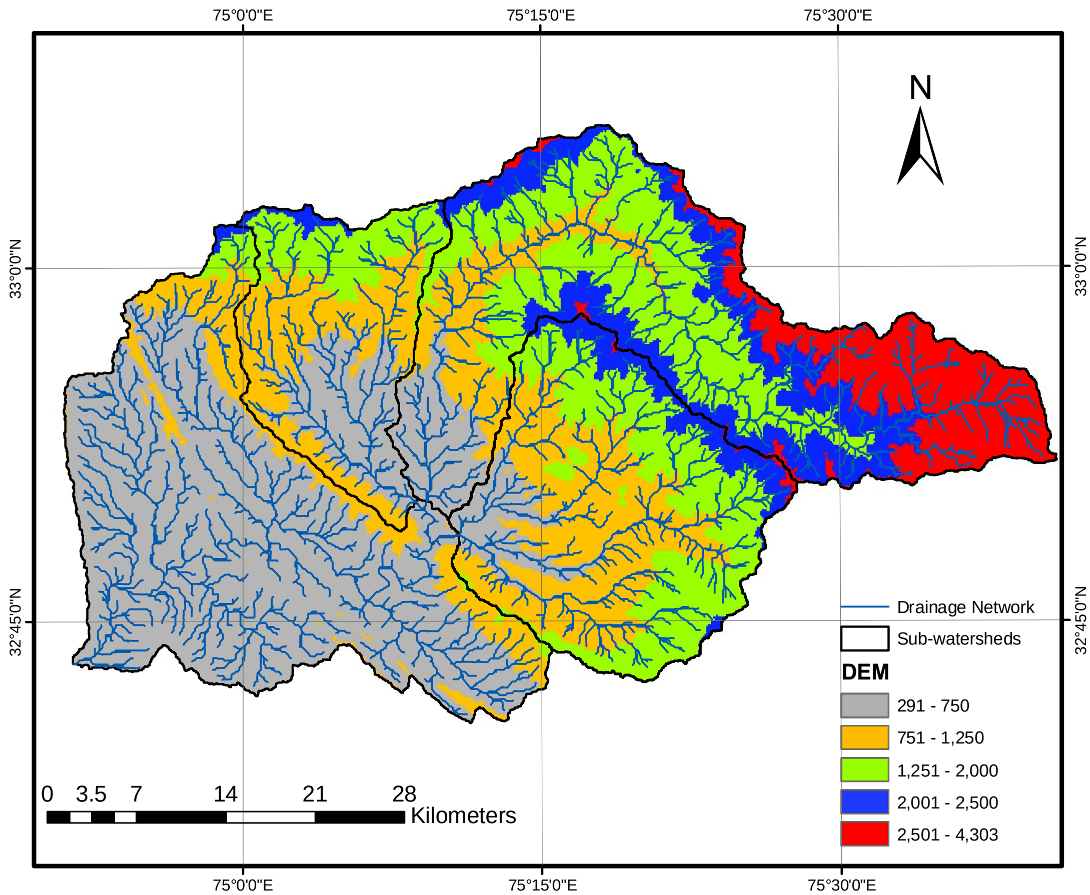
CLIMATE CHANGE EFFECTS ON HYDROLOGY OF THE TAWI BASIN IN WESTERN HIMALAYA



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JUNE - 2016

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ABSTRACT

This study has been conducted to assess future climate change impacts on hydrology of the Tawi River Basin using Soil Water Assessment Tool (SWAT). Model parameters were identified using sensitivity analysis and long-term calibration procedures, which enabled the historical behaviour of the catchments to be reproduced. Following validation, the parameters were used to simulate the effects of climate change on future streamflow. During the model development, the monthly observed stream flows matched well with simulated flows with Correlation coefficient and Nash-Sutcliffe coefficients values of 0.72, 46% during calibration (1983ï 1992) and 0.92, 84% during validation (1993ï 1997) respectively. The reanalysis data of NCEP has been used for setting up the downscaling model for GCM. Future daily time series of precipitation, maximum and minimum temperature have been downscaled from the HadCM3 GCM using the multiple linear regression based statistical downscaling model SDSM for the medium-high (A2) and medium-low (B2) SRES mission scenario, as drivers of the hydrological simulations during the future scenarios. Changes in streamflow were in general agreement with the projections of daily precipitation and temperature fields. It has been found from the model results that the average annual streamflow might increase in the 2020s, 2050s and 2080s of the century. The results also indicate that streamflow in future may widely spread in the months as compared to the past which will ensure the good quantity of flow in the river for more months in a year, but there will be decrease in lean season flows due to the projected future climate change.

Keywords: Climate change, Statistical Downscaling Hydrological impact, Hydrological modelling, SWAT

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Chapter 1

1.0 INTRODUCTION

1.1 BACKGROUND

The fourth assessment report (AR4) of the Intergovernmental Panel on Climate Change (IPCC, 2007) has listed the various climate scenarios and its drivers. The rising demand for water and the possible decline in future water resources due to climate change, will pose a significant challenge to water resources planners (Chiew et al., 2010). Therefore, a proper assessment of probable future precipitation and its variability over time should be included in climate change studies (Anandhi et al., 2008).

Global Circulation Models (GCMs) are considered as effective tools available today which uses transient climate simulations to generate climatic conditions for hundreds of years into the past and the future. They play a crucial role in generating future projections of climate change using different emission scenarios (Hashmi et al., 2009). However, GCMs are available at a coarse grid resolution of 1° to 2°. Consequently, products of GCMs cannot be used directly for climate impact assessment on a local scale. This has led researches to undertake to development of suitable downscaling methodologies to transfer the GCM information to local scale information.

A study of the impacts of climate change on the environment and the surroundings includes an account of the hydrological regime for the present and the future years. In order to accurately assess the water balance, generation of future hydrological scenario is essential.

1.2 CLIMATE CHANGE

Climate change is defined as a significant and lasting change in the statistical distribution of weather patterns over periods of time affecting areas both small and large. Climate change may be natural or human-induced (anthropogenic). This phenomenon has had discernible impacts on the physical, ecological and the biological systems of the Earth. Climate change is expected to adversely impact water resources, water quality and freshwater ecology. Thus, it is important to quantify the impacts of climate change to frame mitigation and adaptation measures (Whitehead et al., 2009). The Special Report on Emission Scenarios (SRES) establishes different future world development possibilities in the 21st century, taking into consideration the possible changes in various factors including economic development, technological development, energy intensities, energy demand, and structure of energy use, resources availability, population change, and land-use change. The possibilities of changes in future developments are categorized mainly in the form of four major storylines quantified as four scenarios namely A1, A2, B1 and B2 (shown in the matrix below). The scenarios include the expected range of emissions of greenhouse gases (GHGs), sulphur and their respective driving forces.

	ECONOMIC EMPHASIS →		
GLOBAL INTEGRATION ↑	**A1 storyline**	**A2 storyline**	**REGIONAL EMPHASIS ↓**
	World: market-oriented Population: 2050 peak, then decline Governance: strong regional interactions; income convergence Technology: three scenario groups: ➢ A1FI: fossil intensive ➢ A1T: non-fossil energy sources ➢ A1B: balanced across all sources	World: differentiated Economy: regionally oriented; lowest per capita growth Population: continuously increasing Governance; self-reliance with preservation of local identities Technology: slowest and most fragmented development	
	B1 storyline	**B2 storyline**	
	World: convergent Economy: service and information based; lower growth than A1 Population: same as A1 Governance: global solutions to economic, social and environmental sustainability Technology: clean and resource- efficient	World: local solutions Economy: intermediate growth Population: continuously increasing at lower rate than A2 Governance: local and regional solutions to environmental protection and social equity Technology: more rapid than A2: less rapid, more diverse than A1/B1	
	ENVIRONMENTAL EMPHASIS →		

1.3 DOWNSCALING

Downscaling, or translation across scales, is a set of techniques that relate local and regional- scale climate variables to the larger scale atmospheric forcing (Hewitson and Crane, 1996). The downscaling approach was developed specifically to address present requirements in global environmental change research, and the need for more detailed temporal and spatial information from

GCM (Figure 1.3). Most impacts models require information at a sub-grid scale featuring topography, clouds and land use-land cover (Tisseuil et al., 2010). Downscaling bridges the gap between large and local scale climatic data. It tries to link what has been provided by the global climate modelers and what is needed by the decision makers (Walsh, 2011). The translation across scales is based on the assumption that similar synoptic atmospheric patterns produce similar climatic conditions.

The following are some assumptions of spatial downscaling (Tripathi et al., 2006):

(i) The GCM being used should be able to simulate well, those atmospheric features which will influence regional climate, e.g. jet streams and storm tracks

(ii) The downscaling technique should be based on a climate variable which does not exhibit

(iii) large sub-grid scale variations, i.e. it is better to use a variable such as mean sea level pressure rather than precipitation

(iv) The variables used in the downscaling process should a direct model output (e.g. sea level pressure) and not outputs based on parameterisations involving other model variables, as is the case with precipitation

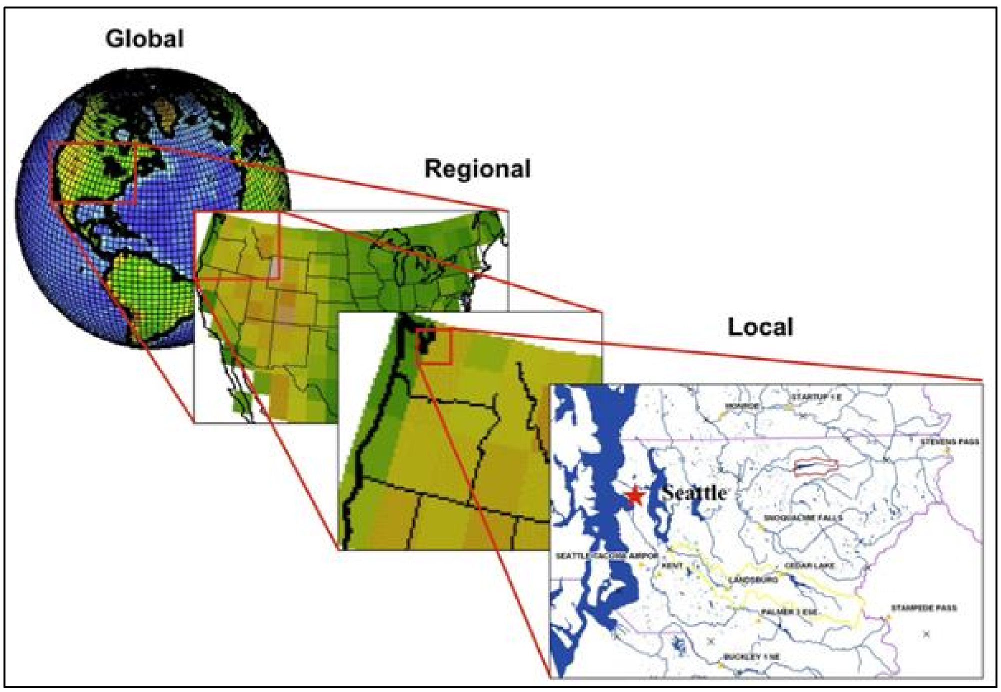

Figure 1.1 Downscaling from Global to Local scale (image courtesy of Dr. Andrew Wood, NCAR, source https://www.earthsystemcog.org)

The Downscaling process plays a crucial role in driving impact assessment models such as drought analysis, water resources management, water demand availability, ecological impacts and risk and vulnerability assessments.

There are three types of downscaling:

Dynamic Downscaling: Nesting a regional climate model into an existing GCM is known as dynamic downscaling. This technique drives a regional dynamic model at a mesoscale with the synoptic and large scale information from a GCM (Jenkins and Barron, 1996). In other words, a regional climate model (RCM) is embedded in a GCM (Tripathi et al., 2006). To achieve this, a specific location is defined and certain driving factors from the GCM are applied to the regional climate model. A regional climate model is a dynamic model, like a GCM, but it can be thought of as being composed of three layers. One layer is largely driven by the GCM itself, another layer builds on some locally specific data that is available, and the third layer uses its own physics based equations to resolve the model based on data from the other two layers. The results are comparatively local predictions that are informed by both local specifics and global models. This process requires significant computational resources because it is dependent on the use of complex models and results (Environment Canada, www.ccsn.ec.gc.ca). However, dynamic downscaling is best used for the long run. Some of its disadvantages are its difficulty to overcome the interface between the GCM and the nested model (e.g. how to relate the coarse resolution grid cell of the GCM to the boundary conditions of the finer scale nested model) and the non-availability of many nested models for the southern hemisphere (Environment Canada, www.ccsn.ec.gc.ca). It is also common for systematic biases to creep into the RCM from the host GCM.

Statistical Downscaling: Statistical downscaling technique involves translation using statistical regressions. There are a variety of such methods ranging from multiple regressions that link local variables to particular drivers in GCMs, to more complex methods using multilayer, input-output arrangements like neural networks and support vector machine. Also known as empirical downscaling, it is primarily a data driven approach. The general procedure is to first establish the relationship between large scale variables and local level climate conditions. Once this relationship has been developed for existing conditions, it can be used to predict for the future.

A quantitative relationship between circulation and local climate in the form y=f(x) is established:

local climate response = f (external, larger scale) é (1.1)

The above stated relationship (or function) is called a transfer function and is derived from long term observational data. The more the ability of the transfer function to capture non-linear aspects of the circulation-local climate relationship, the more efficient it is considered.

Stochastic Weather Generators: A third strategy for downscaling data is also statistically driven. It uses stochastic weather generators that develops a series of statistical linkages among variables to predict weather at that particular location by using long term weather data for a particular area. Such empirically based models can be used to downscale variables generated from GCMs to predict the local result of driving variables (Hewitson and Crane, 1996).

1.4 HYDROLOGICAL MODELING

Hydrological modeling is the mathematical representation of the long-term hydrological patterns of the basin and its behaviour. The fundamental objective of hydrological modeling is to gain an understanding of the hydrological system in order to provide reliable information for managing water resources in a sustained manner. Hydrological models can be of two types: Lumped models and Distributed models. In lumped model, spatial heterogeneity is not taken into consideration i.e. the watershed is taken as a single entity with a single rainfall value for the whole area. It assumes that the whole grid is homogenous and physical properties such as soil, land cover, climate, etc. are same everywhere in the area. These models do not use physical formulae to derive water balance components. Also variations in meteorological, hydrological and geological parameters are considered as one aggregated value. Whereas in distributed models, grid heterogeneity is considered by dividing the whole area into a number of homogenous units and all the properties lying in the area are given equal weightage (Singh and Frevert, 2006).

Physically based-distributed models contain equations that describe the physical interaction of different components of the water and energy balance. Model parameters relate these abstract physical laws (or scale-dependant approximations of these laws) to the specific basin at hand. They take an explicit account of spatial variability of processes, input, boundary conditions, and system (watershed) characteristics such as topography, vegetation, land use, soil characteristics, rainfall, and evaporation etc. but they need detailed high-quality data to be used effectively.

Inevitably, all models are imperfect representations of reality; each is a different perspective on a system. Many parameters are observable (e.g. basin area, slope, elevation, vegetation type) although some parameters are unobservable conceptualizations of basin characteristics. One of the major problems in distributed modeling is parameter identifiability, owing to a mismatch between model complexity and the level of data which is available to parameterize, initialize, and calibrate such models (Troch et.al, 2003). AVSWAT (ArcView Soil and Water Assessment Tool), ArcSWAT, MIKE-SHE, Variable infiltration Capacity (VIC) model, HEC-HMS (Hydrologic Engineering Centre-Hydrologic Modelling System) are some of the physically based distributed hydrologic models. In the present study the ArcSWAT (ArcGIS Soil and Water Assessment Tool), hydrologic model has been used for modeling the river flow regime.

1.5 OBJECTIVES OF THE STUDY

Furthermore, the intensification of the hydrological regime due to impacts induced upon hydrological and meteorological parameters by climate change in the future also needs to be studied and analysed sufficiently. This implies the need to develop future climate change scenarios and study its implication on future hydrological characteristics of the region of interest. The preparedness for the future scenario leads to a more efficient natural resources

A number of studies have been reported from other countries to assess the impact of climate change scenarios on hydrology of various basins and regions; however, little work has been done on hydrological impacts of possible climate change for Indian regions/basins. The aim of the research was primarily to understand the concept of statistical downscaling, explore the best possible techniques to statistically downscale precipitation. The outcome of the downscaling model has been used to drive the hydrological model. The study has also determined the evaluation criteria for evaluating the performance of the model. And finally, the downscaled local scale variables have been used generate the hydrological regime for a time period in the future. The study has assessed the changing scenario of the river hydrology in the future which can be an important input for developing the precise adaptation strategies with better planning, resource management and improved decision making. The study was proposed with the following objectives.

- To model the streamflow in the Tawi basin
- To develop the downscaling Model for GCM for simulating the future climate scenarios for Tawi Basin
- To evaluate the impact of climate change on streamflow of the Tawi basin in coming decades under different scenarios

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2.0 STUDY AREA

2.1 ORIGIN AND LOCATION

The River Tawi, which passes through the heart of the Jammu city, is one of the major left bank tributaries of the river Chenab. It rises from the lapse of Himalayan glaciers at a place named Kalikundi and adjoining areas. The basin shape in the upper part is elongated while broad in the lower part. The catchment of Tawi river upto Jammu is about 2167 sq. km. falls mostly within the districts of Jammu and Udhampur of J&K state. Just below the bridge at Jammu Ranbir canal also crosses the river. Immediately below the canal crossing, the river divides into two channels. These two channels are termed as Nikki Tawi which flows towards left and Waddi Tawi flows towards right. Location of the Tawi catchment is shown in Fig. 2.1.

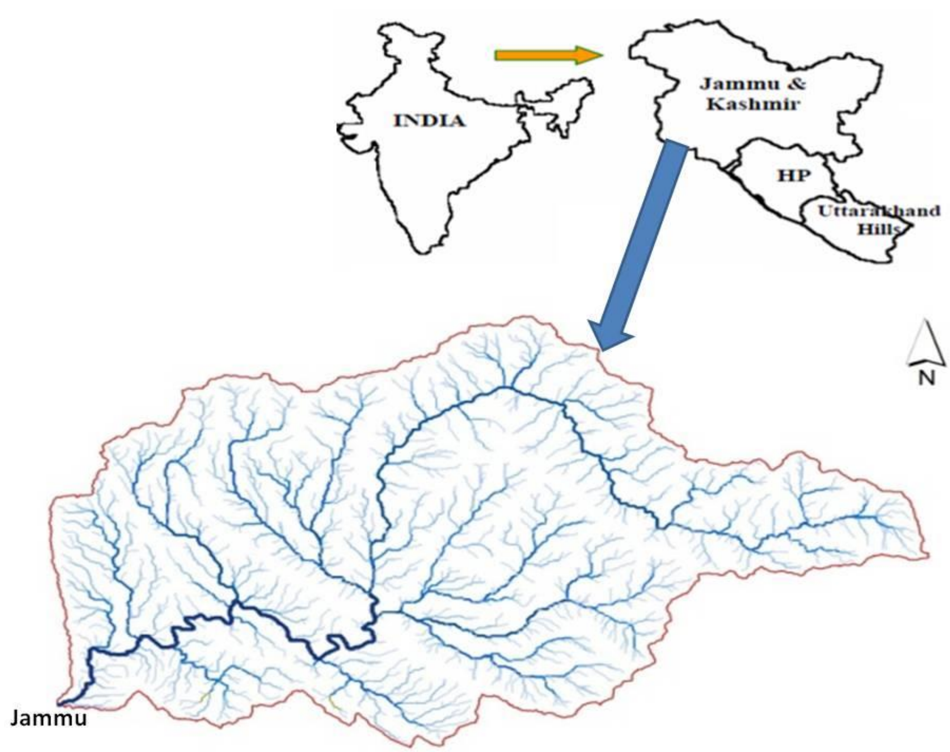

Fig. 2.1: Location Map of Tawi Catchment

2.2 TOPOGRAPHY

The upper part of the catchment is characterized by rugged mountainous topography; whereas lower catchment consists of low hills and aggradatioal plain. The average height of the catchment is about 2200 m above mean sea level (MSL). The catchment elevation varied from 4000 m in the upstream to about 300 m above MSL in the plains. The variation in elevation can be understood by the Digital Elevation model (DEM) of the Tawi catchment (Fig. 2.2). The slope of the basin is from east to west in the upper part and north east to south west in the lower part. From origin to outfall the longitudinal section of the river exhibits wide variation. The gradient changes from very steep at upper part to concave and flat in the lower part of the river.

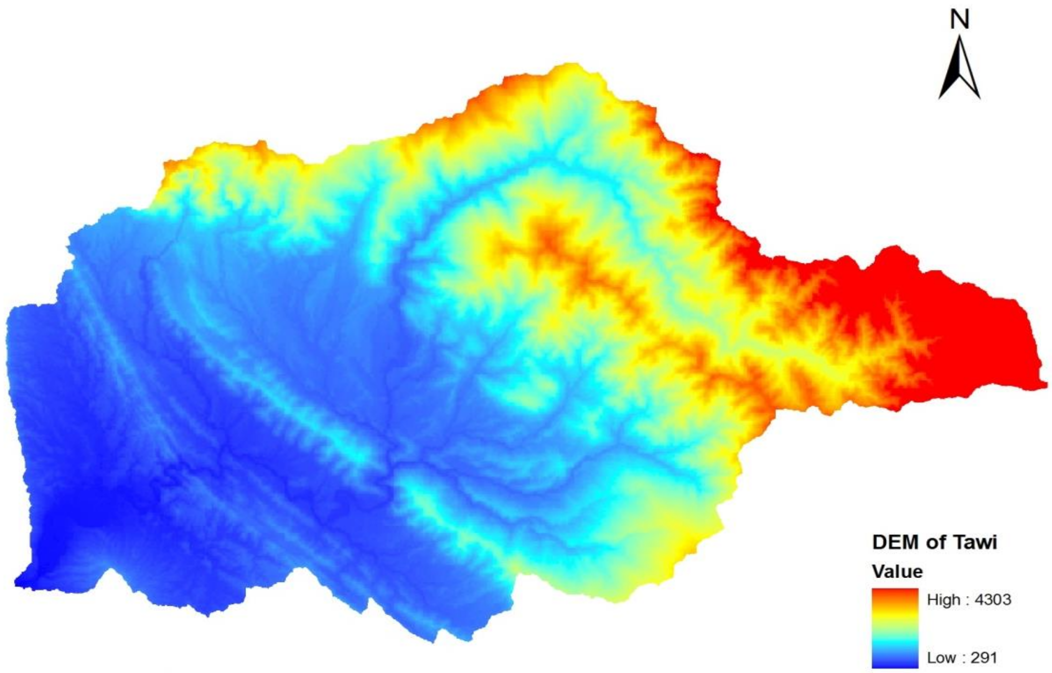

Fig. 2.2: Digital Elevation model (DEM) of the Tawi Catchment

2.3 THE TRIBUTARIES OF THE RIVER TAWI

Being a mountainous river Tawi has more than 2000 numbers of tributaries and sub-tributaries. However, there are nine numbers of predominant tributaries of the river Tawi have been identified as follows:

Kali Kundi: This tributary has a long and concave profile. Itõs about 4 kms long and its elevations vary from 4000 m to 3200 m.

Pich: It is 2.0 km long and predominantly degrading in nature. Its elevations vary from 3600 m to 3200 m.

Magri: The stream profile indicates two breaks; first at 3200 m and second on 2600 m elevation. It is 9.5 km long and elevation varies from 3600 m to 2000 m.

Chenani: This left bank tributary of Tawi River flows between the altitude of 1100 m to 1700 m and is around 7.5 km long.

Dhak Nalla: The profile of this river also shows steepness varying from 900 m to 800 m. msl. Its length is about 2.5 Km.

Naddal Khud: The profile represents small breaks due to the tectonic structure of the area. Its elevations vary from 1200 m to 700 m and it is about 5.8 km long.

Calari: The profile of this Shiwalik stream shows a straight line without any break. The aggradational process is predominant in the basin of Calari because of the absence of high slope. It is about 15 km long and elevation range. is from 900 m to 700 m.

Pharos: Its profile presents a steep gradient with high degradational processes. The 5.25 km long river course is between elevations 3600 m to 2400 m.

Gamhi: The course of river is generally straight with small breaks at places. Its length is about 19 km while elevation varies from 700 m to 400 m.

2.4 CLIMATIC CONDITIONS

The region experiences hot summers and severe winters. Temperature is lowest between November & February when the minimum night temperature dips below zero degree in the hill area and 3° ï 4° C in the outer plain area. Temperature rises from March onward. It becomes unbearable during May-June. Maximum day temperature in June touches sometime 47° C in the outer plain and about 30°- 35°C in the hills. The climate of the catchment is characterized by three distinct features:

(i) The north eastern part comprising Bhadarwah and adjoining area where the climate is of the extra tropical mountain type. The mountain type climate has wide variation in temperature and rainfall depending on location and direction of land features.

(ii) The central part comprising Udhampur district where the climate is mountain type but is influenced by southwest monsoon.

(iii) The southwestern part comprising Jammu district where the climate is warm and mainly influenced by monsoon. It could be categorized as the subtropical wet and dry climate.

2.5 HYDROLOGY OF TAWI CATCHMENT

2.5.1 Precipitation

Most of the rainfall is received through the southwest monsoon which lasts from the last week of June to end of September. During the remaining period, rainfall is sporadic and scanty. July and August are the principal rainy months contributing about 55 % of the total annual rainfall. The average annual rainfall over Jammu district Varies from 900 to 1000 mm, over Udhampur district from 1400 to 1900 mm and over Doda district from 900 to 1400 mm. Rainfall in lower parts and snow fall in upper parts of, the catchments occur in winter in association with passage of western disturbances and troughs in the westerlies. Snowfall is very heavy in the months December to February in upper reaches. At Higher elevations snowfall 1s experienced even during the month of May. Winter precipitation contributes nearly 45 % of the annual precipitation.

2.5.2 Discharge

The percentage dependable flows of Tawi river at Jammu bridge site during different months are shown in table 2.1 and the various water balance component are given in table 2.2.

Table 2.1: Percentage dependable flows of Tawi river at Jammu bridge site

Probability (%)	Discharge (cumecs)										
	Feb.	**Mar.**	**Apr.**	**May.**	**Jun.**	**Jul.**	**Aug.**	**Sep.**	**Oct.**	**Nov.**	**Dec.**
60	34.52	26.47	21.00	22.00	22.65	102.00	168.30	46.47	16.61	8.00	10.00
70	31.33	17.72	12.86	16.00	20.00	95.20	153.63	35.39	12.89	7.85	5.58
80	21.00	12.39	6.27	11.00	16.81	61.87	127.87	26.00	10.91	6.56	3.18
90	17.00	2.55	1.74	7.90	9.27	51.75	77.04	17.00	7.00	6.21	2.54

2.5.3 Ground Water

In the Tawi basin, exploitation of ground water is practically confined within Jammu district only. Central Ground Water Board has been carrying out the requisite survey work for the same. Since a long-time, CGWB has also carried out the studies only in Jammu district and for Udhampur & Doda the studies are in progress.

According to Ground Water Information Booklet prepared by CGWB for Jammu District, J&K rainfall is the major source of groundwater recharge apart from the influent seepage from the rivers, irrigated fields and inflow from upland areas whereas discharge from ground water mainly takes place from wells and tube wells; effluent seepages of ground water in the form of springs and base flow in streams etc. Ground water resources and irrigation potential for Jammu district have been computed as per the GEC-97 methodology the resources for the year 2004 and are as follows.

Table 2.2: Various Water Balance component of Tawi River

1.	Annual Replenishable GW Resource during monsoon & non-monsoon period (MCM)	850.77
2.	Natural Discharge during Non-monsoon Season (MCM)	85.08
3.	Net Annual Ground Water Availability (MCM)	765.69
4.	Annual Ground Water Draft (MCM)	134.90
5.	Demand for Domestic and Industrial uses (Projected up to 2025) (MCM)	117.21
6.	Ground Water Availability for Future Irrigation (MCM)	582.12
7.	Stage of Ground Water Development (%)	18

The stage of ground water development in Jammu district is 18% and falls under ñSafeò category. There is thus scope for further ground water development. Depth to water level in the Jammu region varies from less than 1 m to 28 m below ground level. The Kandi belt in general has deeper water levels.

2.5.4 Ground Water Quality

CGWB monitors the ground water quality of shallow aquifers at 64 National Hydrograph Networks Stations located in the Jammu district every year in pre-monsoon period. The range of chemical parameters hydrograph network stations of CGWB in the Jammu district are given in table 2.3.

Ground water quality in the Jammu is in general good both for irrigation and domestic purpose. From the samples collected from ground water sources of Dug well, the EC in ground water is generally below 1000 εS/cm at 25° C. Other chemical parameters are within the permissible limits. Thus it can be concluded that the overall quality of ground water is good and suitable for domestic and irrigation use except some part of the Jammu district.

Table 2.3: Water quality parameters of Tawi River at Jammu.

			Range	
S. No.	Parameter	Unit	Min	Max
1	pH	-	7.12	8.39
2	EC	εS/cm	168	940
3	HCO3	mg/l	62	915
4	Cl	mg/l	11	255
5	NO3	mg/l	0.52	22
6	F	mg/l	0	1.02
7	Ca	mg/l	45	137
8	Mg	mg/l	4.7	73
9	Na	mg/l	3.2	110
10	K	mg/l	0.6	57
11	TH as CaCO3	mg/l	15	319

2.6 GEOLOGY AND SOIL

Western Himalaya is geologically described as lying within moving belt of earthœ crest. Like other parts Tawi basin mainly consists of Shiwaliks, Murree and Granite intrusion. The upper part of the basin is covered by hard granite intrusive rocks and the lower part by loose and soft Shiwalik rocks. Tawi basin has three Meso-geomorphic regions:

1. Kaplas Granite zone from Kaplas range to Panjal thrust. Kaplas granite associated with Bhaderwah slate, Sewa para gneiss etc. are the main features of the area. Maximum elevation of Kaplas range is 400 m.

2. Thrust zone from Panjal thrust to Udhampur thrust having same tectonic structures like Panjal thrust. The height of this region is from 700 m to 1900 m.
3. Shiwalik zone: - Lying between Udhampur thrust and Jammu. Most of the Region consists of hilly as well as plain areas.

Comprehensive soil survey for Tawi basin has not yet been done. However, NBSSLUP has prepared the soil map of J&K state in the scale of 1:2, 50,000. The soil classification of Tawi basin exhibits zonal properties as follows:

In Doda districts, of which a very small portion is lying with in the basin, the soils are mainly alluvial in nature. Whereas in the midlands or foots hills, the process of colluviation seems predominant. Generally, the silt or other material, brought down by the action of water gets deposited at the foot hill and give rise to soil formation. The texture, in general varies from sandy loam, sandy, to silty clay loam. In Udhmapur part, the soils are moderately deep too deep on the mid hills and plateaus whereas deep to very deep at the foothills. The texture in general is coarse to medium.

Soils of district Jammu are alluvial subtropical having a texture varying between sandy loams to silty clay loam. The lower part is recent alluvium whereas the outer plains are Pleistocene. The foothills of Shiwaliks are moderately deep to deep soils with coarse texture having stony face in general and due to lack of irrigation; these are left as uncultivated fallows.

2.7 WATER RESOURCES DEVELOPMENT

Since last few decade various state Govt. Departments have attempted to formulate and execute numbers of power, irrigation domestic water supply and recreational projects of which few have seen lights, some are under execution, some are under investigation and few have been shelved due to inadequacy of data or other technical reasons. Details of these projects are described here.

2.7.1 Hydro-power

Chenani Power Project

The river Tawi at Chenani flows in a steep gradient. In order to utilize its natural fall for power generation, a cascade system of power projects in five stages was proposed. The system envisages construction of power houses in three stages named as Chenani Hydel Project stage -1 (CHP -1), CHP-2 and CHP-3. Beyond stage 3, two more stages named as CHP-4 and CHP-5 has been envisaged. The existing CHP-1 is located in Udhampur district on river Tawi.

First three units each of 4.66 MW were commissioned in 1971. The balance two units of 4.66 MWs each were commissioned in 1975. 200 cusecs of water has been diverted near Bani-Sang by constructing a 68.58 m long weir across river Tawi. The total head available for power generation is 366 m; Two penstocks of 1.5 m and 1.22 m dia to carry 7.84 cumecs of discharge have been installed for feeding the water to turbines of power house. To utilize the tail race discharge of the power house (stage I), it was proposed to construct two more power stations down-stream nearing CHP stage 2 & 3. The net head available for power generation in stage-2 is 32 m. The water will be fed to the turbines by means of a steel penstock having a dia of 2.6 m. The installed capacity of Chenani hydel project No. II is 2.1 MW. The third stage i.e. CHP III has installed capacity of 4 MWs in phase I and additional 2 MW in phase-II. The water conductor system of stage-III is designed for discharge of 11-12 cumecs. The tentative head available for power generation will be 66.3 m.

The Chenani IV Hydro Power Project (7MW) is to be set up at Tawi River (Tributary of Chenab), district Udhampur in the State of Jammu & Kashmir on BOOT basis for procurement of power for long term. The tail race waters of stage III will be discharged back into river Tawi and will be again picked up for the power generation in stage IV & V. The head available for generation of 9.00 MWs is 110 m in stage IV and head available for generation of 8 MWs will be 65 m in stage V. These two schemes are under investigation.

2.7.2 Irrigation

Alluvial mountainous tracts of Jammu bounded by the rivers Ravi, Chenab and foothills of lower Shiwaliks are identified as major irrigation land. An area of about 44,000 hectares between Ravi and Tawi has been considered, irrigable form the river Tawi. The status of irrigations & agriculture in the three districts of the river Tawi basin is given in Table 2.4 and 2.5

Table 2.4: Extent of Area Irrigated in Tawi basin Year 1985-86

District	Area sown		Area irrigated		% of area irrigated to area sown	
	Gross	Net	Gross	Net	Gross	Net
Jammu	209926	109872	96462	51285	49.95	46.68
Udhampur	105506	65601	6873	5869	6.51	8.95
Doda	69234	59679	7797	7130	11.26	11.96

Table 2.5: Net area irrigated from different sources (000 ha) 1985-86

District	**Canals**	**Tanks**	**Wells**	**Other Sources**	**Total**
Jammu	49.09	-	1.71	0.48	51.28
Udhampur	6.68	-	-	1.19	5.87
Doda	3.75	0.01	0.01	3.37	7.14

Canals form the most important system of irrigation in Jammu region. Where the soil is soft and alluvial and canals can be easily dug. Also lift irrigation by pumping water to a higher level and then carrying it to the fields through canals has to begin in recent past.

Tawi Lift Irrigation Canal

This project envisages construction of a lift channel for minimum capacity of 300 cusecs from river Tawi with its pumping station located on the left bank of river Tawi, below Bahu fort, opposite Jammu city. The canal covering a length of 28.8 km. from Bahu to Devak nallah, commands enroute an area of 35,000 acres (CCA). The canal starts with a command level of R.L.: 1082.0 ft. above MSL and terminates at a level of R.L.: 1045.0 ft above MSL. The maximum discharge is being lifted through a gross head of 32.31 m by means of five nos. (Plus one stand by) electrically driven vertical turbine pumps each of 60 cusecs capacity. The distribution system comprises 11 distributaries with 28 minors and sub-minors having a length of 172 km. The work on the construction of this project, costing Rs. 747.6 lakh was started during 1969-70 and completed in all respects in the year 1977-78. Tawi canal is designed to irrigate 4,757 hectares in Kharif and 8,279 hectares in Rabi, thereby generating a total irrigation potential of 13,036 hectares in 125 villages of district Jammu.

Udhampur Canal

It flows near Udhampur and about 26.5 km long. This canal irrigates about 2400 acres of land. Now it is also used for generating electricity upto 8000 KW. It was built at a cost of 6.11 lacs.

Subsidiary Lift Scheme on Tawi Canal at Raya

A subsidiary lift scheme to irrigate 1100 hectare of fertile tract of land: uphill of Tawi canal in village Raya has been envisaged. The project caters for Rabi season only in the first instance but after completion of these darn (Shahpur Kandi barrage), when full share of Ravi water shall be available, it shall cater to 50% of the area under Kharif crops as well. The water for Rabi crop is available in Tawi canal at present. The work on the same is in prowess.

Upto end of 7th Plan, out of total length of 8 kms of main water conductor and 6 Nos distributaries the work on 5 kms of conductor and 2 nos. distributaries is in advance stage of completion. The original estimated cost based on March 1980 rates was Rs. 315 lacs. The revised estimated cost may be of the order of Rs. 690 lacs. The scheme shall be completed in the 8th five year plan subject to availability of funds.

2.7.3 Drinking Water Supply

Tawi basin as reported earlier consists of Jammu, Udhampur and a small part of Doda districts. The drinking water supply of the region prior to independence used to be mainly met from the local Kacha and Pacca tanks, rivulets and springs in mountainous area.

To meet the demand of drinking water supply a master Plan for augmentation and improvement of water supply to Greater Jammu under long term basis to the areas falling within its limits were formulated in 1976. This project was revised and envisaged to cover the total requirements of a designed population of Jammu.

The designed demand or projected population of 1991 at 50 gallons/day/head works out to 35.84 MGD. The supply level before start of the project in 1979 stood at 11.45 MGD and covering of gap of 24.38 MGD is envisaged in the project. The gap of 24.38 MGD has been proposed to be covered by tapping of river Tawi at Sitlee located at 8 km. u/s of Jammu and sinking of 66 tubewells in different subzones of the Master plan along the outer boundaries of city. The gap covered by river Tawi at Sitlee has been proposed as 8.4 MGD.

2.7.4 Recreation

Tawi Barrage (Artificial Lake)

The Tawi project conceived in the year 1964 envisaged construction of a barrage across the Tawi river in the vicinity of Sidra village about 15 Kms. U/S of Jammu, for diverting 500 cusecs discharge into canal en the left bank to irrigate about 36000 acres. It was proposed to locate the barrage on left side of this channel on high ground such that during the construction season, the main channel on right bank would be available for the diversion of the river. The barrage would have been tied to the banks by embankments. Guide banks were proposed on the U/S of the barrage for ensuring normal approach and exit of flows. The maximum designed flood as recommended by H&S Directorate of CWC was 5.14 lacs cusecs for water way design and 5.92 lacs cusecs for design of foundation of barrage. However, it is gathered that the project did not see light due to insufficient information required for design planning of the proposal.

2.8 LAND USE

The Tawi basin is a mainly a forested mountainous catchment of Shiwaliks range of western Himalaya. Agriculture is the second most used class of landuse. The major landuse /land covers classes in the Tawi catchment are depicted in the Fig. 3 below which has been prepared by the National Remote Sensing Centre (NRSC), Hyderabad.

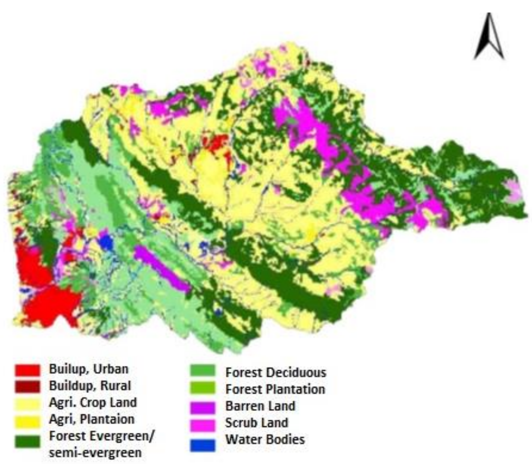

Fig. 4: Landuse /Land cover in the Tawi Catchment (Source: http://www.nrsc.gov.in)

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Chapter 3

3.0 DATA AND METHODOLOGY

3.1 DATA USED:

3.1.1 Observed Data:

This study has been planned to access the impacts of climate change on the hydrology of the Tawi river basin in future. The SWAT model has been used in the study for hydrological modeling, which is a semi-distributed lumped model and also take care of the physically processes of the catchments. For setting up the SWAT model a variety of data are required, mainly the climatic parameters, hydrologic data, soil data and the land use land cover information. The source, period resolution of the various data used in the study area depicted in the table 3.1.

Table 3.1 Details of various data used in the study

Data	Source	Scale	Period	Description
Topographic Data	SRTM	30m	2014	Elevation, aspect, slope, flow direction and accumulation
Soil Data	NBSSLUP	1/500,000	1999	Soil component parameter
Satellite Images	USGS	-	1995	To build the land use maps for different time periods
Hydrological Data at Jammu Bridge	CWC	Daily	1983-1997	Water level, streamflow
Meteorological Data (Observed) at Jammu	IMD WHRC	Daily	1983-1997	PCP, HMD, TEMP, SLR, WND
Reanalysis Data	NCEP	Daily	1961-2001	26 Parameters
GCM Data	HadCM3	Daily	1961-2099	26 Parameters

SRTM: Shuttle Radar Topography Mission
NBSSLUP: National Bureau of Soil Survey and Land Use Planning
USGS: United States Geological Survey
CWC: Central Water Commission, Jammu
IMD: Indian Meteorological Department, Pune
WHRC: Western Himalayan Regional Centre, NIH, Jammu
CCCR: Centre for Climate Change Research, IITM, Pune

Although the catchment area of Tawi is more than 2000 sq. km but it has only one discharge measuring point at Jammu which has been considered as the out of the basin and the entire study is focused on the catchment up to Jammu bridge.

3.1.2 Reanalysis data: Past climate data

The re-analysis data of atmospheric variables were, derived from the national center of environmental prediction (NCEP) on 2.50 latitude x 2.50 longitude grid-scale for 40 years (1961ï 2001) are obtained from the Canadian Climate Impacts Scenarios (CCIS) website (http://www.cics.uvic.ca/scenarios/sdsm/select.cgi).

3.1.3 GCM data: Future climate data

The large-scale daily predictors of Hadley Center's GCM (HadCM3) for HadCM3 A2 and B2 future scenarios for 139 years (1961-2099) on 3.75° latitude x 3.75° longitude grid-scale are also obtained from the Canadian Climate Impacts Scenarios (CCIS) website (http://www.cics.uvic.ca/scenarios/sdsm/select.cgi). HadCM3 is a coupled atmosphere-ocean GCM developed at the Hadley Centre of the United Kingdom's National Meteorological Service. HadCM3 has been chosen because of its' wider acceptance in many climate change impact studies in India. Further, it provides daily predictor variables, which can be exclusively used for the SDSM model.

3.2 PREPARATION OF INPUT DATA FOR SWAT

The basic spatial input datasets used by the model include the digital elevation model (DEM), land use/cover data, soil data and climatic data. The brief methodology for preparation of the data is described below.

3.2.1 Digital elevation model

The digital elevation model (DEM) of the basin was generated using Shuttle Radar Topography Mission (SRTM) data (https://lta.cr.usgs.gov/SRTM1Arc). **SRTM 1 Arc-Second Global** elevation data offer worldwide coverage of void filled data at a resolution of 1 arc-second (30 meters). For this study, a TIFF file with embedded geographic information grids i.e. Georeferenced Tagged Image File Format (GeoTIFF) tile covering the study area was downloaded from USGS website (http://earthexplorer.usgs.gov/) and DEMs of the study areas were prepared (Fig. 3.1).

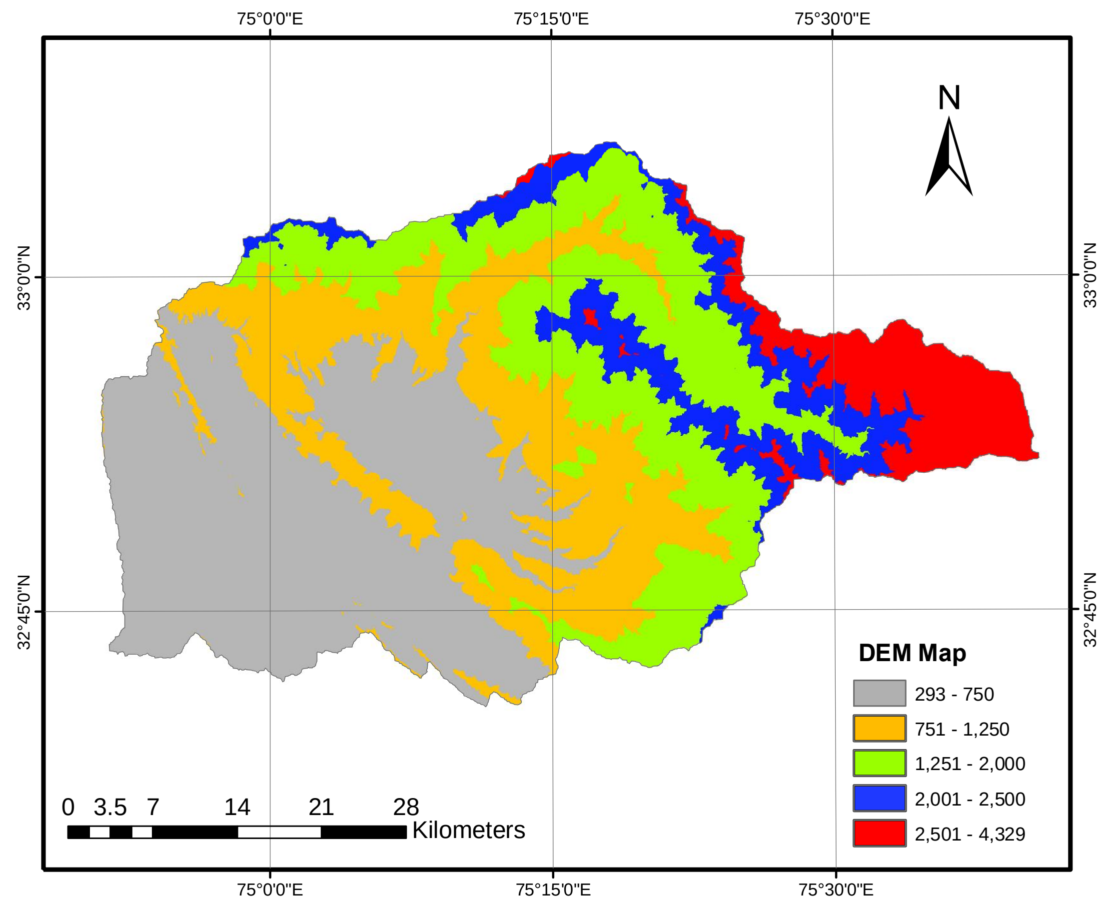

Fig. 3.1: DEM of study area in Tawi river basin

3.2.2 Land use/cover data

The land use map of the study area was prepared using satellite data of LandSat of May 15, 1995. The classification of satellite data mainly follows two approaches i.e. supervised and unsupervised classification. The intent of the classification process is to categorize all pixels in a digital image into one of several land cover classes, or themes. This categorized data then used to produce thematic map of the land covers present in an image. In the present study, the unsupervised classification method was used for preparation of the land use maps (Fig. 3.2) due to remote and inaccessible areas in the study catchments. The land use categories and their coverage in the study catchment is presented in Table 3.2.

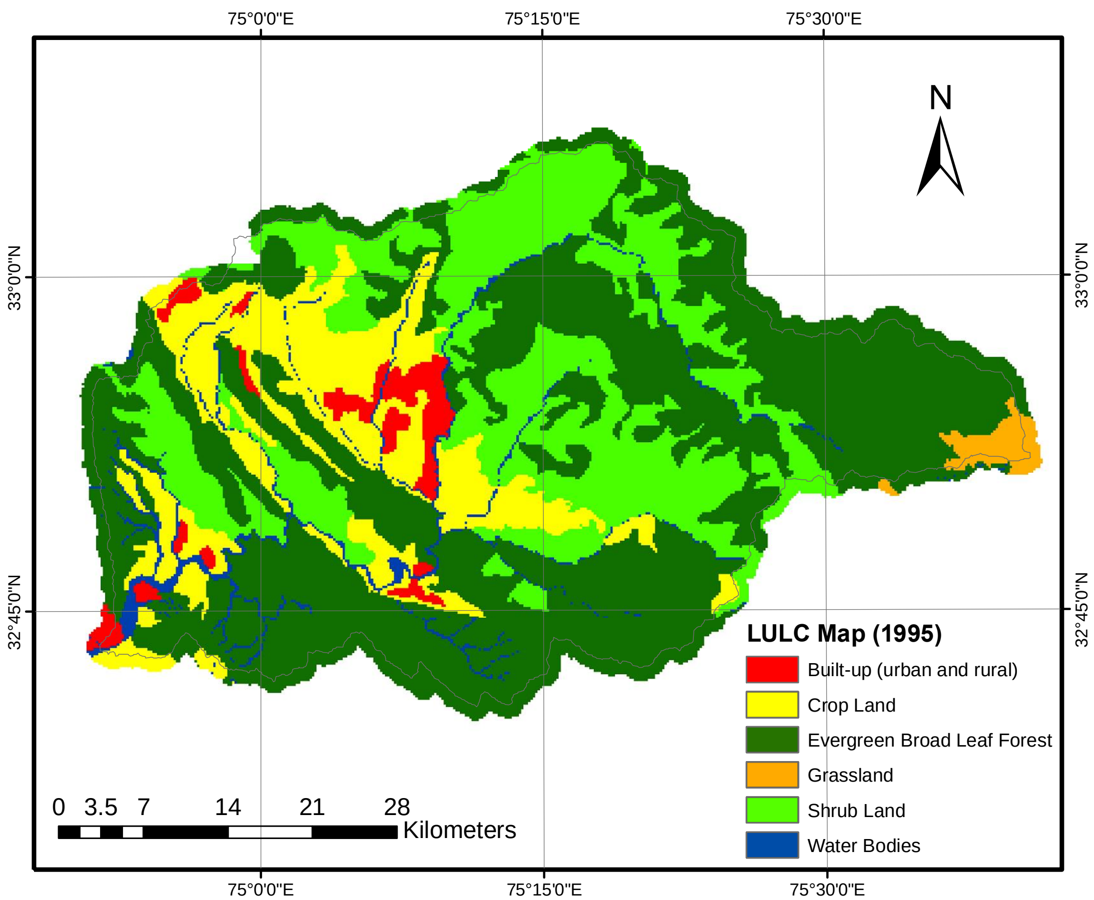

Fig. 3.2: Land use map of study area in Tawi river basin

Table 3.2: Major land use classes in study areas of Tawi basin

Land use Class	Area (km^2)	% Total
Built-up (Urban & Rural	62.23	2.87
Crop Land	317.04	14.63
Evergreen Broad Leaf Forest	1147.16	52.94
Grassland	25.02	1.15
Shrubs Land	552.45	25.49
Water Bodies	63.10	2.91
Total	2167.00	100

3.2.3 Soil data

Soil maps of the study area was digitized using soil maps of the National Bureau of Soil Survey and Land Use Planning (NBSS & LUP) at a scale of 1:50,000. The soil properties like soil texture, hydraulic conductivity, organic carbon content, bulk density, available water content are required by SWAT as input to the model for simulating various hydrological processes. Information on the missing soil parameters were collected from various sources and available literature. Soil map prepared by NBSS & LUP was used as a base map. Based on the analysis, it was observed that the soils in the study areas fall in the hydrologic soil group C & D. The soil maps of study areas in Tawi river basin is shown in Fig. 3.3 and the few of the physical and chemical properties of the soil series in the basin watershed is shown in Table 3.3

Table 3.3 Physical and chemical properties of soil series in Tawi River basin

Soil Type	SANDY_LOAM		LOAM		CLAY		FINE LOAM	
	Layer 1	Layer 2	Layer 1	Layer 2	Layer 1	Layer 2	Layer 1	Layer 2
SOL_Z (mm)	300	1000	300	500	300	500	60	190.00
SOL_BD (g/cm3)	1.3	1.7	1.1	1.3	1.2	1.2	1.62	1.65
SOL_K (mm/hr)	55.66	5.47	21.28	7.52	13.43	13.7	9.83	22.41
SOL_CBN (%)	0.4	0.3	1.5	1	0.7	0.3	0.34	0.25
CLAY (%)	13	21	26	31	41	42	15.30	7.90
SILT (%)	9	9	30	29	34	32	49.20	50.20
SAND(%)	78	70	44	40	25	25	35.50	41.90
USLE_K factor	0.283	0.283	0.252	0.252	0.2902	0.2902	0.17	0.17

3.2.4 Weather data

A hydrological and meteorological observation network is being maintained by IMD and CWC across the country. The daily data of meteorological parameters (viz. rainfall, temperature, wind speed, relative humidity etc.) and river discharge at Jammu station in the Tawi river basins has procured from IMD and CWC respectively. The daily data of rainfall, and maximum and minimum temperatures of Jammu station for the period 1983 to 1997 were used in the study. Some of the missing meteorological daily data of wind speed, relative humidity and solar radiation for the Tawi catchment and was downloaded for the available stations from the NASA website at URL: http://power.larc.nasa.gov/cgi-bin/cgiwrap/solar/agro.cgi?email=agroclim@larc.nasa.gov .

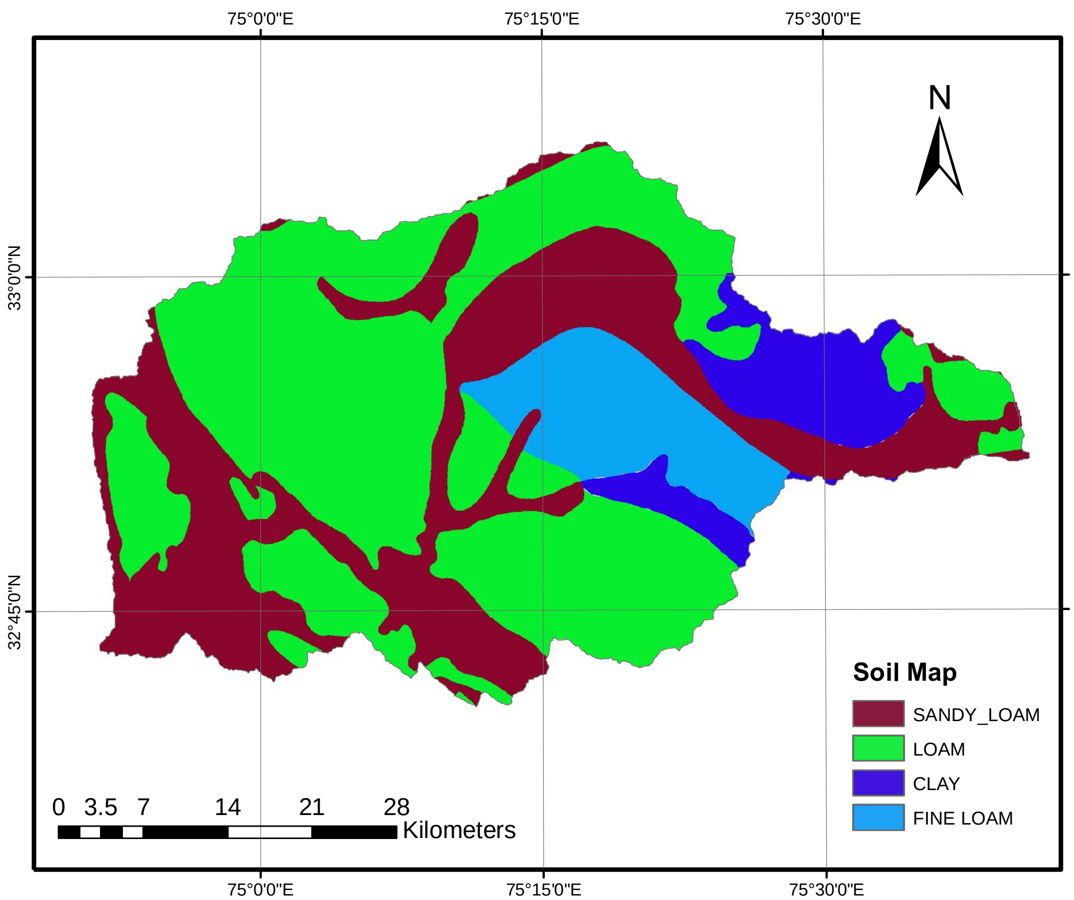

Fig.3.3: Soil map of study area in Tawi river basin

3.2.5 Hydrological data

The daily discharge data monitored by CWC at Jammu gauging sites on Tawi river was utilized in the study. This gauging sites was monitored for 24 hours during the monsoon period to observe the high floods. The daily data for the years 1983 through 1997 for Jammu gauging sites was collected and processed.

3.3 MODEL SET-UP, CALIBRATION AND VALIDATION

SWAT model was set up on Tawi river basin up to Jammu Bridge. The ArcSWAT interface compatible with SWAT 2009 was used for the setup and parameterization of the model. A digital elevation model (DEM) was imported into the SWAT model. A masking polygon (in grid format) was loaded into the model in order to extract the area of interest, delineate the boundary of the watershed and digitize the stream network in the study area. The minimum threshold area for generation of streams was taken as 3000 ha and no sub-basin were created as we were having only one discharge site at basin outlet at Jammu. The land use/cover and soil maps of the study watersheds (in grid format) were also imported into the model and overlaid to obtain a unique combination of land use, soil and slope. Multiple HRUs with 15% land use, 15% soil and 30% slope thresholds were set to eliminate minor land uses and slope classes in basin as recommended in the SWAT user manual (Neitsch *et al*., 2002). The daily data of rainfall, minimum and maximum temperature, relative humidity, wind speed and solar radiation were prepared in the appropriate file format and imported into the model.

The daily flow data for the period 1983 to 1992 of Jammu gauging sites were used for calibration. The data of initial one year in both catchments were utilized for warming up and initialization of the model variables. The warm up period was not used for evaluation of the model predictions. The SWAT model includes a large number of parameters that describe different hydrological conditions and characteristics across the watershed. These parameters need to be calibrated to adequately simulate streamflow and sediment processes in the study catchments. Parameters can either be calibrated manually or automatically. In this study, the calibration was done manually based on physical catchment understanding and sensitive parameters from published literature (Bärlund et al., 2007; Xu et al., 2009) and calibration techniques from the SWAT user manual. The hydrological component and the erosion component of the model were calibrated sequentially until the average simulated and measured values were in close agreement. Results of many studies have indicated that SCS curve number (CN_2), a function of soil permeability, landuse and antecedent soil water conditions, is an important parameter for surface runoff (Oeurng *et al.,* 2011; Das *et al*., 2007; Parajuli *et al*., 2009; Arabi *et al*., 2008; Wang *et al*., 2008). The runoff curve numbers were adjusted within ±10% of the tabulated curve numbers. The other important parameters that were calibrated for simulation of flow included óbaseflow recession coefficientô (ALPHA_BF), ósoil evaporation compensation factorô (ESCO), óplant water uptake compensation factorô (EPCO), ósurface runoff lag timeô (SURLAG), ógroundwater delayô (GW_DELAY), ódeep aquifer percolation factorô (RCHRG_DP), óManningôs óónôô value for tributary channelsô

(CH_N1), óManningôs óónôô value for main channelô (CH_N2), and óManningôs óóNôô for overland flowô (OV_N). SWAT uses MUSLE (Williams, 1975) for prediction of sediment concentration. Therefore, the MUSLE ñcrop cover and management factorô (C), ósupport practice factorô (USLE_P), and the channel sediment routing variables, viz., a linear parameter for calculating the maximum amount of sediment that can be entrained during channel sediment routing (SPCON), an exponential parameter for calculating the channel sediment routing (SPEXP) were adjusted during the calibration.

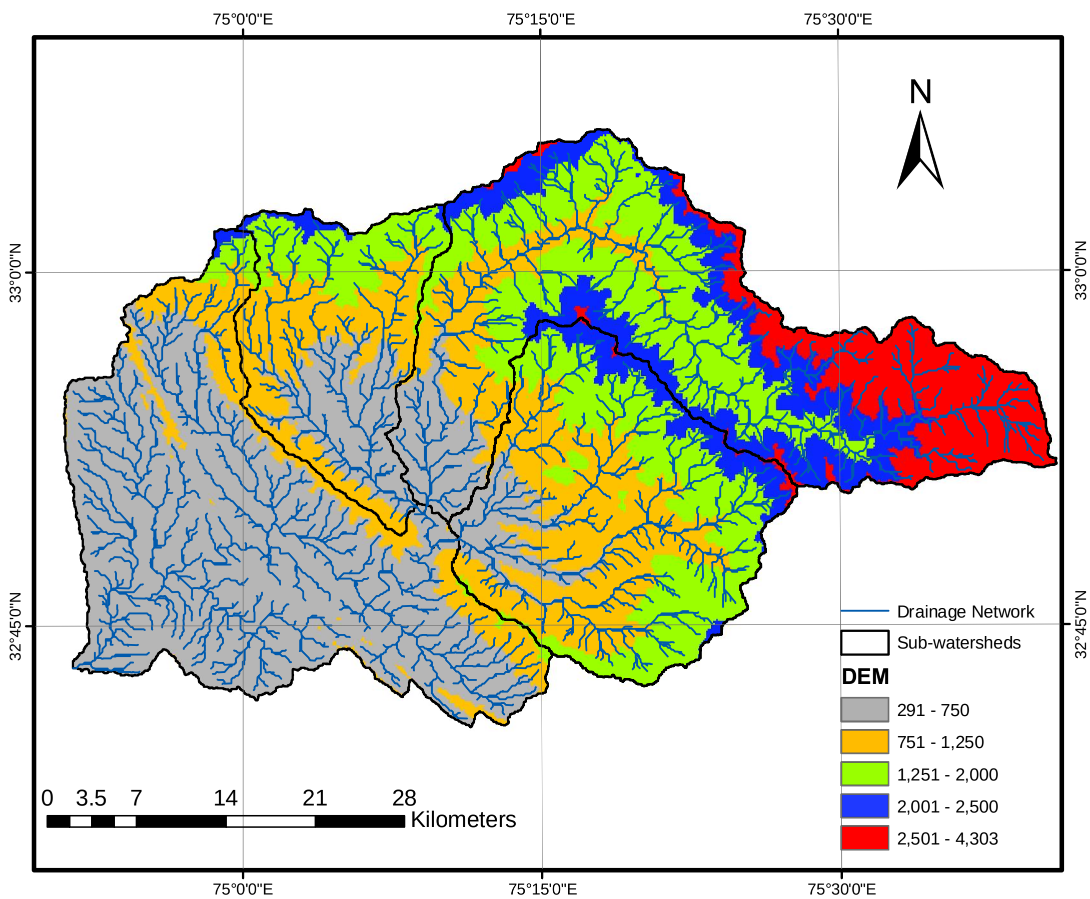

Fig. 3.5: Drainage network and Sub-watershed of the Tawi river basin

In the validation process, the model was run with calibrated input parameters and the model predictions were compared with an independent set of observed data of the period 1993 to 1997 for Tawi River.

3.4 CRITERIA FOR MODEL EVALUATION

Evaluations always involve a comparison of the model's output to corresponding measured variable. When presenting model results, the model developers typically do not provide consistent or standard statistical evaluation criteria to assist the readers or users in determining how well their model reproduces the estimated data and how well their model compares to other models. Haan et al. (1982) suggested that the graphical representation of the results could easily be interpreted if the calibration is done for only one watershed at one stream gauge location. In the present study continuous time series of the observed and estimated data and prepared a scattergram of the same. Although scattergram method does not preserve the flow sequence contained in the time series plots, difference between a linear regression line through the plotted points and equality line of scattergram help to identify errors that cannot be detected as easily from the time series plot. Several types of statistics provide useful numerical measures of the degree of agreement between model outputs (estimated results) and recorded (observed data) quantities. Selection requires choice on how to aggregate groups of measured differences in a single statistic. The numerical and graphical performances criteria described below are used in the study.

3.4.1 The coefficient of determination (R2)

It describes the proportion of the total variance in the observed data that can be explained by the model. It ranges from 0.0 to 1.0, with higher values indicating better agreement, and is given by

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i-\bar{O})(S_i-\bar{S})}{\left[\sum_{i=1}^{n}(O_i-\bar{O})^2\right]^{0.5}\left[\sum_{i=1}^{n}(S_i-\bar{S})^2\right]^{0.5}}\right]^2 \qquad é\ (1)$$

where O_i and S_i are the observed and simulated values, n is the total number of paired values and $\bar{O}$ is the mean observed value. Where $\bar{S}$ is the mean of simulated values. R2 ranges between 0 and 1. The value of 1 implies that the computed values are in perfect agreement with the observed data.

3.4.2 The coefficient of Correlation (CC)

The quantity CC, called the linear correlation coefficient, measures the strength and the direction of a linear relationship between two variables. The linear correlation coefficient is sometimes referred to as the Pearson product moment correlation coefficient in honor of its developer Karl Pearson.

The mathematical formula for computing r is:

$$r = \frac{n\sum O_i S_i - \sum O_i \sum S_i}{\sqrt{n\sum O_i^2 - \left(\sum O_i\right)^2}\sqrt{n\sum S_i^2 - \left(\sum S_i\right)^2}}$$ é (2)

3.4.3 Nash-Sutcliffe Efficiency (NSE)

The Nash-Sutcliffe efficiency (NSE) is a normalized statistic that determines the relative magnitude of the residual variance (ñnoiseò) compared to the measured data variance (ñinformationò) (Nash and Sutcliffe, 1970). NSE indicates how well the plot of observed versus simulated data fits the 1:1 line. NSE is computed from the following equation:

$$NSE = \left[1 - \frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}\right] \times 100$$ é (3)

where O_i and S_i are the observed and simulated values, n is the total number of paired values and $\bar{O}$ is the mean observed value. The NSE varies from 0 to 100 with 100 denoting perfect fit. Generally, NSE is very good when it is greater than 75%, satisfactory when it is between 36 and 75%, and unsatisfactory when it is lower than 36% (Nash and Sutcliffe, 1970; Krause et al., 2005). However, a shortcoming of the Nashï Sutcliffe statistic is that it does not perform well in periods of low flow, as the denominator of the equation tends to zero and E_{NS} approaches negative infinity with only minor simulation errors in the model (Oeurng *et al.,* 2011). This statistic works well when the coefficient of variation for the data set is large.

3.4.4 Mean Absolute Error (MAE)

It is a quantity used to measure how close forecasts or predictions are to the eventual outcomes. The mean absolute error is given by:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|O_i - S_i\right|$$ é (4)

3.4.5 RMSE-Observations Standard Deviation Ratio (RSR)

RMSE is one of the commonly used error index statistics (Chu and Shirmohammadi, 2004; Singh et al., 2004). It is commonly accepted that lower the RMSE the better the model performance. Singh et al. (2004) suggested a model evaluation statistic, named the RMSE-observations Standard Deviation Ratio (RSR). RSR standardizes RMSE using the observations standard deviation, and it combines both an error index and the additional information recommended by Legates and

McCabe (1999). RSR is calculated as the ratio of the RMSE and standard deviation of measured data, as shown in the following equation.

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\sqrt{\sum_{i=1}^{n}(O_i - S_i)^2}}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}} \qquad (5)$$

RSR varies from the optimal value of 0, which indicates zero RMSE or residual variation and therefore perfect model simulation, to a large positive value. Lower is the RSR, lower will be the RMSE, and better will be the model performance (Moriasi et al., 2007). In the present study, criterion suggested by Moriasi et al. (2007) and shown in Table 5.1 are adopted for evaluating the performance of the model.

Table 3.4 General performance ratings for recommended statistics for a monthly time step

Performance rating	RSR-Range	NSE-Range
Very Good	0.00 < RSR < 0.50	0.75 < NSE < 1.00
Good	0.50 < RSR <0.60	0.65 < NSE <0.75
Satisfactory	0.60 < RSR <0.70	0.50 < NSE < 0.65
Unsatisfactory	RSR >0.70	NSE < 0.50

3.5 STATISTICAL DOWNSCALING OF GCM

The statistical downscaling model (SDSM) is a multiple regression-based tool for generating future scenarios to assess the impact of climate change. It has the ability to capture the inter-annual variability better than other statistical downscaling approaches. This approach involves three sub-classes such as weather typing, weather generator and regression/transform function. The model requires two types of daily data, i.e., (i) the local data known as 'Predictand' (viz. rainfall and temperature) and (ii) the different atmospheric variables known as 'Predictors'. Formulating an empirical relationship between predictand and predictor is central to the downscaling technique. This can be derived by various methods such as parametric (multiple linear regression) and non-parametric (artificial neural network; support vector machine). This study uses the Multiple Linear Regression (MLR) method which falls under parametric methods. The downscaling has been carried out using SDSM tool version 4.2.9.

3.5.1 Selection of predictors

For downscaling predictand, the selection of suitable predictors is one of the most important and time consuming steps during downscaling. The appropriate predictor variables are selected through scatter plots, positive and negative correlation and partial correlation analysis between predictand (rainfall) and predictors (most appropriate out of 26 possible parameters). The observed daily NCEP reanalysis data set for the periods 1961-2001 was used for the selection of predictors.

3.5.2 Model calibration and validation

Model calibration is carried out to development of an empirical relationship between the predictand and the predictors using multiple linear regression. NCEP reanalysis data for the period 1961-1990 was used for model calibration, and rest of the data from 1991 to 2001 is used for validation purpose. Validation process enables to produce synthetic daily data based on inputs of the data considered during the model calibration. The model performance was evaluated based on the coefficient of correlation (R) between the observed values during the validation period and the modeled values.

3.5.2 Rainfall and Temperature Scenario generation

The validated regression model is applied to generate future scenario for the watershed utilizing the simulated HadCM3 A2 and B2 GCMs data. The study assumes that the relationship between predictor and predictand remains valid under the future climate conditions. Twenty ensembles of daily synthetic rainfall and temperature (both minimum and maximum) for a period of 139 years (1961- 2099) have been generated. The ensemble values are averaged and divided into four separate time period viz. past (1983-1997), 2020s (2020-2049), 2050s (2050-2079) and 2080s (2080-2099) and used for simulating the river flow in future using SWAT model.

3.6 EXPERIMENT DESIGN FOR CLIMATE CHANGE IMPACT

To assess the impacts of the climate change on streamflow of Tawi River, the flows from 2020 to 2099 have be simulated for three periods: the 2020s (i.e., 2020ï 2049), the 2050s (i.e., 2050ï 2079), and the 2080s (i.e., 2080ï 2099). The simulated streamflow for each future period scenario have compared to the corresponding values for the baseline period (1983ï 1997) under the no-change scenario. To analyze only the impact of climate change on streamflow, the future LULC have been assumed to be the same as the LULC (1995) used for model development.

Chapter 4

4.0 DATA AND METHODOLOGY

4.1 SWAT Modelling

SWAT model has been setup as per the method described in chapter 3 for the Tawi River basin up to Jammu for the assessment of effects of climate change on the hydrology of river in future. The model was calibrated for 10year (1983-1992) and validated for 5years (1993-1997). The subsequent section describes the results pertaining to the hydrological modelling of the basin using SWAT model.

4.1.1 Model Calibration

The structure of any model built with various parameters or components which has replicate the model directly or indirectly. However, it is necessary a good relationship between results of observed data and modeled data. Most of the model inputs are physical based which has taken from observations as well as available literatures. A model has developed successfully, means the observed data is near to match with modeled values. In other words, how well the model is calibrated. In SWAT model has both calibration techniques are available namely as manual calibration and automatic calibration. However, the manual calibration process is more appropriate technique. It also been used worldwide by various researchers. Manual calibration is tedious and time consuming approach and output of calibrated model is depending on the experience of modeler and knowledge of the watershed being modeled. In present study, manual calibration process has been utilized. During the calibration process, it is necessary to note down the tuned values of the parameters. Visual examine of simulated and observed hydrograph is also essential task for improvements of results during the calibration process. In the SWAT model parameters such as curve number, soil available water content, effective hydraulic conductivity, soil bulk density, threshold depth of water in shallow aquifer, groundwater ñrevapò coefficient, soil evaporation compensation factor, average slop steepness, manningôs ñnò, average slope length, baseflow alpha factor, ground water delay, plant uptake compensation factor etc. were taken into consideration for calibration of water. However, among of these parameters varies between its upper and lower limits. The process of calibration has been adopted after sensitivity analysis in SWAT model. Since many of the input parameters were available for the basin, they were not to be calibrated. The model simulates the water balance in daily/monthly time steps. In present study, calibration process was carried out on monthly basis at Jammu during 1983-1992. The first one years (1983-1984) of the modelling period has been taken as reserved for ñmodel warm-upò in order to realistically set-up the states of its internal hydrological components e.g. groundwater store, soil moisture content etc. Further, starting fourteen years and remaining five years has been considered for calibration and validation respectively. Parameter changes in the SWAT affecting hydrology were done in a distributed way for selected reach. Parameters were modified by replacement and by multiplication of a relative change depending on nature of the parameter. However, a parameter has never been allowed to go beyond the predefined absolute parameter ranges during the calibration. Thus, the model can be applied for further analysis.

4.1.2 Simulation of Discharge using Pre-calibrated SWAT Model

Initially, the time series of the observed and pre-calibrated (SWAT model) simulated monthly discharge values of Jammu for the years 1984-1992 were compared graphically (Fig. 4.1). The value of pre-calibrated simulated discharge hydrograph continuously over-predicts from observed discharge in most of the years. The observed and simulated monthly discharge for the pre-calibration period along with 1:1 line is shown in Figure 4.2. It is observed from the figure that the simulated discharge values are distributed almost continuously above 1:1 line (except for some small flow values), indicating that the model over-predicts the monthly values of discharge. Further, the efficiency of the model for pre-calibration period was tested by statistical analysis and results are presented in Table 4.1.

It is evident from Table 4.1 that the value of coefficient of correlation (CC) and determination (R^2) are quite good (0.71 and 0.51) but it has to be noted that R^2 estimates the combined dispersion against the single dispersion of the observed and predicted series which is one of the major drawbacks of R^2 if it is considered alone and a model which systematically over or under predicts all the time will still result in good R^2 values close to 1.0 even if all predictions were wrong (Krause et al., 2005).

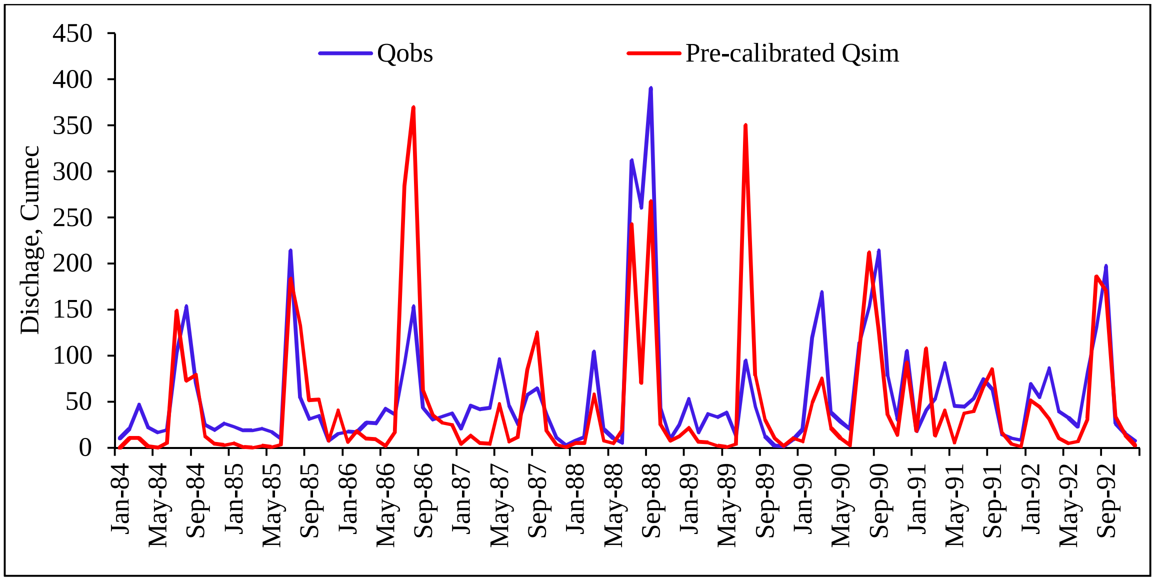

Fig. 4.1 Pre-calibrated observed and simulated discharge for the year 1984-1992

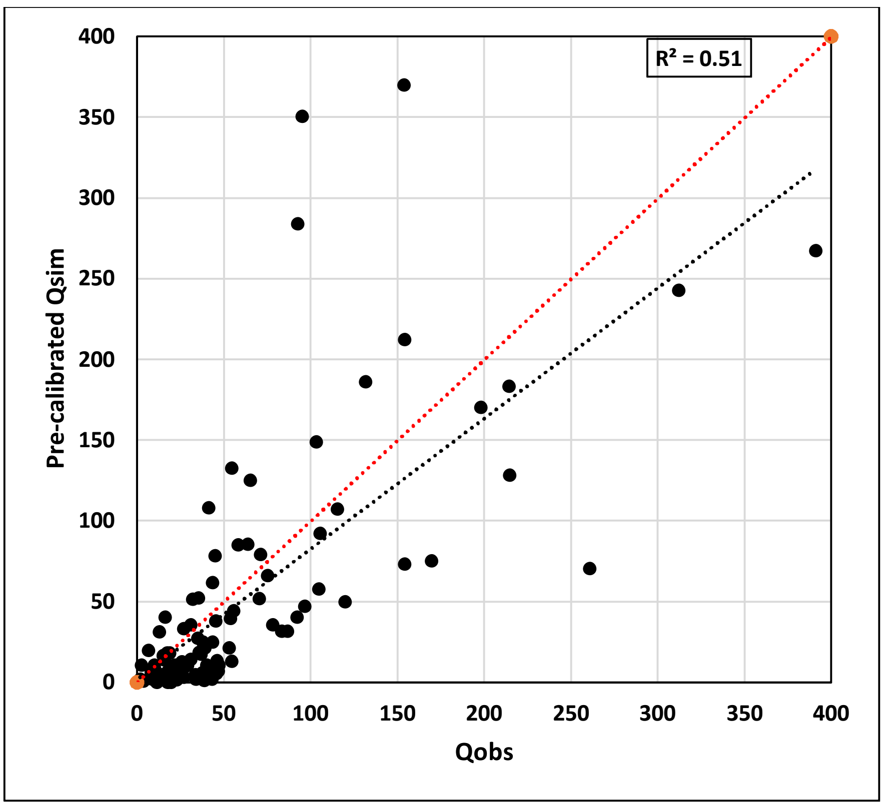

Fig. 4.2 Comparison between the pre-calibrated simulated and observed discharge 1983-1992

Table 4.1 Statistical analysis of pre-calibrated monthly observed and simulated discharge during 1990-2006

Statistical Parameters	Discharge at Jammu during 1983-1992 (m^3/sec)	
	Observed	Simulated
Mean	55.7	47.0
Standard Deviation	64.2	72.6
Maximum	390.9	370.3
Coefficient of Correlation (CC)	0.71	Very good
Coefficient of determination	0.509	good
Nash-Sutcliffe efficiency	0.32	Unsatisfactory
MAE	0.25	-
RSR	0.83	Unsatisfactory

Nash-Sutcliffe efficiency (NS) was found to be 0.32 for pre-calibrated model results for discharge. For the quantification of discharge predictions this leads to an overestimation of the model performance during peak flows and an underestimation during low flow conditions. Similar to R^2 the Nash-Sutcliffe is not very sensitive to systematic model over or under prediction especially during low flow periods (Krause et al., 2005). RSR value of un-calibrated model is about 0.83 which is indicates unsatisfactory level of model efficiency. Detailed statistics of pre-calibrated model results shown in Table 4.1

Sensitivity analysis was carried out to examine the relative changes in the model output with respect to change in model input variables. The sensitivity analysis indicated the importance of all the parameters in determining the streamflow in the study area. This result illustrates how parameter sensitivity is site specific and depends on land use, topography and soil types, as compared to other studies elsewhere. In present study manual calibration procedure has been adopted. However, the calibration process is nothing but the trial and error approach. The parameter for SWAT model has been tune up to the optimum limit or until the acceptable range. Input variables used for model calibration were soil conservation service (SCS) curve number, Soil evaporation compensation factor, Available water capacity of the soil layer, Threshold depth of water in the shallow aquifer for revap to occur, Threshold depth of water in the shallow aquifer required for return flow to occur, Groundwater-revap coefficient, hydraulic conductivity in main channel, Manning coefficient for main channel and Surface runoff lag coefficient.

Table 4.2 SWAT parameters with rank according to sensitivity to the simulated output

Rank	Name	Description	Lower Bound	Upper Bound	Process
1	CN	SCS runoff CN for moisture condition II	-25	25	Runoff
2	ESCO	Soil evaporation compensation factor	0	1	Evaporation
3	GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	-1000	1000	Groundwater
4	SOL_Z	Soil depth	-25	25	Soil
5	REVAPMN	Threshold depth of water in the shallow aquifer for revap to occur (mm)	-100	100	Groundwater
6	SOL_AWC	Available water capacity of the soil layer (mm/mm soil)	-25	25	Soil
7	CANMX	Maximum canopy storage (mm)	0	10	Soil
8	BLAI	Maximum potential leaf area index	0	1	Crop
9	SOL_K	Soil conductivity (mm hr)	-25	25	Soil
11	GW_REVAP	Groundwater -revap coefficient	-0.036	0.036	Groundwater
12	EPCO	Plant evaporation compensation factor	0	1	Evaporation
13	CH_K2	Hydraulic conductivity in main channel (mm hrs)	0	150	Channel
14	SLOPE	Average slope steepness (mm)	-25	25	Geomorphology
15	GW_DELAY	Groundwater delay (days)	-10	10	Groundwater
16	SURLAG	Surface runoff lag coefficient	0	10	Runoff
17	CH_N2	Manning coefficient for main channel	0	1	Channel
18	BIOMIX	Biological mixing efficiency	0	1	Management
19	SLSUBBSN	Average slope length (m)	-25	25	Geomorphology
20	SOL_ALB	Soil albedo	-25	25	Evaporation
27	SFTMP	Snowfall temperature (°C)	0	5	Basin
27	SMFMN	Melt factor for snow on December 21 (mm water °C-day)	0	10	Basin
27	SMFMX	Melt factor for snow on June 21 (mm water °C-day)	0	10	Basin
27	SMTMP	Snow melt base temperature (°C)	-25	25	Basin
27	TIMP	Snow pack temperature lag factor	0	1	Basin
27	TLAPS	Temperature lapse rate (°C km)	0	50	Sub Basin

4.1.2 Simulation of discharge using calibrated SWAT model:

Simulation of streamflow was carried out from calibrated SWAT model and comparison of the monthly simulated values from corresponding observed values has been graphical presentation (Figure 4.3). In this study, the model has been validated at Jammu site which is located near to outlet of the basin.

The monthly predictions were generally good for simulation period, except for the months with extreme storm events and hydrologic conditions. This may be due to (1) overestimation of base flow during early monsoon and (2) slightly lower assignment of CN. Generally, it is observed that during the initial phase of commencement of monsoon rains, the observed discharge was less than the simulated discharge. On the contrary, model may over-predict the discharge if high intensity rainfall occurs on the following few days of dry spells which leads to unsaturated soil condition. Nevertheless, the model predicted discharge is found to be close to the observed values for well-distributed rainfall events. One of the other possible reasons for lower prediction of discharge may be due to lesser density of meteorological stations (data) at higher altitudes areas from which higher discharge is generally expected.

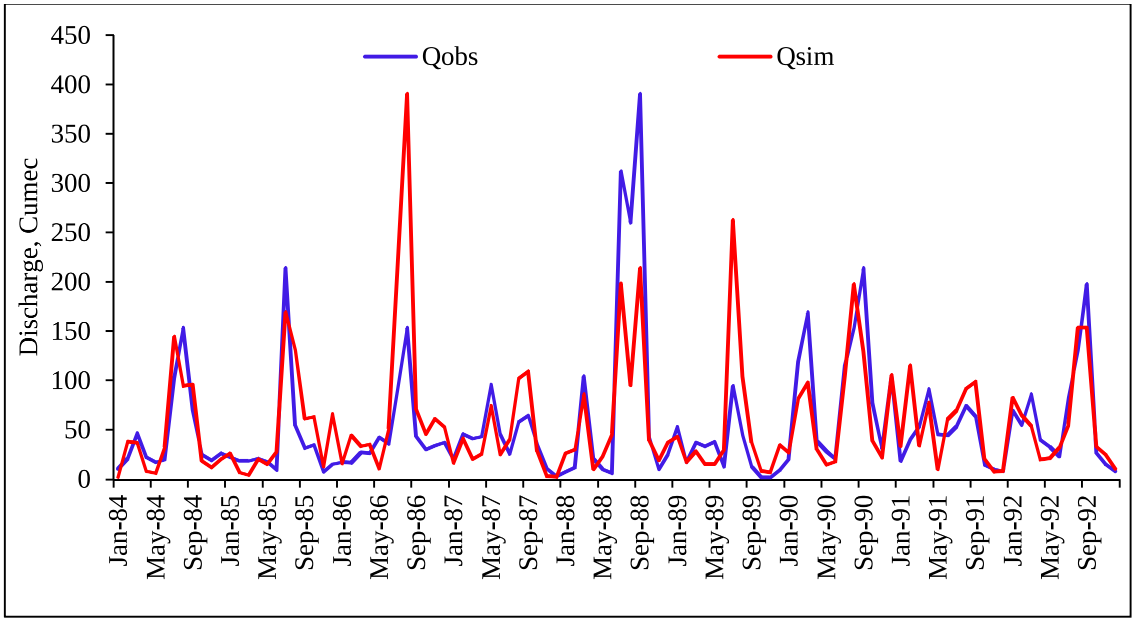

Fig. 4.3 Observed and simulated discharge during Calibration period (1984-1992)

The observed and simulated monthly discharge during calibration and validation (combined) along the 1:1 line is illustrated in Fig. 4.4 and 4.5. It is observed from the figure that the simulated discharge values are distributed uniformly about the 1:1 line for upper values of observed discharge. For high values of observed discharge, the simulated values are slightly above 1:1 line, indicating that the model over-predicts the high values of discharge. After calibration and validation, the value of Coefficient of correlation, determination, Nash-Sutcliffe coefficient, and RSR were found about 0.92, 0.854, 0.84 and 0.53 respectively. A high value of coefficient of determination (R^2 = 0.854) indicates a close relationship between the observed and simulated discharge. Further, the efficiency of the model for simulating discharge was tested by statistical analysis and the results are presented in Table 4.3 for both calibration and validation.

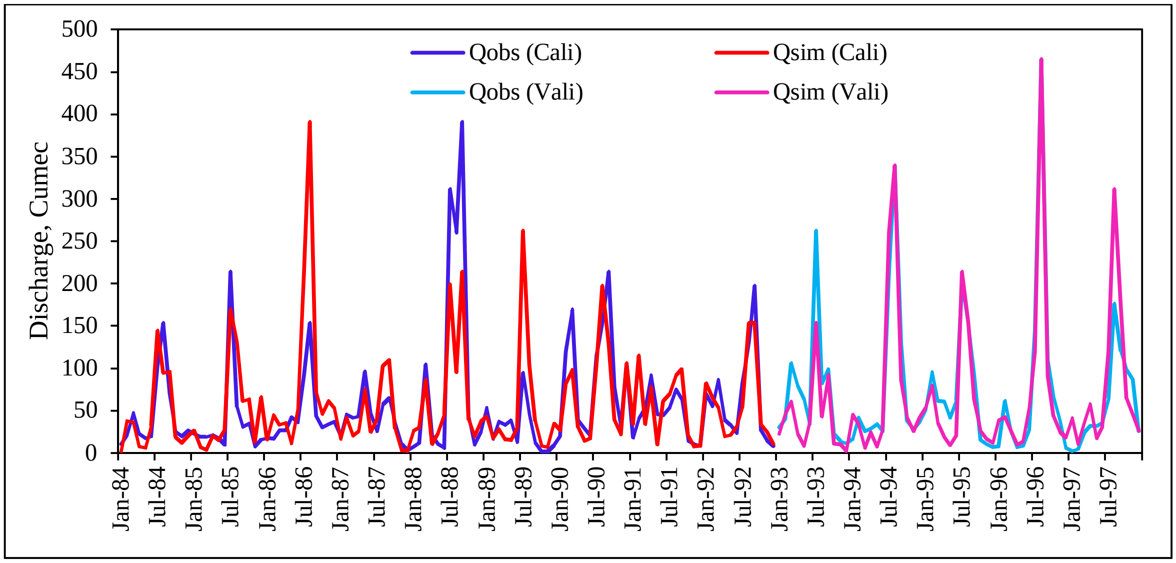

Fig. 4.4 Observed and simulated discharge during Calibration period (1984-1992) and validation period (1993-1997)

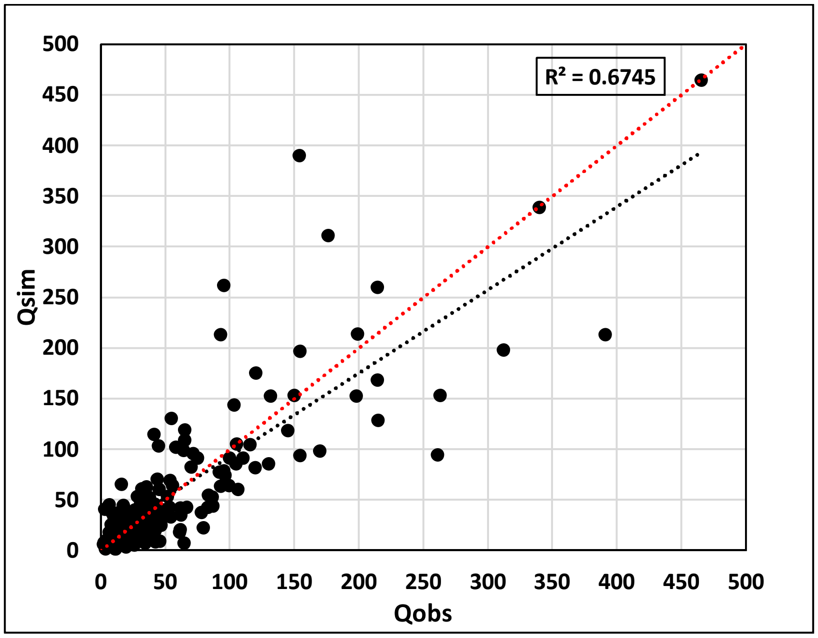

Fig. 4.5 Comparison between observed and simulated discharge during calibration period (1984-1992) and validation period (1993-1997)

Table 4.3 Statistical analysis of monthly observed and simulated discharge during calibration and validation

Statistical Parameters	During Calibration (1983-1992)		During Validation (1993-1997)	
	Observed	Simulated	Observed	Simulated
Mean	55.7	58.2	72.2	67.6
Standard Deviation	64.2	61.3	83.1	87.7
Maximum	390.9	390.9	465.1	465.1
Coefficient of Correlation (CC)	0.72	Very Good	0.92	Very Good
Coefficient of determination	0.513	Good	0.854	Very Good
Nash-Sutcliffe efficiency	0.46	Unsatisfactory	0.84	Unsatisfactory
MAE	0.35	-	0.6	-
RSR	0.64	Satisfactory	0.53	Good

4.2 STATISTICAL DOWNSCALING OF GCM

Climate change is a long drawn process which is contributed by various factors that affect directly or indirectly the various hydrological processes such as runoff. Climate change and its impact on water resources is difficult to assess but is definitely felt at basin and regional scale. Global Circulation Models (GCMs) reflect the climatic conditions at global as well as local levels and are based on concentration of greenhouse gases (Mitchell et al., 1995). Due to the courser spatial resolution of the GCMs, these cannot be directly used for hydrological modelling and needs to be downscaled. Downscaling is the technique, which provide the fine scale numerical values from coarse resolution. Statistical downscaling is a regression based downscaling which works on empirical relationship between the local scale predictands and regional scale predictor(s).

4.2.1 Selection of predictor variables

A list of predictor variables (NCEP and GCM) of a grid-box closest to the Tawi river basin of Jammu and Kashmir is presented in Table 4.4. A total of 26 largescale predictor variables have been considered in the initial screening process. These are categorized into five types based on the atmospheric pressure levels. The predictors are selected based on the correlation and the partial correlation analysis of NCEP predictors and observed weather variables for the period 1961-2001 in SDSM model. Variables with best correlation coefficients between predictand and predictors were chosen for model formulation for scenario generation. The selection of predictors has been carried out using correlation coefficients, partial correlation and p-values between predictand and

NCEP predictors. For example, in this case, mean sea level pressure, 500 hPa geopotential height, 850 hPa geopotential height, 500 hPa zonal velocity, Mean temperature at 2m and surface specific humidity are identified as the best suited predictors for this case study. The corresponding correlation coefficients, partial correlation and p-values between the predictand and NCEP predictors are shown in Table 4.5.

Table 4.4: Name and description of all NCEP and GCM predictors (26 predictors)

S. No.	Atmospheric pressure level	NCEP Variables Descriptions	Code	Unit
A	1013.25 hPa (1)	Mean sea level pressure	ncepmslpas	Pa
B	1000 hPa (6)	Surface airflow strength	ncepp__fas	m/s
		Surface zonal velocity	ncepp__uas	m/s
		Surface meridional velocity	ncepp__vas	m/s
		Surface vorticity	ncepp__zas	s^{-1}
		Surface wind direction	ncepp_thas	degree
		Surface divergence	ncepp_zhas	s^{-1}
C	850 hPa (8)	850 hPa airflow strength	ncepp8_fas	m/s
		850 hPa zonal velocity	ncepp8_uas	m/s
		850 hPa meridional velocity	ncepp8_vas	m/s
		850 hPa vorticity	ncepp8_zas	s^{-1}
		850 hPa wind direction	ncepp8thas	degree
		850 hPa divergence	ncepp8zhas	s^{-1}
		850 hPa geopotential height	ncepp850as	m
		Relative humidity at 850 hPa	ncepr850as	%
D	500 hPa (8)	500 hPa airflow strength	ncepp5_fas	m/s
		500 hPa zonal velocity	ncepp5_uas	m/s
		500 hPa meridional velocity	ncepp5_vas	m/s
		500 hPa vorticity	ncepp5_zas	s^{-1}
		500 hPa wind direction	ncepp5thas	
		500 hPa divergence	ncepp5zhas	s^{-1}
		500 hPa geopotential height	ncepp500as	m
		Relative humidity at 500 hPa	ncepr500as	%
E	Near surface (3)	Surface specific humidity	ncepshumas	g/kg
		Mean temperature at 2m	nceptempas	^{0}C
		Near surface relative humidity	ncephumas	%

Table 4.5: Selected NCEP predictors and their relationship with rainfall

SI No.	Selected predictors	Correlation coefficients	P value
1	nceptempas	0.604	0.0001
2	ncepp500as	0.485	0.0001
3	ncepp850as	-0.660	0.1987
4	ncepshumas	0.678	0.0001
5	ncepmslpas	-0.647	0.002
6	ncepp5_uas	-0.558	0.0001

4.2.2 SDSM calibration and validation results

Since the predictand-predictor relationship is governed by wet-day occurrences, a threshold value of 0.5 mm rainfall is considered during model calibration. Results of the observed and estimated monthly rainfall during calibration and validation period are shown in Table 4.6. Monthly average and annual statistics of observed and estimated rainfall are also presented in Table 4.6. It can be seen that, the SDSM model shows a good agreement between the observed and estimated monthly average and annual (minimum, maximum, average and standard deviation) statistics of rainfall during calibration and validation period. Model efficiency have been estimated with correlation coefficients between observed and estimated in both the cases. However, the values of coefficient of determination during calibration and validation were estimated as 0.776 and 0.799 respectively. In other, words, it can be concluded that the performance of SDSM model using MLR is good on monthly basis for future estimation of rainfall under HadCM3-A2 and B2 emission scenarios.

4.2.3 Projection of monthly rainfall using HadCM3 (A2 & B2 scenario)

Projection of future scenarios has been carried out using the HadCM3 A2 & B2 emission scenarios with selected predictors. However, MLR downscaling technique has been utilized for future projection of predictand. Further, whole time series of monthly predictand has divided into decadal form (10-year time scale) for better representation of results.

Table 4.6: Statistics of observed and SDSM simulated rainfall during calibration and validation period

Month	Calibration		Validation	
	Observed	**Simulated**	**Observed**	**Simulated**
Jan	74.4	73.0	73.5	63.2
Feb	69.8	70.6	87.3	57.2
Mar	56.5	47.1	70.9	42.4
Apr	38.3	54.6	46.9	60.8
May	23.7	103.7	21.9	115.4
Jun	118.8	176.6	70.7	187.7
Jul	418.8	334.4	453.2	336.4
Aug	441.5	388.5	489.7	365.0
Sep	139.3	219.0	137.1	194.1
Oct	23.0	28.7	32.9	34.8
Nov	11.1	1.3	11.5	1.8
Dec	9.5	7.8	13.2	8.8
Minimum	1102.5	1409.0	1107.7	1359.0
Maximum	1926.7	1756.5	1776.7	1593.6
Average	1424.6	1505.3	1508.8	1467.6
SD	272.4	127.4	283.1	84.1
R2	0.776		0.799	

Box plot of decadal time steps are used to determination of pattern in predictand. The projected rainfall i.e., 2021-2030, 2031-2040, 2041-2050, 2051-2060, 2061-2070, 2071-2080, 2081-2090 and 2091-2099 are shown in Figs. 4.6 and 4.7. The middle line of the box shows the median values, whereas the upper and lower edges give the 75 percentile and 25 percentile of the dataset, respectively. The difference between the 75 percentile and 25 percentile are known as Inter Quartile Range (IQR). The box plot of rainfall shows the increase in future rainfall in both cases of A2 and B2 scenarios.

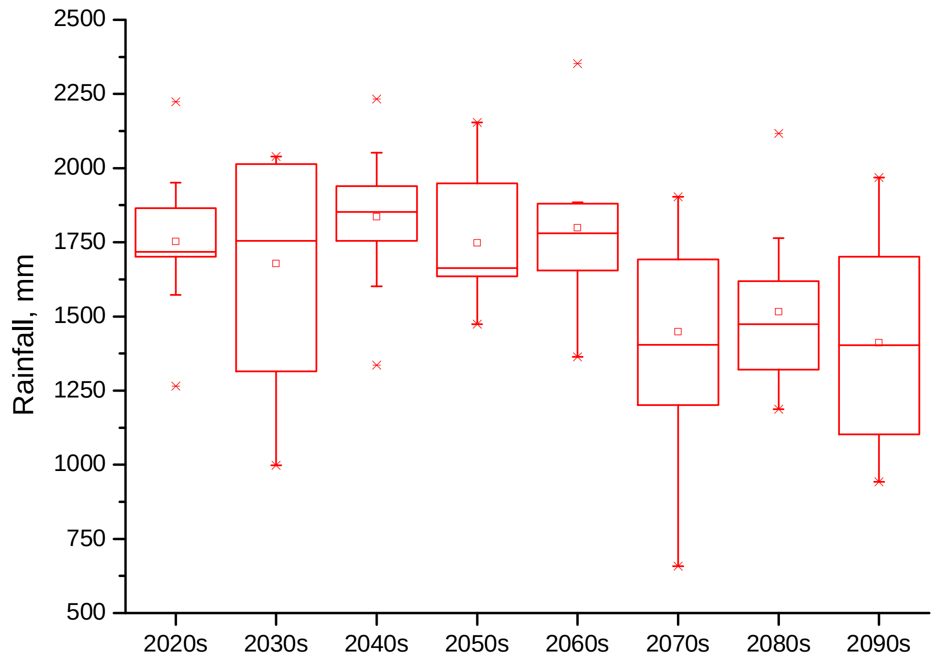

Fig. 4.6 The box plot of future rainfall under A2 scenario

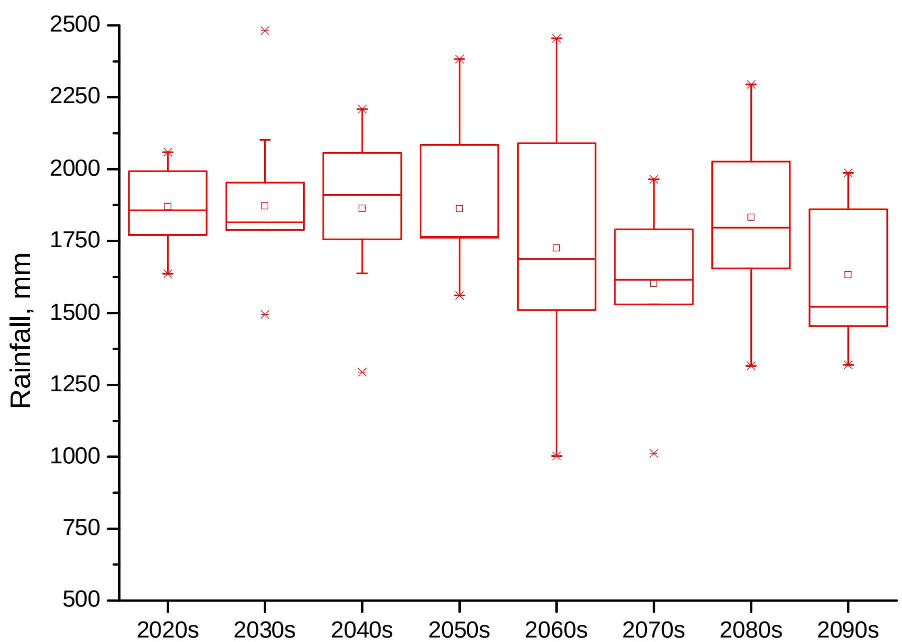

Fig. 4.7 The box plot of future rainfall under B2 scenario

Using the MLR based SDSM model, the future rainfall under HadCM3-A2 and B2 emission scenarios are estimated with the identified predictors. The estimated rainfall is represented into four different time steps, i.e., past (1961- 2010), 2020s (2020-2049), 2050s (2050-2079) and 2080s (2080-2099) and the detailed statistics are represented in Table 4.7. The monthly rainfall predicted for the study area during the periods 2020s, 2050s and 2080s, indicates an increasing trend (Fig 4.8 and 4.9). In A2 scenario, annual rainfall varies from 983 to 1927mm in past, 997 to 2233mm in 2020s, 658 to 2353mm in 2050s and 942 to 2117mm in 2080s. Similarly, under B2 scenario, the annual rainfall varies from 1294 to 2481mm in 2020s, 1003 to 2455mm in 2050s, 1316 to 2295mm in 2080s. Under both A2 and B2 scenarios, there is an increasing trend of rainfall in the study basin. It also has been observed that the future rainfall under the B2 scenario is always higher than under the A2 scenario.

Table 4.7: Detailed rainfall statistics for different time steps (scenarios)

		Monthly Avg, mm												Annual, mm			
	Period	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Min	Max	Avg	SD
	Past	57.4	72.3	71.9	41.6	32.3	99.4	396.6	348.4	152.3	26.8	12.7	23.9	983	1927	1336	273
HadCM3 A2	2020s	48.1	38.0	85.4	143.8	218.0	285.0	286.5	248.6	249.5	133.6	9.1	10.0	997	2233	1756	284
	2050s	22.8	21.2	74.6	132.2	219.8	289.4	267.6	229.6	228.0	161.7	13.6	4.4	658	2353	1665	314
	2080s	23.0	22.5	61.1	114.3	218.2	235.6	194.0	183.1	237.8	160.5	6.7	6.7	942	2117	1463	309
HadCM3 B2	2020s	43.9	41.6	75.1	158.5	216.3	287.6	291.8	254.8	264.9	176.8	47.6	9.5	1294	2481	1868	222
	2050s	36.3	28.1	55.0	144.4	232.0	287.0	270.5	232.4	249.4	158.0	36.0	1.4	1003	2455	1731	348
	2080s	19.1	34.0	61.1	144.0	231.2	278.1	280.2	219.7	267.0	150.3	28.9	18.9	1316	2295	1733	266

Rainfalls in the said future periods are increasing in both the scenarios. It can be observed that the rainfall in rising for 2020s and 2050s but it gets reduce in 2080s, although the average rainfall of all the three future period is higher than the past or baseline period. The graphical representation of the past and the future rainfalls for different period is also given in Fig. 4.8 and 4.9. there is considerable reduction in winter months and the pre-monsoon and post-monsoon month are showing more rainfalls as compare to the past. The average rainfall of the main monsoon months viz. July and August are getting reduced as moving from past to future.

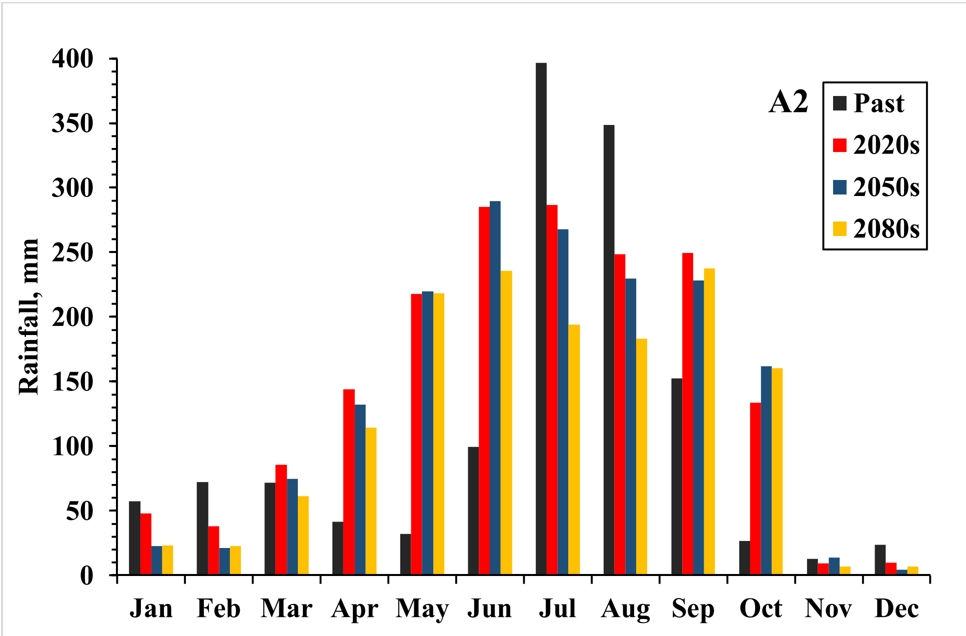

Fig. 4.8: Monthly rainfall for various periods under A2 scenario

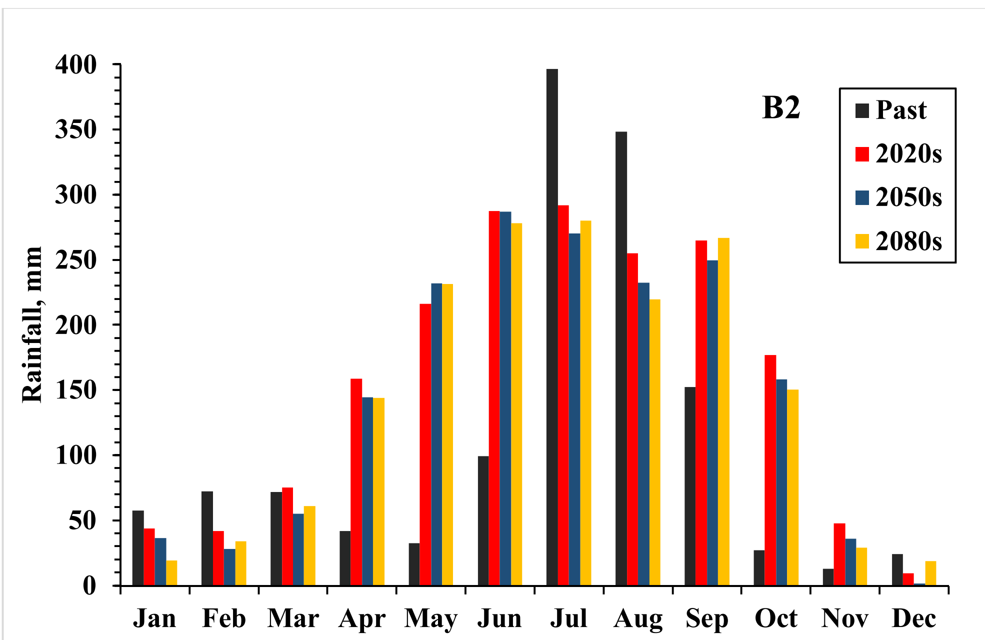

Fig. 4.9: Monthly rainfall for various periods under B2 scenario

4.3 IMPACTS OF THE CLIMATE CHANGE ON STREAMFLOW

The HadCM3 GCM downscaled climatic inputs have been used to run the calibrated and validated SWAT model for the simulation of future streamflow for Tawi River basin at Jammu. The simulation was done on monthly basis for all the three future periods similar to that of rainfall i.e. 2020s, 2050s and 2080s. These simulated value have been compared with the past flow statistic to assess the impacts of the climatic changes of the river hydrology. The monthly statistic for both the scenario is given in the table 4.8

Table 4.8: Detailed rainfall statistics for different time steps (scenarios)

		Monthly Avg, Cumec												Annual, Cumec			
	Period	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Min	Max	Avg	SD
	Past	26.2	42.2	62.2	46.1	38.6	29.3	135.9	169.8	115.9	36.8	22.0	22.5	29.9	100.3	62.3	20.2
HadCM3 A2	2020s	8.2	11.5	31.0	57.6	119.0	134.7	103.3	111.1	113.2	122.5	6.3	3.5	30.9	118	68.5	25
	2050s	7.3	14.1	25.1	69.6	116.7	132.1	107.3	119.5	123.7	166.1	28.8	4.3	27.7	125	68	26
	2080s	3.6	4.3	19.3	41.8	101.9	156.1	99.8	108.1	138.0	130.7	11.1	1.4	22.4	94.3	51.7	22
HadCM3 B2	2020s	7.0	6.5	13.1	45.6	119.0	149.9	98.7	109.3	159.1	123.4	21.4	1.2	36.2	130	76.2	26
	2050s	2.2	5.8	11.2	36.1	97.8	118.0	52.9	51.8	88.4	145.9	6.7	2.9	30.9	128	71.2	26
	2080s	2.4	10.5	12.0	47.0	113.1	139.3	103.8	81.7	116.7	150.0	23.4	9.7	30.3	123	67.5	25

From the table 4.8 it can be observed that the average annual flows of the Tawi river are going to be increase in the 2020s and 2050s in both the scenarios. In 2080s in A2 scenario the average annual flow has gone below the past average. This verify the strong rainfall-runoff relationship in the basin. Further, the lean season flows in the future are deteriorating and falling significantly as compare to the past lean season flows whereas, the pre-monsoon and post-monsoon monthly flows are getting high in compare to past. The major monsoon months July and August flow are lowering in future. Overall, the distribution of the flows in future is widely spread in the months as compare to the past which shall be ensure the good quantity of flow in the river for more months on the other hand the river shall be getting drier in the lean season.

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5.0 SUMMARY / CONCLUSION

In this study three aspects have been covered and those are (i) runoff and sediment modelling using ArcSWAT model (ii) Statistical downscaling of GCM to get the future climate and (iii) impacts of the changing climate on the hydrology of Tawi River. The conclusions drawn in respect of above three aspects are given below.

5.1 RUNOFF MODELLING USING ARCSWAT

SWAT model was calibrated and validated to examine its applicability for simulating monthly flow from catchments of Tawi river basin. The Coefficient of Correlation, coefficient of correlation (R) and Nashï Sutcliffe efficiency (NSE) were used for performance evaluation. The model simulated the monthly discharge of Tawi catchment with a high degree of accuracy with R and NSE values as 0.72, 0.513 and 46% during calibration and 0.92, 0.854 and 84% respectively during validation. These results indicated a very good performance of SWAT in simulating the discharge from Tawi River. Although, the model underestimated and overestimated daily discharge for some flood events, predictions were within acceptable limits despite some inconsistency in observed data and possible inaccuracies in derivation of model input parameters in view of remote and inaccessible areas. In General, the results of the study indicated that the SWAT model performed well on both the study catchments and hence can be used as a useful tool for estimation of runoff and sediment yield from Himalayan catchments.

5.2 STATISTICAL DOWNSCALING

Statistical downscaling module SDSM 4.2.1 was used in the study to downscale the future climatic parameters viz. rainfall and temperature from the HadCM3 GCM model outputs for A2 and B2 Scenarios. It uses the principle of multiple linear regression (MLR) to develop a relationship between the pretictand and the predictors and assume that this relation remain valid for the future as well as. Five out of total 26 largescale predictor variables have been selected for downscaling. The SDSM model showed a good agreement between the observed and estimated monthly average and annual statistics of rainfall during calibration and validation period. values of coefficient of determination during calibration and validation were estimated as 0.776 and 0.799 respectively between observed and estimated in both the cases. It can be concluded that the performance of SDSM model using MLR is good on monthly basis for future estimation of rainfall under HadCM3-A2 and B2 emission scenarios.

5.3 IMPACTS OF THE CLIMATE CHANGE ON STREAMFLOW

The average annual flows of the Tawi river are going to be increase in the 2020s and 2050s in both the scenarios. In 2080s in A2 scenario the average annual flow has gone below the past average. This verify the strong rainfall-runoff relationship in the basin. Further, the lean season flows in the future are deteriorating and falling significantly as compare to the past lean season flows whereas, the pre-monsoon and post-monsoon monthly flows are getting high in compare to past. The major monsoon months July and August flow are lowering in future. Overall, the distribution of the flows in future is widely spread in the months as compare to the past which shall be ensure the good quantity of flow in the river for more months on the other hand the river shall be getting drier in the lean season.

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