of settlement of bench marks, geodetic survey points and transverse markers.

Periodic observations of the various instruments/devices and the seepage measurement from the drainage holes /galleries are made in the field in accordance with the instructions contained in the operation and maintenance Manuals. Thereafter, the field data is processed and conclusion drawn regarding the behaviour/performance of the dam are presented in the Annual Observation Reports.

6 Techniques for Inflow Determination

6.1 Introduction

Hydrology and water resources management are intrinsically linked. One of the most important data used in stimulating reservoir operations is the inflow to the reservoir. Synthetic inflows are generated using stream flow forecasting models that are often used in simulation studies to evaluate the response of the water resource system to possible future scenarios. The development and implementation of such models require the past inflow data of reservoir. Based on the historical records stream flow forecasting can be done. The validation of the model is done by comparing the statistics of the generated inflow sequence with the historical sequences.

6.1.1 Description of inflow model

Thomas and Fiering (1962) used autoregressive (AR) model, to simulate and generate synthetic runoff series by treating the hydrologic data as time series which has random and deterministic components. Matalas (1967) and Vicens et al. (1975) developed ARIMA (Autoregressive Integrated Moving Average). ARIMA has good accuracy for short term forecasting but it becomes flat for a longer period forecasting. ARIMA uses past and present dependent variable by ignoring the independent /random variable completely to produce accurate short term forecasting (Hendranata 2003).

Dogan et al. (2007) compared daily stream flow forecasting techniques using artificial neural network (ANN) and autoregressive (AR) models. The authors concluded that ANN yields better output than AR methodology. Among different forecasting models, Thomas and Fiering model is extensively used in inflow forecasting by the investigators because of its simplicity in implementation and reliability by the investigators. The model takes into account the seasonal variations in monthly inflow means, standard deviation and lags one autocorrelation coefficients. Since high flows are likely to follow high flows and low flow likely to follow low flows, there is persistence in natural time series. Such persistence is computed by serial lag coefficients with lag interval of one or several time units.

6.1.2 The Thomas - Fiering Model

Stream flow forecasting techniques are an integral part of real time operation models. Stochastic stream flow models are generally used in simulation studies to assess the response of the water resource systems to future scenarios. The development and implementation of such models require the historical record of flows. Based upon the historical record, the parameters of the rainfall or stream flow forecasting model are generated. The verification of the model is then carried out by comparing the statistics of the generated sequences with the historical sequences.

The Thomas-Fiering model (Thomas- Fiering 1962; Fiering 1967) is a lag -one Morkov model. In order to forecast inflow into the reservoir it is sufficient to assume first order Markov structure exists. The Thomas Fiering model is fitted to the standardised monthly flows, $y_{i,j}$ is given by

$$y_{i,j} = \left(x_{i,j} - \overline{x_j}\right)/\sigma_j \qquad \textit{6.1}$$

where$x_{i,j}$ is the original flow for year i and month j, and $\overline{x_j}$ and σ_j are sample estimates of the mean and standard deviation respectively, for month j.

The model is based on lag- one auto regressive Markov process, and the standardised generated flow is given is given by

$$y_{i,j} = \beta_j y_{i-1,j-1} + \varepsilon_{i,j} \quad 6.2$$

where $\varepsilon_{i,j}$ is the random component as described by

$$\varepsilon_{i,j} = \sqrt{1-\beta_j^2} \times Z_{i,j} \quad 6.3$$

And $Z_{i,j}$ is the randomly generated normal variate with zero mean and unit variance, β_j is the lag-one serial correlation coefficient between month j and $j-1$ is given by

$$\beta = \frac{\sum d_x d_y}{\sqrt{\sum d_x^2 X \sum d_y^2}} \quad 6.4$$

where d_x and d_y are the deviation of inflows in month j and $j-1$ from their respective means.

6.1.3 Methodology for Synthetic Sequence Generation

A suitable starting value and the sample estimates of monthly parameters $\overline{x_j}$ and σ_j are required to generate a continuous sequence of T years of synthesised monthly flows, x_{ij}, where i = 1, T and j=1, 12 for monthly flows. Since the next period's inflow can be estimated from the previous period's inflow, equation (6.2) can be used recursively to generate a synthetic sequence of any length. The mean and standard deviation of the generated sequence are generally well preserved when the individual monthly flow are normally distributed. When the original data do not perfectly fit or may not be acceptable for the assumption of normal distribution and some unacceptable results are obtained, in terms of the mean or standard deviation or lag one correlations. They do not compare well with the observed or the generated values. Then, compute the logarithms of the flows; that means, original data may not be normal distributed, but it is possible that the logarithms of the flows may be normally distributed, which means that the flows can be approximated as log normal distributions. When the probability distribution of the monthly flows are skewed, they can often be normalised by transforming to the logarithmic scale. Both the model are used to first generate standardised data which is followed by inverse standardisation. If the log transform is used, inverse log transformation is carried out to obtain the synthetic sequence.

A computer program (Annexure-4) is used to generate the random numbers with normal variate having zero mean and unit variance. This random generation is referred to as a pseudo-random generation. These created values are not truly "random" because a mathematical formulation is used to generate the random values. To generate values by a mathematical algorithm with a given starting number used in this study is called seeding. Seed used in this study is 9001. If the seed value is not provided to the program, different sequence will be generated each time.

The statistics presented in Table 6.1clearly indicate that the mean and standard deviation of the sequence generated by the Thomas-Fiering model were in good agreement with the corresponding historical values. Inflow records of Satluj river from 1999 to 2018 obtained from the Bhakra Beas Management website were used to generate synthetic record from 2019 to 2037 in order to have forty years data that could be utilized for further planning and investigation. The historical data (1999-2018) was analysed to obtain statistics such as monthly means, standard deviation and lag correlation coefficient. The python code was written to generate several synthetic sequences. The generated sequence were then compared with the historical sequence in terms of basic statistics.

Table 6.1Statistics of observed flow and synthetic sequence

	Synthetic Sequence			Observed Flow		
Month	Mean	Std Deviation	Correlation	Mean	Std Deviation	Correlation
Jan	5834.014	649.1559	0.112795	5563.75	766.458	0.227655
Feb	5609.013	785.8238	0.256504	5626.2	922.113	0.551696
Mar	8086.953	1498.8398	0.606168	7415.4	1793.753	0.401201
Apr	12261.19	2914.9026	0.494471	10994.6	2550.228	0.605125
May	24018.01	6227.8138	0.746671	21938.45	5808.079	0.491462
Jun	31249.11	8503.0354	0.405144	32920.2	8193.273	0.410272
Jul	43522.62	8108.6	0.47688	45904.45	8201.92	0.399201
Aug	48642.51	8960.7912	0.484978	48152.7	8091.543	0.389443
Sep	28712.41	5121.5147	0.553433	27123.6	5783.09	0.47229
Oct	11922.88	1337.4898	-0.062198	12069.421	1897.099	0.700927
Nov	7635.302	917.8997	0.334091	7652.368	991.837	0.853892
Dec	6144.237	691.901	0.881475	6191.368	653.42	0.742986

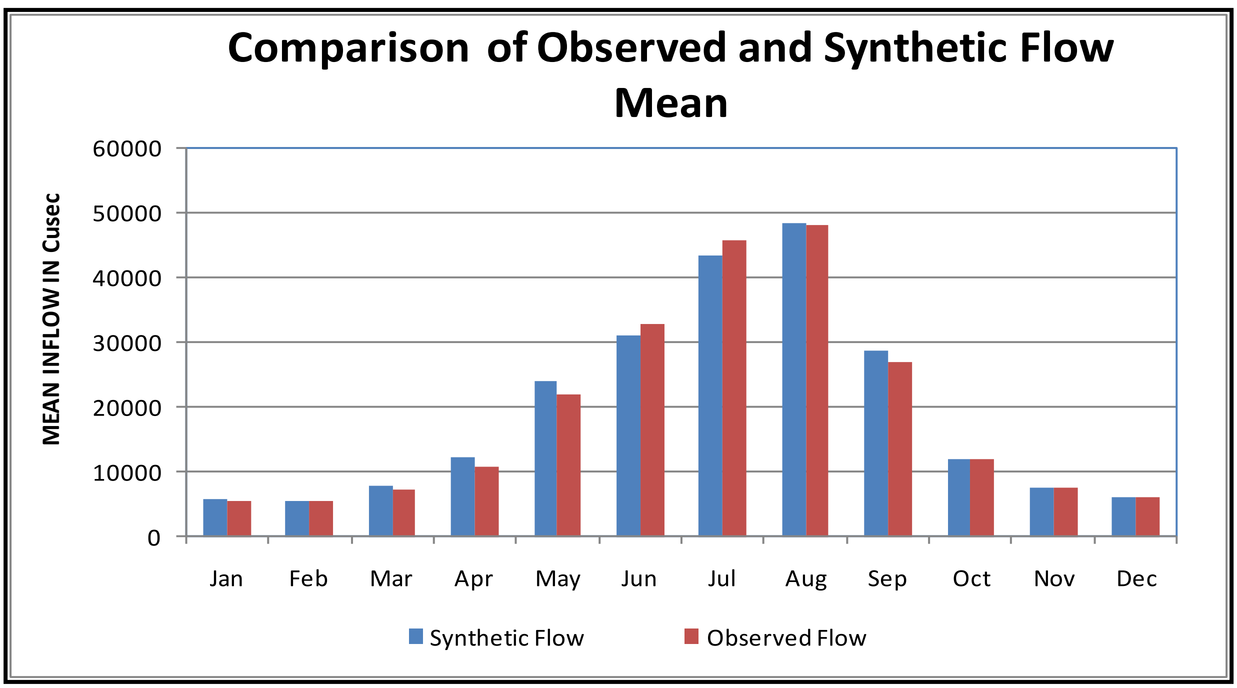


Figure 6.1Comparison of observed and synthetic mean

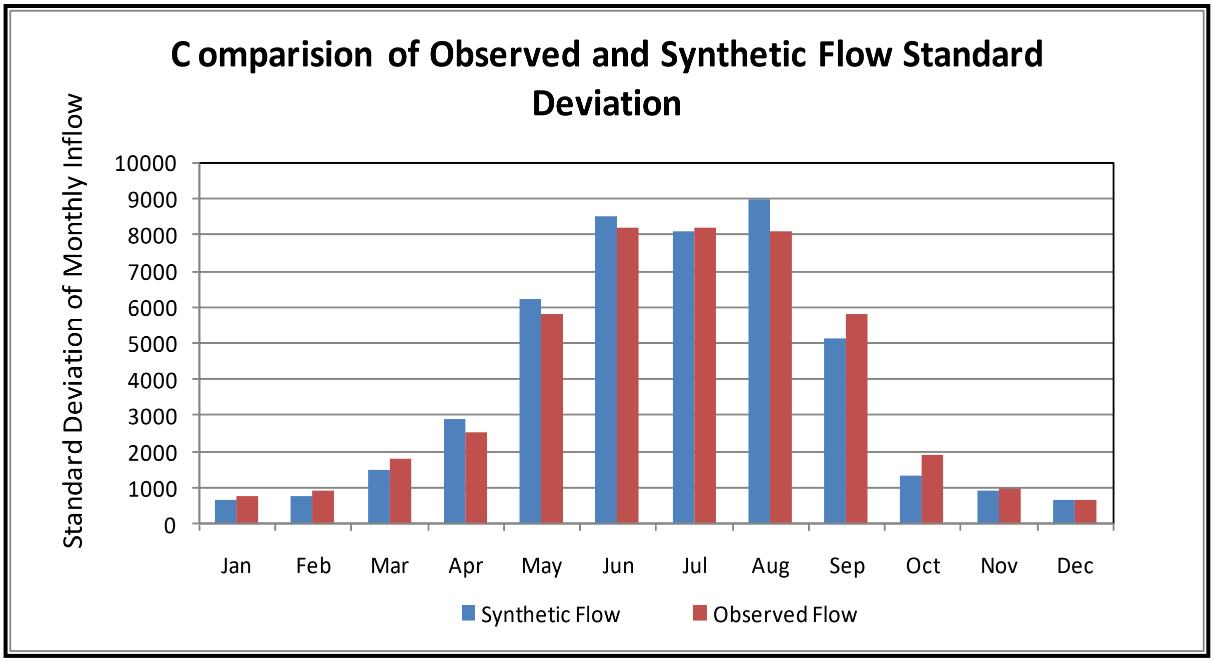


Figure 6.2. Comparison of observed and synthetic Standard deviation

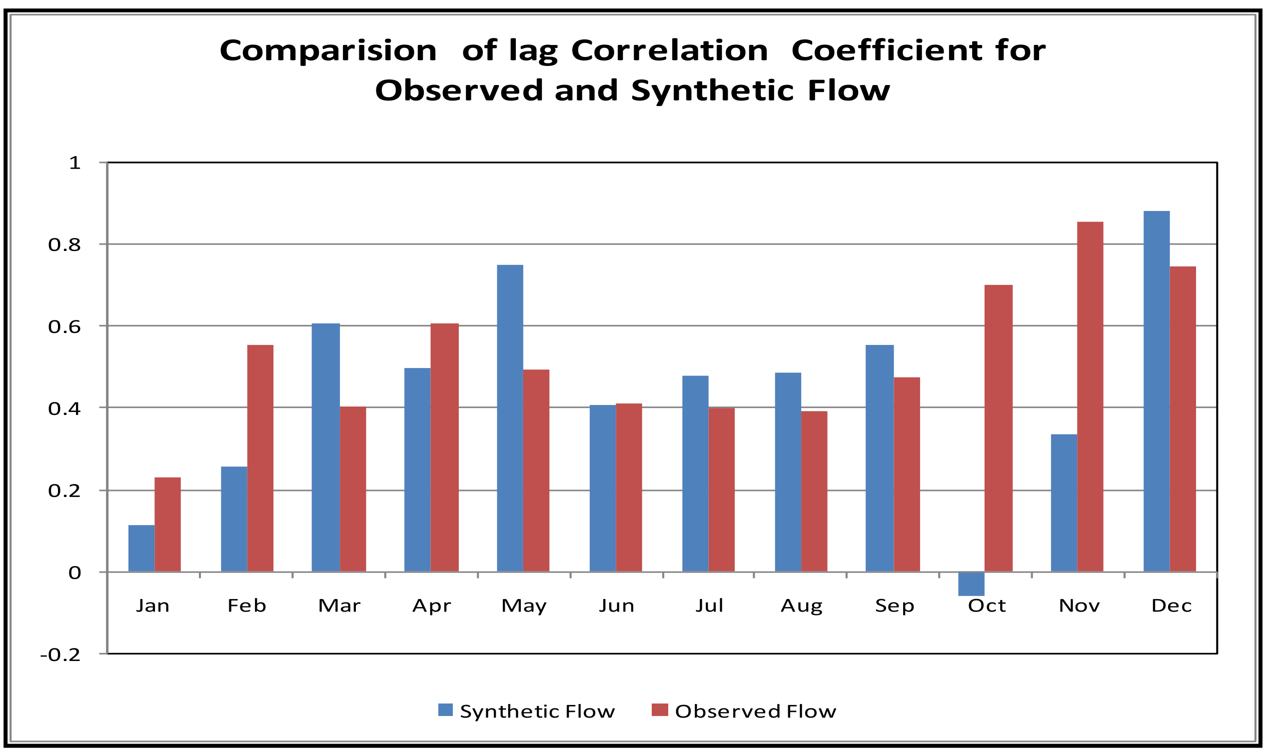


Figure 6.3 Comparison of Lag Correlation Coefficient for observed and synthetic flow

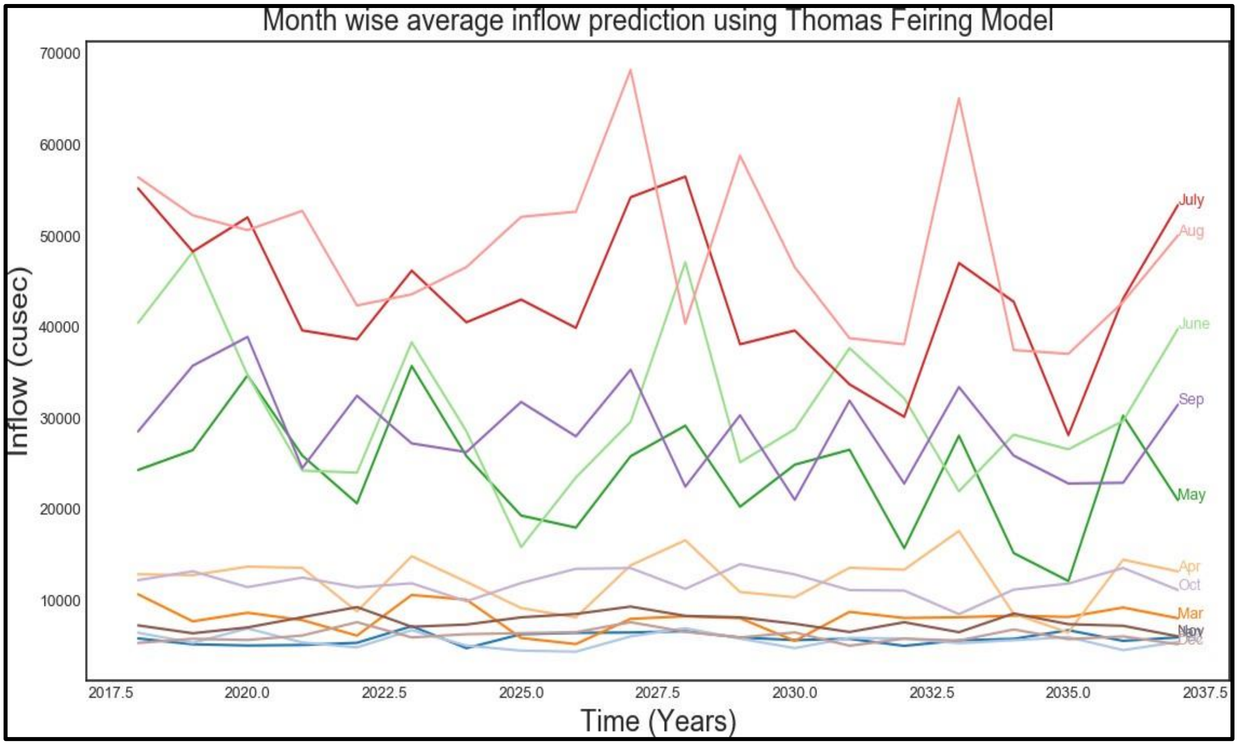


Figure 6.4 Month wise average inflow prediction using Thomas Feiring Model

6.2 Long Short Term Memory (LSTM)

6.2.1 Introduction

LSTM model was developed to estimate daily inflow as real time inflow forecast will help reservoir in efficient operation of water resources. Daily variations in release can be monitored efficiently and reliability of operation will improve. The proposed LSTM model is used to derive the forecast of daily inflow. The work also proposes a naive anomaly detection method to find out the forecasted inflow and if the difference is significant from the average usually inflow for that duration it can indicate flood or drought. LSTM is claimed to be more efficient than other stochastic models for time series predictions as it can satisfactorily simulate non stationarity and non-linearity (Hochreiter and Schmidhuber 1997). In this work we have conducted several empirical experiments over Bhakra Nagal dam inflow data of last

20 years and build LSTM model to predict inflow with higher accuracy. Comparisons are made with daily inflow predictions generated by Thomas Fearing model to show that the LSTM significantly improves upon the root mean error (RME) over inflow data. Although, experiments are run on data from Bhakra Dam Reservoir in India, LSTM model and anomaly detection algorithms are general purpose. The purpose of these experiments is to give empirical evidence in support of efficacy of LSTM and can be applied to any setting i.e. for different reservoir systems without much changes.

Operation of reservoir systems optimally is essential to meet the objectives of water demand. Various techniques to achieve optimal operation have been used to treat non-convex, non-linear behaviour of reservoir. Dynamic Programming (DP) (Bellman 1966) is the widely accepted technique for optimal operation of reservoir, as these are characterized by large number of variables that can be defined in terms of non linear inequalities and modelling these also needs accounting of stochastic features, these things can be translated into a DP problem. Thomas-Fiering model is also used to forecast monthly inflow and can be effectively used for deciding reservoir release policy for average year. (Sargent 1979)used transition probabilities to generate sequences of daily stream flows and preserved the important characteristics of the daily inflow hydrograph. In the past many approaches were experimented with to forecast inflow and in this paper a novel LSTM based neural network architecture is proposed.

6.2.2 Statistics of observed data

The observed daily inflow for the period 1999 - 2018 at Bhakra is available on the website of Bhakra Beas Management Board (BBMB). The Table 6.2 shows the statistics of the observed daily inflow data at Bhakra for three periods. It is subdivided into Training set, Testing set and validation set. It includes minimum, maximum, mean, standard deviation, Kurtosis, Skewness and auto correlation for 1 day lag to 3 day lag(R1, R2, R3) of daily inflow data. Auto correlation indicates high degree of dependency on previous day inflow.

Table 6.2 Statistics for Training Set ,Validation Set and Testing Set of observed daily inflow data

Parameters	**Training Set**	**Validation Set**	**Testing Set**
Minimum	3101	4471	2767
Maximum	149075	92890	131488
Mean	19226.518	18079.232	19754.6
Standard Deviation	17161.079	16353.411	16957.402
Kurtosis	2.314	1.875	1.334
Skewness	1.486	1.526	1.314
R1	0.974	0.969	0.955
R2	0.945	0.951	0.936
R3	0.926	0.946	0.918

6.2.3 Daily historical inflow data and reservoir operation

It is considered that the Satluj region is significantly vulnerable to adverse effects of global warming. Due to change in climate, precipitation pattern changes, causes variation in stream flow. Figure 6.5 explains various observed trends within the last 20 years of operations in Bhakra Nangal Dam. The first figure explains the relationship between Inflow and discharge using time series data of last 20 years. Second figure shows trend in reservoir levels on which the dam operates, notice the crests and troughs of each year throughout 20 years are spaced evenly indicating strong correlation in months and reservoir levels. Figure 6.5 indicate reservoir levels at the end of filling period is El.1680(Ft).

In general, the reservoir operation strategies consist of controlled release of water downstream considering the inflow and the available storage in the reservoir. The objective of operation is to fulfil the demand with respect to power, irrigation, water supply and flood control among other demands.

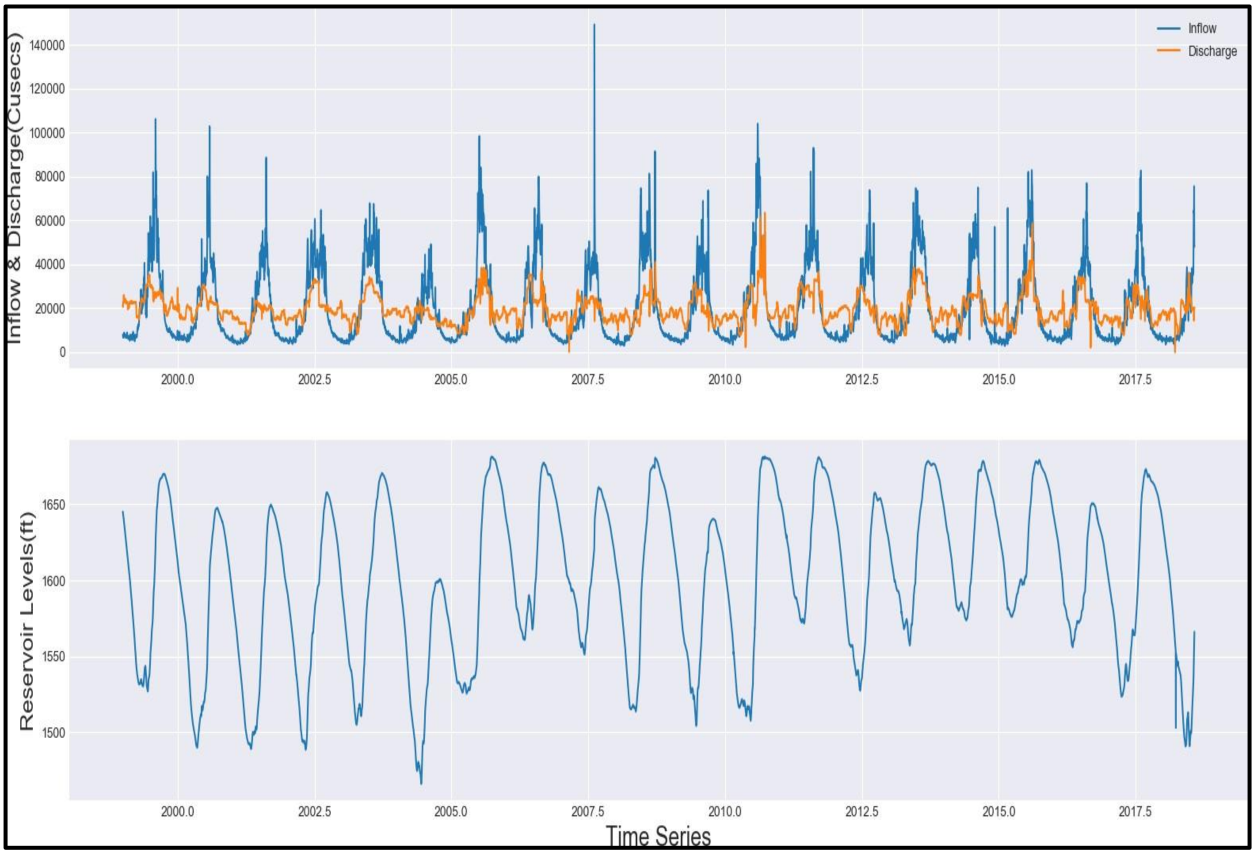


Figure 6.5 Inflow, Discharge and reservoir levels statistics for Bhakra Reservoir.

For the purpose of reservoir operation at Bhakra, an year is divided into two parts. The filling period is from 21stMay to 20thSeptember, whereas the depletion period is from 21stSeptember to 20thMay of the next year. The water accounts are prepared separately for the filling and depletion period. The excess/shortages of one period are not carried over to the next period. The present procedure of meeting the water indents require to supply full water requirements during filling period irrespective of the type of the year (above or below average) expected to encountered.

Depending upon whether the year is going to be wet or a dry one, a suitable reservoir factor is estimated for the touches down the dead storage level after which only the runoff of the river is passed down. For the above purposes the reservoir factor is defined as a factor by which indents are to reduced for making the releases and is equal to the ratio:

$$Reservoir factor = \frac{Available\ storage + Total\ river\ flow\ during\ the\ remaining\ period\ of\ the\ year}{Total\ water\ indent\ during\ the\ remaining\ period\ of\ the\ year} \quad (6.5)$$

where 'Available storage' is water available at the end of filling period, it also considers the reservoir losses during the remaining period of year. Total river flow during the remaining period of the year is calculated for average 10 daily discharges obtained from the discharge observations for the corresponding 10 day periods for various years for which the discharge record is available, it also includes the effect of losses or gains during the remaining period of the year. The reservoir factor is effective only when its value is 1 or less than 1. Estimating the reservoir factor according to above definition requires estimating the likely inflow during the depletion period. The accuracy of the reservoir factor would thus depend upon the degree of accuracy to which likely inflow during the depletion period can be estimated. Current operational strategies for inflow determination in remaining period depends upon averages of 10 daily inflow of historical data. The Standard Mean square Error (RMSE) of inflow forecast of current strategies is 29.4% and coefficient of determination (R^2) is 0.6571. The results clearly indicate variation persists between actual inflow and predicted inflow.

The rule curve of Bhakra Dam enumerated below shows that filling of dam is correlated with levels to be attained by certain dates.

- The elevation level of reservoir should not be more than El.1650ft by 31st July
- Reservoir level should not be filled beyond El. 1670ft by 15th August.
- The reservoir level El.1680ft should not fill before 31st August.

The reservoir should not be filled beyond El. 512.06 (1680ft) and also this level should not reach earlier than 31st August and filling the reservoir above this designated level of elevation is only done after all the due safety measures have been undertaken.

6.2.4 Long Short term Memory(LSTM)

A considerable success has been achieved with the use of machine learning techniques which are able to solve wide range of problems in optimization and operation research. Recently attempts have been made for successful determination of precipitation but naive deep learning based architectures are difficult to train them to learn and investigate temporal correlation over arbitrary length. Artificial Neural Networks(ANN) are essentially functions that consist of large set of parameters i.e. weights that try to fit the data by tuning them. ANNs does not have any consideration of the temporal sequence within the data. On the other hand, recurrent neural networks (RNNS) have self referencing feedback loop in their architecture. When considered theoretically, RNNs are capable of learning to track relationships for arbitrary lengths in temporal input. However, in practice the tractability of keeping account of learning for arbitrary length RNN fails as gradients being used for computation cannot keep values for arbitrary precision which then turn to zero or explode.

Precipitation and inflow prediction are essentially time series problems and have a temporal correlation in the data. Since the period for such repetition will be no less than an year, it can be safely concluded that remembering gradients for such long iterations to take into account data for last year can cause problems in case of RNNs due to their limitations of vanishing gradients. RNN could be employed for cases when month wise average inflow needs to be computed for the reservoir system. Monthly average inflow predictions cannot reveal significant information for design of strategies for daily operation of reservoir, and are therefore not applicable to real world problems. The Long Short Term Memory (LSTM, Hochreiter Schmidhuber, 1997) is a RNN with forget gate capabilities to overcome vanishing gradient problem. LSTMs and RNNs are trained via back propagation through time.

LSTM networks follow the standard computation graph model to facilitate the extraction of knowledge from continuous input streams of data. The network consists of several gates ”forget gate”, ”input gate” and ”output gate” in sequence. The Equations (6.6-6.11) represent the order in which computation for each gate is done within a LSTM cell. The key to LSTM is that it contains a cell state c_t which maintains the state of each cell and its update is shown in Equation 6.9. Also, it can be noticed that the cell state runs through the LSTM in Figure 6.6b on top and has minimal interaction with rest of the cell. The forget is described as f_t which is a number between 0 to 1 and is multiplied to cell state to regulate how much of information does it need to keep. The input gate and output gate along with hidden layer computation are defined in Equations (6.7),(6.10) and (6.11) respectively.

$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$ 6.6

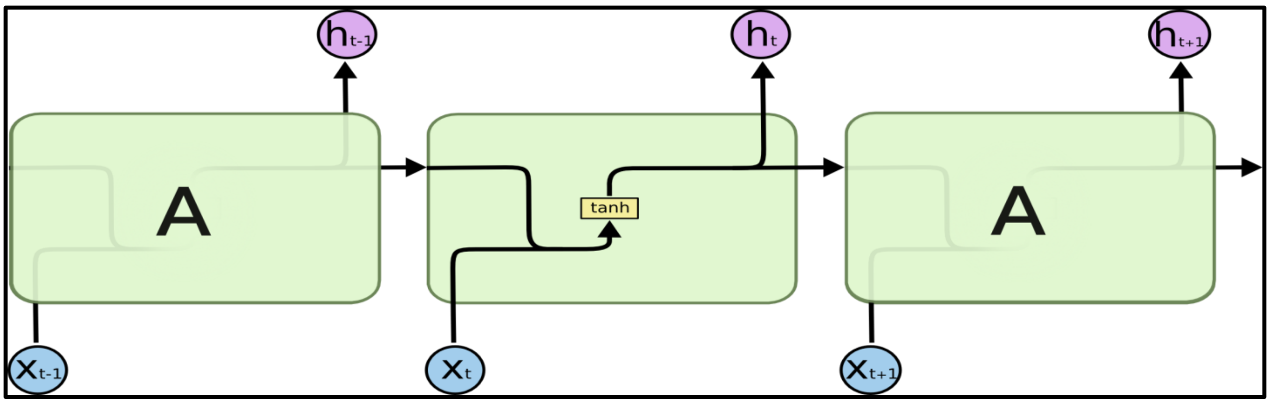
$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$ 6.7

$\hat{c_t} = \sigma(W_{\hat{c}}[h_{t-1}, x_t] + b_{\hat{c}})$ 6.8

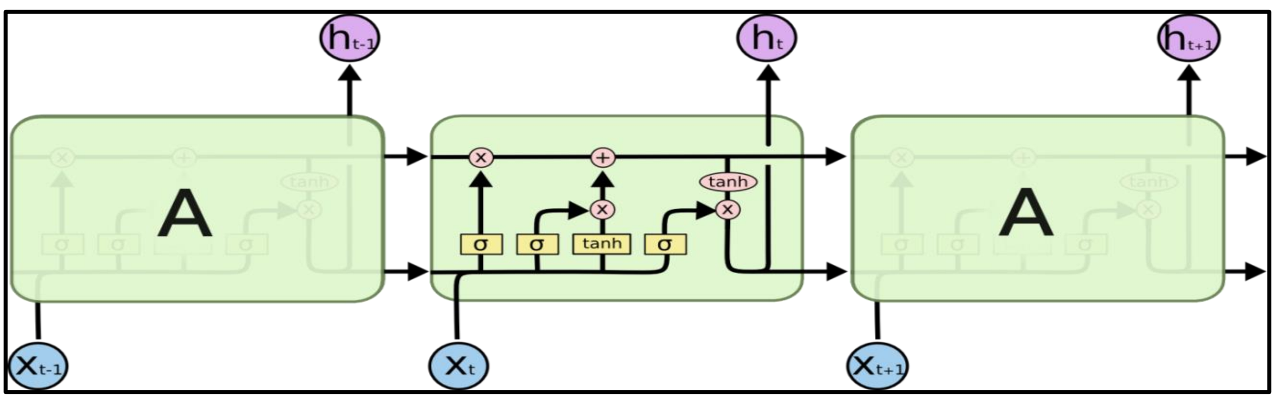
$c_t = f_t \odot c_t - 1 + i_t \odot \hat{c_t}$ 6.9

$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$ 6.10

$h_t = o_t \odot \varphi(c_t)$ 6.11



(a) Recurrent Neural Networks consist of the loop within the network and is unwrapped through time in the above figure to explain the flow of input and gradients in the model. The simple model consists of an tanh activation at heart that takes current input and output.



(b) LSTM unwrapped through time shows how the model is designed differently from a RNN model which consists of two different loops acting as an input an output at each time step. One is the output from ”output gate” and other is output from the ”forget gate”.

Figure 6.6 Architectural Differences of RNN and LSTM

The design of LSTM cell helps it in resetting itself and forgetting the old temporal sequences at appropriate times, this is done by releasing internal memory weights or gradients. The novelty of ”forget gate” is that it locks the gradient which helps in remembering long term dependencies of the input data. Therefore the information from the forget gate is not propagated back in time. Thus, it helps to remove the vanishing gradient descent problem that the Recurrent Neural Networks(RNNs) faces and is the reason why RNNs tend to perform poorly to keep in memory and exploit temporal relationships that extend over large times steps. Figure 6.6 indicates architectural differences of RNN and LSTM. LSTM with forget gates, however, easily solve them in an elegant way as compared to other sequential models such as RNNs and Hidden Markov models.

6.2.5 Experiments

To test the efficacy of the proposed model multiple experiments are run for training and testing. The effort is made to keep the empirical evidence transparent and reproducible, implementation details i.e. code and data is made public https://github.com/Anurag14/Inflow-Prediction-Bhakra. Figure 6.7 describes visualization of the network with the help of open libraries (keras and graph viz). We use a variant of LSTM with two densely packed layers. The first entry, that is, 15 in each of tuples across all the layers of network denotes the batch size. It is the size of input data for which network runs the predictions in parallel. It helps in leveraging graphic processing unit(GPU) for faster computations and training of network. Network can be designed with different batch sizes ranging from 1 to length of data. We use batch size of 15 because it perfectly divides both our train and test datasets and helps us in faster computation by leveraging GPU. The second number in the tuple, that is, 3 in input is look back. In other words, it is the number of past days needed to make prediction for coming day. Similar to batch size, look back can be adjusted in the parameters fed to the LSTM while training. For all the experiments and results obtained in the given section look back of 3days was considered. The input batch is of size 15. The respective layers have 96 ,144 and 5 trainable parameters, including both weights and biases. There are a total of 245 trainable and 0 non trainable parameters in the network.

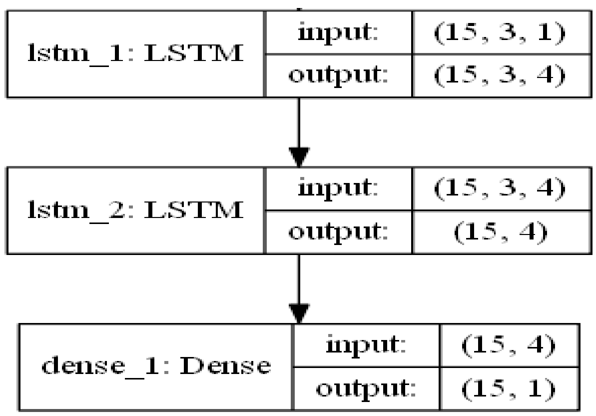


Figure 6.7 Architecture of Stacked LSTM network used in experiments

6.2.6 Training and RMSE

The Stacked LSTM is trained using tensor flow framework on a NVIDIA 920 M GPU for 100 epochs with batch size of 15 throughout. The Standard Mean square Error (MSE) is used as an estimate of loss to train the model to fit the data. The model is trained on past data of 20 years of inflow data at Bhakra Dam obtained from Bhakra Beas Management Board. Two thirds of the data, that is, first 13 years of data is used for training. One tenth of the data from first 13 years of training set, that is, last one year is kept aside as validation set for validation after every 5 epochs. The rest of data is never shown to the model, 7 years of latest data upon which we make inference and test our model. Figure 6.8 describes the time series view of observed data in blue versus training data in orange and test data time series in green. It can be observed that the predictions of the model after 100 epochs tightly follow the trends observed in original data making the time series generated by the model. We used Root Mean Square Error (RMSE) and coefficient of determination R^2 as a metrics to evaluate the error correlation of predictions made by the model with the actual data set.

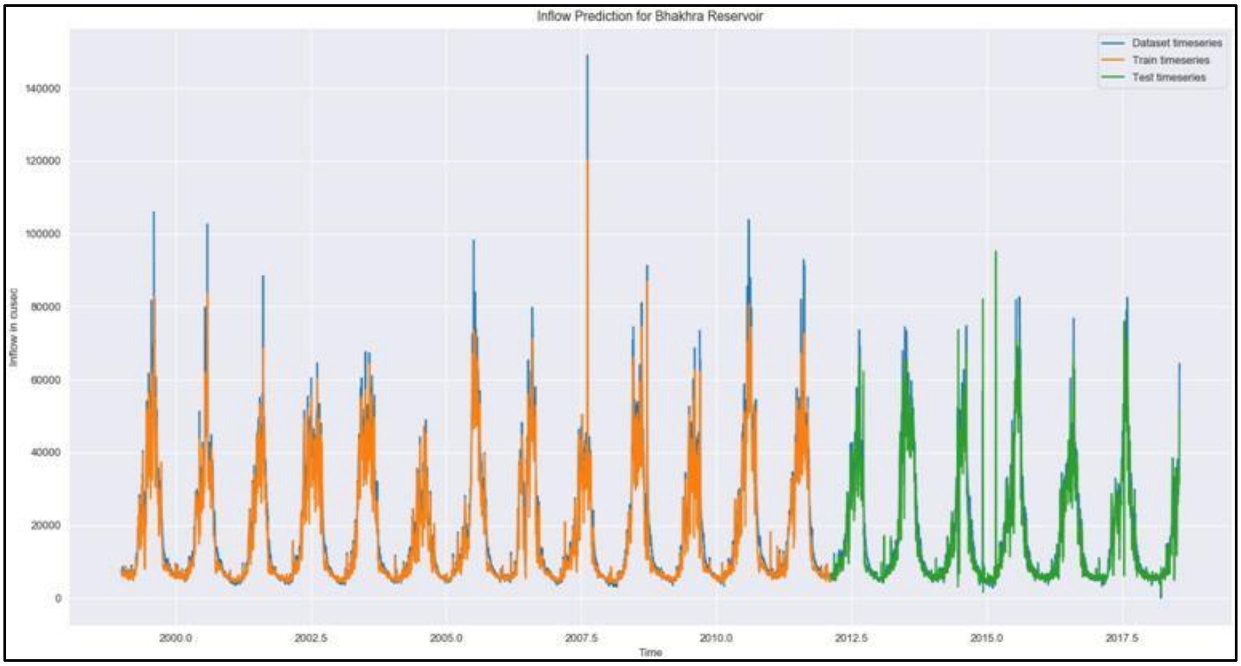
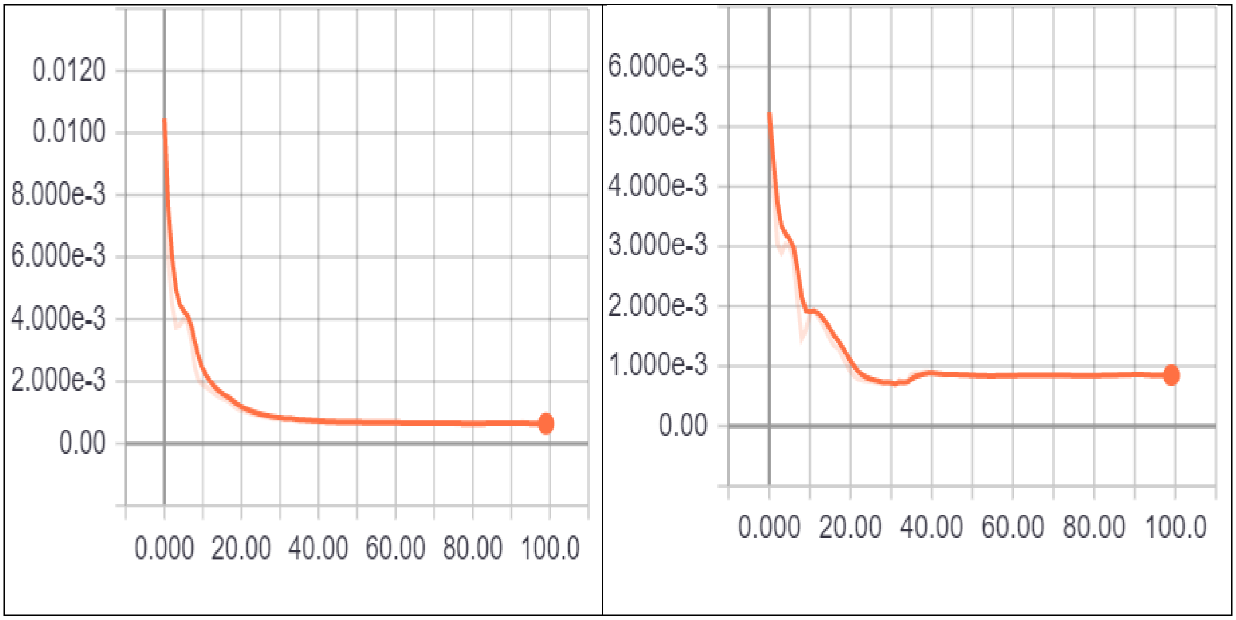


Figure 6.8 The time series plot of original dataset and train and test forecast

The input inflow time series that is fed to the LSTM network is first normalized between 0 to 1. The standard normalization is done using min max normalization.

$$\hat{\mathcal{X}}_{\mathrm{i}} = \frac{\mathcal{X}_i - \min\limits_{\forall_i} \mathcal{X}_i}{\max\limits_{\forall_i} \mathcal{X}_i - \min\limits_{\forall_i} \mathcal{X}_i} \qquad 6.12$$

The root mean squared values are also calculated for the normalized input throughout in the experiments. The mean squared error also acts as the loss for the training of model. The loss graph during the training versus the number of epochs is shown in Figure 6.9



(a)Train Loss (b) Validation Loss

Figure 6.9 Training and Validation loss plots for 100 epochs

The learnable parameters are kept simple in the LSTM model as we use the basic stacked LSTM version explained with 245 parameters, which shows that if more powerful networks is used for the problem even better predictions can be made.

Table 6.3 Epoch wise RMSE and R^2 *of stacked LSTM Model for train and test data*

Dataset		Epochs						
		1	10	20	30	40	50	100
Test	RMSE R^2	0.11 0.9165	0.04 0.9256	0.04 0.9215	0.03 0.9193	0.03 0.917	0.03 0.914	**0.03** **0.9053**
Train	RMSE R^2	0.11 0.9027	0.04 0.9520	0.03 0.9507	0.03 0.948	0.03 0.948	0.03 0.949	0.03 0.9434

In Table 6.3, the RMSE and (R^2) for LSTM train set and test set is given. It can be noticed that the RMSE performance for both tests and the training set improves as the model tends to learn to make predictions on the basis of data. It can be observed that the model learns parameters and after one full epoch of learning, the model is able to make predictions on trains set with RMSE of 0.11 and test set RMSE 0.11.

6.2.7 Comparison of inflow forecast results

Table 6.4.gives the comparison of forecast of results obtained using various techniques. Root Mean Square Error (RMSE) and coefficient of determination (R^2) are used to measure the performance of the model. The Thomas- Fiering model is the standard model which has been used for inflow determination using the observed average monthly inflow for past 20 years (1999 -2018). The method uses the auto correlation to relate the average monthly inflow of present month with the previous month. Since, the Thomas-Fiering model just uses lag-1 auto-correlation it tends to estimate the presence of any trend based on observation of just one previous entry. It can be seen from Table 6.4 that the monthly average estimates made using Thomas-Fiering model tend to give a RMSE of 0.1207 and $R^2$of 0.8933.

We extended the Thomas-Fiering model to forecast daily inflows at Bhakra. The results were compared to observed daily inflow for a duration of one year (1stMay, 2018 to 30thApril, 2019). A RMSE value of 0.1420 and R^2value of 0.6766 was obtained. The performance of the existing strategies of inflow estimation at Bhakra Dam was also evaluated. Inflow forecast depends upon the averages of 10 daily inflow of the available historical data. The RMSE value of 10 daily forecasts for the duration 1st May, 2018 to 30th April, 2019 was observed to be is 0.294, whereas a R^2 value of 0.6571 was obtained.

LSTM network is trained using past daily inflow data of 20 years from 1999-2018 at Bhakra Dam. The model used two-third of data set for training and the rest of the data is used for testing the model. Within the training data, 10 percent of data was used for validation. The result obtained using LSTM model for 20 years prediction and comparing the results with 20 years observed data are more promising having RMSE value of 0.03 andR^2 value of 0.9053. For the one-year forecasts, the RMSE value of 0.0503 and R^2 value of 0.9389 was obtained.

Table 6.4 RMSE and R2 Values for Monthly and Daily Inflow forecast results

Evaluation from 1stMay, 2018 to 30thApril, 2019	Metrics	
	RMSE	R^2
Thomas Fiering Model, Monthly	0.1207	0.8933
Thomas Fiering Model, Daily	0.1420	0.6766
10 Daily	0.2940	0.6571
LSTM Daily	**0.0503**	**0.9389**

It can, therefore, be concluded that the Thomas Fiering model is not very suitable for accurate predictions of inflow in a reservoir. The daily inflow bears more significance for real time operations of the reservoir as compared to the monthly average inflows. LSTM based neural network architecture proposed in this research is shown to have a RMSE of 0.03 on daily inflow data of 20 years. It can be concluded that the accuracy of the proposed model is very high compared to the synthetic monthly and daily inflows generated using the Thomas-Fiering model. The LSTM model was found to perform significantly better than the existing operating strategies followed at Bhakra Dam. With the forecasts made using LSTM, significant improvement in the operation of reservoir at Bhakra can be made.

6.2.8 Anomaly Detection

Inflow prediction for reservoir operation helps in making better and sound real time micro management strategies. Daily inflow prediction with significant accuracy can help in creating better awareness regarding what inflow to expect on normal days. However, in certain scenarios there might be instances where the predictions are very different from the observed values. The model is trained on cases borrowing data from large set of past data, enabling it to learn parameters and generalize. It has to be robust to anomalies or outliers to be good at making general predictions. There are several techniques of regularization used in machine learning community to prevent the model from over-fitting to such anomalies as it leads to poor predictions in real world. There are sometimes cases where detection of anomalies is also of great significance. One such use case is flood and drought prediction.

Algorithm 1 Naive Anomaly Detection based on LSTM

```
procedure Predict Flood Or Drought(LSTM, lookback, groundtruth,k,ρ,τ = 0.03)
    Observations ← Normalize Observations(groundtruth)        d Normalize ground truth
    Observations ← Observations [−k :]                        d Inflow of last k days
    input ← Observations[−(k + lookback) : −k]                d Take lookback entries before k
    Predictions ← null
    for k iterations do
        Prediction ← LSTM(input)
        Input ← Input[1 :]                                    d Remove of last entry
        Input. append(Prediction)                             d Insert Prediction
        Predictions. append(Prediction)
    Observed RMSE ← RMSE(Predictions, Observations)
    if Observed RMSE > τ ρ then
        Anomaly is observed
        Total Observed Inflow ← sum(observations).
        Total Predicted Inflow ← sum(predictions).
        if Total Predicted Inflow > Total Observed Inflow then
            return Flood
        else
            return Drought
```

The above algorithm tries to describe the proposed naive algorithm baseline using LSTM models. This naive algorithm baseline can be extended to any deep learning model in future. In summary, the algorithm compares the predictions on previous *k* days with the observed inflow values. Before that, the absolute observed values are first normalized using min max normalization. The comparison is based upon the RMSE values obtained using the normalized data. Here, τ is the empirical RMSE value that is derived using the experiments of training LSTM model on past 20 years of data. Hence, it is safely assumed that the RMSE of the observed value with current prediction must remain in certain tolerance with the empirical RMSE value, that is, τ . Now, that tolerance is defined as $\tau\rho$ where ρ is a multiplier and $\rho > 1$.

6.2.9 Conclusions

A LSTM based deep neural network architecture has been used for reservoir daily inflow forecasts. The major findings of the work carried out herein using the novel approach on LSTM may be summarized as follows.

- Multiple experiments are conducted to prove the efficacy of LSTM in calculating daily inflow levels both by qualitative measure such as shown in Figure 6, and quantitatively as based on Root Mean Square Errors and coefficient of determination R^2 between the predicted and the observed values.
- A naive algorithm baseline for anomaly detection using LSTM has been proposed.
- Based upon the work carried out herein, the release policy may be based upon the following criterion.

$$Daily\ release\ from\ storage = \frac{AverageStorage}{Total\ water\ indent\ during\ remaining\ period\ of\ the\ year} \qquad 6.13$$

$$Total\ Daily\ release = Daily\ release\ from\ storage + Inflow\ predicted\ using\ LSTM \qquad 6.14$$

- Quantity of water available for daily discharge depends upon the daily release possible from available storage at the end of filling period plus the daily inflow forecast using LSTM.
- Using the LSTM, the error in inflow forecast was found to be within 3%, whereas under the existing operating policy at Bhakra dam, the forecast values may differ from the observed values by upto 29.4%. It may be concluded that the decisions based upon the forecasts made using the LSTM model has the potential to significantly improve the existing reservoir operating policies.

7 Conclusions and Recommendations

7.1 Introduction

This chapter summarizes the research reported in this thesis, outlining the limitations of the research and providing suggestions for future research. The present thesis is organized into 7 chapters. The first chapter of this thesis gives a brief description of Bhakra Dam and its importance in the development of the Northern region. The objectives of the thesis have been outlined in chapter 1. Chapter 2 of the thesis presents the literature relevant to the present research. The chapter describes the review of literature on the impact of climate change, methods to predict inflow in the reservoir and various techniques used to decide optimal operational policy. Chapter 3 describes the salient characteristics of the Satluj river basin and Bhakra dam. This chapter also provides the data related to average annual rainfall of this region, the average inflow in dam and release from the dam. Chapter 4 describes various models to estimate the impacts of climate change in the Satluj River basin. Chapter 5 provides information regarding reservoir operation strategies followed at Bhakra. Chapter 6 describes different techniques that can be successfully used to forecast daily inflow. A novel technique based on Long Short Term Memory neural network to forecast daily inflows has been described in this chapter.

The research work carried out in this thesis suggest that the impacts of changing climate shall be considered in deciding the optimal operation policy of the reservoir. With changing climate, efficient reservoir operation is needed to meet power demands and provide reliable water supply demand. The present research proposes novel LSTM based neural network architecture to forecast daily inflow and naive anomaly detection algorithm to predict floods and droughts. The

Major advantage of this technique is that the effect of climate change is taken into account. This chapter summarizes the research reported in this thesis, outlining the limitations of the research and providing suggestions for future work. Following this introduction, section 7.2 represents the deliverables of this research. Section 7.4describes the limitations and section7.5provides the recommendations for future research.

7.2 Deliverables of the Research

The research presented in this thesis is subdivided into three distinct stages. First part of this thesis focuses on the analysis and interpretation of historical climate change using the data obtained from the climate research unit of the University of East Anglia for the Satluj basin. The whole region is divided into 56 nodes. For each node, an analysis of hydro meteorological data is carried to detect any discernible trends. Determination of temperature and precipitation trend provide critical evidence of the impacts of anthropogenic activities on the climate. The analysis of the time series data trend reflects the changing climate at various nodes. The analysis of the minimum temperature of this region reflects a statistically significant increasing trend. With the rise in minimum temperature, it is imperative that ice cap will retreat. It is likely that with the increase in minimum temperature and a decrease in precipitation, many aspects of water resource systems will be impacted. An immediate impact of increased temperature in this region is likely on the hydrological cycle. With increased warming, the vigour of the hydrological cycle is likely to intensify. The changes in the hydrological cycle are accompanied by erratic and uncertain patterns of rainfall in the basin. For a large reservoir such as Bhakra, changes in flow patterns or changes either in quantity or in timings can produce serious impacts on the livelihood for those engaged in the agriculture or allied activities in the region. The predicted change in inflow, both for the short and the long term, would have serious implications for the operating strategies being currently followed by the reservoir managers at Bhakra. Expected warming in this region has created the need to consider the effect of climate change while formulating operating strategies for a large dam such as Bhakra that control the flow to several irrigation systems in Northern India and is a major source of water for power generation. Inferences drawn are based on observed trends for maximum temperature, minimum temperature and precipitation at 56 nodes selected in Satluj basin.

7.2.1 Analysis of Climate Data Based on RCPs

The second part of the thesis describes the collection and analysis of the projected climate data under several combinations of GCMs, RCPs, and future time scales. Using RCP, temperature anomalies for duration 2020-2039 and 2040-2059were obtained from Climate Change Knowledge Portal (CCKP) of the World Bank. Projected temperature anomalies clearly indicate substantial warming under all the combinations of GCMs and RCPs considered in this research. There is, however, a high inter-model variability in the projections of temperature anomalies for both the periods of analysis, that is 2020-2039 and 2040-2059. But all the models considered in this research indicate positive temperature anomalies over the Satluj region for both the future time period considered in this research, regardless of emission scenarios, except in a very few cases where temperature anomalies were found to be negative. The negative temperature anomalies in a very few cases could be attributed to modelling errors as most models project positive temperature under all combinations of models, RCPs and future time periods. As expected RCP8.5 projections were the most extreme for both the future periods and all models, whereas the RCP2.6 projected the least warming. The other two RCPs, namely RCP4.5 and RCP6.0, projected moderate increase in temperatures. Among the models, GFDL is the most extreme model, whereas the bcc_cm_1_1projections, particularly for 2020-39, were very close to change in monthly temperature compared to the reference period of 1986-2005.

The average temperature increase over the Satluj basin by the mid of the 21st century is projected to be anywhere between 3°C to 4°C for RCP8.5. For the design of water resource systems, projections based on RCP8.5 shall be considered. By the end of 2030 it is projected that the average annual temperature will rise by around 1.5°C to 2°C. It is evident that the increase in temperatures of the magnitude identified in this research will have implication on many aspects of natural resources, including the water resource system. An immediate impact of increased temperatures in a region is on the hydrological cycle. The inferences drawn in this research are based on the projections of several GCMs that suffer from inherent uncertainties responsible for reducing the accuracy of projections. The uncertainties in the projections arise due to inadequate representation of the physical processes describing our climate system. Owing to the advent of sophisticated computer models, the accuracy of models is likely to improve significantly, thus leading to more credence to the projections made by these models in the near future.

7.2.2 Long Short Term Memory Based Forecasts

The third distinct part of the research describes the development and application of an LSTM model for the forecasts of inflows to Bhakra reservoir. With the use of machine learning techniques, a wide range of problems in optimization and operations research can be efficiently solved. Deep learning has become ubiquitous in recent state of the art solutions that are being employed to a wide array of tasks. The LSTM based inflows have been forecast for different time horizons ranging from 1 day to 1 year. LSTM is a powerful temporal sequence detector. These results are achieved using a simple LSTM model. Design of more complex neural network architecture shall facilitate much better training, predictions and better RMSE values. Daily inflow predictions using LSTM will enhance operational performance of the reservoir. The Streamflow generation model is used to synthesize daily inflow sequences considering previous inflow. The LSTM model is able to predict daily inflow with Root Mean Square error of 3% and R^2value 0.9053, which is very satisfactory. The Thomas-Fiering model is also extended from monthly prediction to daily prediction. The Root Mean Square error is 14.20% and R^2value is 0.6766 as compared to observed values. Forecasts of inflows were made using both the Thomas-Fiering and the LSTM model. Analysis of forecasts using both the models clearly indicated the superiority of LSTM model. The operation of Bhakra reservoir can be significantly improved using the forecasts based on LSTM model. In cases where the value of RMSE shows large variation between observed inflow and LSTM-based forecast, the probability of occurrence of flood or drought is significantly increased. It is recommended that under changing climate conditions, the operation of the Bhakra reservoir shall be based on the inflows forecast using LSTM model.

7.3 Research Contributions

The contributions of the research carried out in this thesis may be summarized as follows.

- To put the work carried out in this thesis, an extensive review of literature has been carried out
- With a view to understand the impacts of climate change in the Satluj River basin the climate data at several nodes in the basin has been obtained from the CRU of the University of East Anglia, United Kingdom, thus creating a valuable dataset that could be utilized for further research.
- RCP based projections of climate variables at different locations in Satluj River basin have been obtained for several combinations of GCMs and RCPs from the Climate Change Knowledge Portal of the World Bank, thus enabling an analysis

of the impacts of climate change in the basin.

- A Python software based inflow calculator has been developed which would enable engineers and policy makers to determine the storage available in the dam for the given values of water level and release made from the reservoir.
- A Thomas-Fiering model has been developed and applied for the forecast of monthly average and daily inflows.
- An efficient model to forecast inflows to Bhakra has been developed, and its effectiveness in reservoir operations at Bhakra has been clearly demonstrated.

7.4 Limitations of the research

There are some limitations of the research that has been described in this thesis. First, it is difficult to accurately predict the extent of future climate change as hydro meteorological data are stochastic and non-linear in nature. Although an extensive analysis of the projections of climate variability has been carried out in this research, there is inherent uncertainty in the projections of different models. Although the increase in temperature is on expected lines, but intra model variability was observed. There is considerable variability in projections under different RCPs, but the direction of trends is sufficiently clear.

The LSTM model was found to perform better than the Thomas-Fiering model, but the training of the model is a daunting task. Also, the model might become computationally bound as the number of neurons is increased. Another challenge of the present research was in the procurement of data from governmental agencies. Due to security reasons, the visit to the dam site could not be frequent. The LSTM model developed herein is fairly reliable. However, the model output depends to a large extent on the quality of the input data. At present, there are no means to evaluate the reliability of the data provided by the governmental agencies.

7.5 Recommendations for further research

The following recommendations are made for further research in the area climate change impact assessment and inflow forecasting.

- The RCP data may be obtained for a greater number of models and stations than is presently done
- Further research could be carried out to explore if the model trained on a particular location could be used to forecast inflows at another location or basins
- LSTM model may be modified by incorporating a greater number of layers of neurons
- The impact of construction of one or more diversion dams upstream of Bhakra on the occurrence of floods and droughts may be evaluated in future research.

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