CLIMATE CHANGE IMPACT STUDIES FOR WATER RESOURCES OF WARDHA AND KRISHNA RIVER BASINS

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Dedicated to my beloved Parents

P Nagabushanam

P V Ramanamma

& Family

APPROVAL SHEET

This thesis entitled **"Climate Change Impact Studies for Water Resources of Wardha and Krishna River Basins"** by **Ms. P Naga Sowjanya** is approved for the degree of Doctor of Philosophy.

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CERTIFICATE

This is to certify that the thesis work entitled "**CLIMATE CHANGE IMPACT STUDIES FOR WATER RESOURCES OF WARDHA AND KRISHNA RIVER BASIN**" is a bonafide record of work carried out by "**Ms. P NAGA SOWJANYA**", In partial fulfilment of the requirements for the award of the degree of Doctor of Philosophy in "**Civil Engineering**" at National Institute of Technology, Warangal during the period **2013-18**.

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Declaration

This is to certify that the work presented in the thesis entitled **"CLIMATE CHANGE IMPACT STUDIES FOR WATER RESOURCES OF WARDHA AND KRISHNA RIVER BASINS"** is a bonafide work done by me under the supervision of **Dr. K. Venkata Reddy** and **Dr. M. Shashi** and was not submitted elsewhere for the award of any degree.

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ABSTRACT

Climate change is a global phenomenon having varying degrees of regional impacts. Management of river water is an important aspect for governing the political and economic affairs of any country. With the increasing pace of climate change, it has become indispensable to evaluate the impact of climate change over a river basin for efficient management of water resources. To assess the climate change induced impact at basin level, Regional Climate Models (RCMs) database is the most credible source. The RCM database contains the dynamically downscaled products of the coarser resolution Global Climate Model (GCM) outputs to a finer resolution by incorporating the physical laws, boundary conditions and atmospheric processes. Future projections of important meteorological variables of Representative Concentration Pathways (RCP) 4.5, 8.5 climate change scenarios are available for 5 different high-resolution GCM outputs under COordinated Regional Downscaling Experiment (CORDEX). Moreover, encompassing the uncertainty analysis with the future projection will improve the predictability and robustness of real time prediction.

In this research work, RCM database has been used to assess the climate change impact on water resource of river basin, Uncertainty analysis associated with multi model RCMs, meteorological and streamflow drought indices and trend analysis of streamflow for future projections. Spatio-temporal variations of water balance components have been studied with induced climate and Land Use Land Cover (LULC) changes and rule curves are developed for reservoir operating system based on the impact analysis using Stochastic Dynamic Programming (SDP).

Initial part of the research is devoted to investigate the variations in stream flow of Wardha watershed, India under changing climatic conditions. Regional Climate Models (RCMs) data with Representative Concentration Pathway (RCP) of 4.5 and 8.5 scenarios were used to simulate the streamflow for the Historic and Future periods using Soil and Water Assessment Tool (SWAT) model. Sequential Uncertainty FItting (SUFI-2) algorithm of SWAT calibration and uncertainty program (SWAT-CUP) was used for sensitivity analysis, calibration and validation of the SWAT model. SWAT simulated streamflow for the future period has been analysed by dividing the total period into four twenty years spans as 2020-2039, 2040-2059, 2060-2079 and 2080-2099. The results indicate a decrease in future streamflow compared to

earlier periods. Intra and Inter annual variability of stream flows for the future periods is less as compared to historic period.

Krishna river basin, which is over utilized and highly sensitive to climate change was investigated to evaluate the future projections of monthly streamflow under different climate forcings. The uncertainty associated with the multiple RCMs is analysed using Reliability Ensemble Averaging (REA) method. SWAT hydrological model is used to simulate the future projection of streamflow over the basin and model parameters are optimized using SWAT-CUP at multiple gauging stations. The analysis was carried out for four 25-year time slices as Historic (1980-2004), Future1 (2020-2044), Future 2 (2045-2069) and Future 3 (2070-2094). The results indicate that REA data projects reasonably close values when compared to observed values in the middle and lower parts of the Krishna basin. Spatial and temporal variations of ensemble climate variables on annual, seasonal and monthly bases are prepared. Future projections of the precipitation show a decrease of about 20% in the Future period I. Absolute and relative changes in future streamflow compared to historic streamflow projects lower values in monsoon period and higher values in other periods at Huvinhedgi, Mantralayam and Pondhugala gauge stations. Trends in the streamflow throughout the basin show a decrease in the first future period when compared to the other two future periods. The recommendations made from this research work can be used as preliminary measures for formulating water management and adaptation practices for Krishna River basin.

Meteorological and streamflow drought indices are quantified for the future projections (2020 to 2099) using Standardized Precipitation Index (SPI) and Streamflow Drought Index (SDI) for the Krishna river basin. The results show that drought events will be more severe in Tungabhadra and lower Krishna regions during future 1 period and more frequent drought conditions in Bhima, Upper and Middle Krishna regions in future 3 period. Similarly, SDI for the sub basins shows that Tungabhadra basin is less effected by drought whereas Bhima, Middle and Lower Krishna regions will face more drought conditions in the future periods.

The spatiotemporal change of the LULC plays a major role in estimating the reliable predictions in hydrology. In the present research work, combined impact of climate and LULC change on water balance components of Munneru, a sub basin of Krishna river has been carried out using Soil and Water Assessment Tool (SWAT). The decadal LULC change over time is detected for the years of 1985, 1995 and 2005. The dominant land use in the study area is Cropland/Irrigated land and major changes of land use identified are increase of urban area from 42.85km^2 to 93km^2 and deciduous forest from 821.74km^2 to 922.87km^2 of the total area during the 20-year

period. The climate model database obtained projects decrease in precipitation until 2040. Hence, simulations were carried out by adapting LULC change from 1985 to 2005 and climate model data up to 2040. The results project an increase in Evapotranspiration of about 10%, 1.7%, 3.84% in the 2020, 2030, 2040 decades respectively. Decrease in surface runoff of about 50% is predicted in the next three decades with the predicted zero-base flows in most of the sub basins by 2040.

In this research work, adaptive policies are formulated for a reservoir based on climate change impact on water resources for future periods. Nagarjuna sagar dam is a multipurpose reservoir serving flood control, irrigation and hydropower generation located in Middle Krishna basin, India. Hydrologic impacts on the reservoir operation are mitigated considering the performance criteria evaluated using r package known as 'reservoir' for the adaptation policies. It is observed that the reliability decreases with the increase in vulnerability as a result of climate change if the Standard Operating Policy (SOP) using the current rule curves is employed. Hence Stochastic Dynamic Programming (SDP) is employed to develop a suitable adaptation policy to mitigate the impact of climate change. Storage yield curves are developed for all future scenarios with varying reliabilities to minimize the storage volumes to adapt to the climate change for proper management of resources. The monthly rule curves developed indicate that reservoir-operating rules may have to be revised in basins where climate change projects an increasing probability of droughts.

The climate change impact results obtained in this study for Wardha, Krishna, Munneru rivers can be used for devising suitable adaptation plans for managing water resources in these basins. Adaptive policies proposed for Nagarjuna sagar reservoir are useful for effective sharing of water resources between different stakeholders under climate change conditions. The methodology proposed in this research work can be used for other river basins in India and across the world.

Keywords: Adaptive policy, Climate Change Impacts, Drought, LULC, RCM, Reservoir performance, River basin, Streamflow, Uncertainty.

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Nomenclature

The following list gives the notations used in the thesis

P_o	Observed Precipitation
P_m	Model Precipitation
F_m	CDF of P_m
F_o^{-1}	Inverse CDF corresponding to P_o
$TMP_{c(his)}$	Historic temperature corrected
$TMP_{c(fu)}$	Future temperature corrected
TMP_{his}	Temperature historic
TMP_{fu}	Temperature future
$MMTMP_{obs}$	Observed mean monthly temperature
$MMTMP_{his}$	Historic mean monthly temperature
w_{int}	Initial weight in REA
F_{wm}	Weighted Mean CDF
F_{RCM_i}	corresponding CDF of the future simulated i^{th} RCM
SW_{ti}	soil water content at the end of the day (mm H_2O)
SW_o	amount of initial soil water content on day i (mm H_2O)
t	time in days
R_{dayi}	amount of precipitation on day i (mm H_2O)
$Q_{surf\,i}$	amount of surface runoff on day i (mm H_2O)
E_{ai}	amount of evapotranspiration on day i (mm H_2O)
W_{seepi}	amount of water entering the vadose zone from the soil profile on day i (mm H_2O)
Q_{gwi}	amount of return flow on day i(mm H_2O).

R^2	Coefficient of correlation
n	total number of observations
Q_{obsi}	Observed discharge at i^{th} observation
Q_{simi}	Simulated discharge at i^{th} observation
Q_{mean}	mean of observed data over the simulation period.
CV_{inter}	Inter annual Coefficient of Variation
Q_y	Yearly streamflow
$\overline{Q_y}$	Mean of annual streamflow
$STD\ (Q_y)$	Standard deviation of annual streamflow
CV_{intra}	Intra annual coefficient of variation
N	Number of years
Q_m	Monthly streamflow
$\overline{Q_m}$	Mean of monthly streamflow
STD (Q_m)	Standard deviation of monthly streamflow
$V_{i,k}$	Cumulative streamflow volume for the i^{th} hydrological year and the k^{th} reference period
$Q_{i,j}$	Streamflow for the $_j{}^{th}$ month in $_i{}^{th}$ Hydrological Year
$\bar{V}$	mean of the cumulative streamflow values of reference period *k*
S_k	Standard deviation of the cumulative streamflow values of reference period *k*
D	Demand or Target Release
τ	penalty cost exponent
R_t	Time based Reliability
R_v	Volumetric reliability
D_i	Target demand during i^{th} period

$D_i^{'}$	Actual volume supplied during the i^{th} period
φ	Resilience
f_s	Number of individual continuous sequences of failure periods
f_d	Total duration of all the failures.
ή	Vulnerability
s_j	Volumetric shortfall during j^{th} continuous failure sequence

Abbreviations

AGCM	Atmospheric Global Climate Model
AR	Assessment Report
CDF	Cumulative Distribution Function
CORDEX	Coordinated Regional Downscaling Experiment
DEM	Digital Elevation Model
GCM	Global Climate Model
HEC-HMS	Hydrologic Engineering Center Hydrologic Modelling System
HRU	Hydrological Response Unit
IMD	Indian Meteorological Department
IPCC	Intergovernmental Panel on Climate Change
LULC	Land Use Land Cover
MCMC	Markov Chain Monte Carlo
MMTMP	Mean Monthly Temperature
NSE	Nash-Sutcliffe Efficiency
OGCM	Oceanic Global Climate Model
PPU	Percentage Prediction Unit
REA	Reliability Ensemble Average
RCM	Regional Climate Model
RCP	Representation Concentration Pathway
RMSE	Root Mean Square Error
SDI	Streamflow Drought Index
SDP	Stochastic Dynamic Programming
SDSM	Statistical Downscaling Model
SOP	Standard Operating Policy
SPI	Standardized Precipitation Index
SRES	Special Report on Emissions Scenarios
SUFI-2	Sequential Uncertainty Fitting
SWAT	Soil and Water Assessment Tool
TMP	`Temperature
UNFCCC	United Nations Framework Convention on Climate Change

Chapter – 1

Introduction

1.1 General

India is an ancient, tropical country with agriculture as main occupation and agriculture needs sumptuous water for cultivation. The main source of water is surface water from streams, rivers, natural lakes and man-made ponds to a great extent, and groundwater from open wells, for agriculture and domestic use. Rivers in the northern part of the country originate from the Himalayas leaving large amounts of gravel and alluvium as sediments in the northern plains. The favourable climate and adequate water supply in the plains of the Indus and Ganga dominated by the alluvium deposits makes the region highly fertile. The peninsular region contains central islands and Deccan plateau, where the main sources of water are Narmada, Tapti, Mahanadi, Godavari, Krishna and Kaveri rivers. Ground water is considered major source for irrigation and domestic requirements. The water demand is the quantity of water required to fulfil a specific need. Agricultural water demand includes water required for crops, percolation losses, canal seepage and evaporation. India being a developing country, availability of water varies spatially and seasonally, which affects the overall development of society. It is also affected by other geographical factors such as land use, vegetation and topography. Usage of water has increased significantly due to increase in population and expansion of economic activities from the last century. Stream flow is the prime element of water cycle influenced by many meteorological factors such as intensity, amount and duration of precipitation, temperature, evapotranspiration and relative humidity.

Climate is the long-term variation with respect to temperature, humidity, atmospheric pressure, wind, precipitation and other meteorological variables in a region. The factors affecting climate are location, air pressure, mountain barriers, elevation, continental location, ocean currents, wind belts, storms and human activities. The climatic regions of India are dominated by monsoon climate condition. Monsoon precipitation in India is distributed in a highly variable manner in both space and time (Kripalani *et al.* 2007). Temperature and precipitation are two major parameters affecting climatic conditions. In this context, overall increase in annual mean surface temperature by 3.5 to 5.5°C, warming in winter season, decrease in winter precipitation less about 10 to 20% over central India by 2050 are predicted (Mall *et al.* 2006). This results in high evapotranspiration, thus affecting the hydrological process. Lowest temperatures are observed in the northern most part of India. Rainfall in the country is drawn through South-West and North-East monsoons, western disturbances and cyclonic depressions. Maximum amount of rainfall in India is observed between June and September due to South-West monsoon. In contrast, Tamilnadu in south India is mostly influenced by North-East monsoon between October-November. Climate change in IPCC 2014, refers to any change in climate over time, whether due to natural variability or as a result of human activity. This usage differs from that of United Nations Framework Convention on Climate Change (UNFCCC), which defines climate change as, “a change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods”.

1.2 Climate Change Impact Studies

Changes in the climate regime can influence water resources and result in varying hydrologic conditions both globally and regionally. Regional differences in meteorological conditions, pollutant sources, water management, physiographic setting and interaction with local scale land use are the causes of these variations. A consensus is that the change in mean surface temperature may vary between 0.3°C to 0.7°C globally, leading to recurrent hot and cold temperature extremes over most areas of the world (IPCC 2014).

Climate Models are tools to find out what natural processes or human activities may affect a region's environment in the future. The climate model fundamentals are based on established physical laws, such as conservation of mass, energy and momentum along with a wealth of other observations. Models show significant and increasing skill in representing many important mean climate features, such as large-scale distributions of atmospheric temperature, precipitation, radiation and wind and oceanic temperatures, currents and sea ice cover. Models can also simulate essential aspects of many of the patterns of climate variability observed across a range of time scales. Examples include the advance and retreat of major monsoon systems, seasonal shifts in temperatures, storm tracks and rain belts and the hemispheric scale seesawing of extra tropical surface pressures (IPCC 2014). Hence, the term Climate Modeling refers to the use of a model to define the state of Earth's physical system on time scales of seasons to centuries. Climate models are also called as General Circulation Models or Global Climate Models (GCMs). Atmospheric Global Climate Models (AGCM) and Oceanic Global Climate Models (OGCM) are the key components of GCMs along with the sea ice and land surface components. These AGCM and OGCM together form Atmosphere - Ocean Coupled General Circulation Models. GCMs establish skill at the continental spatial scale by assimilating a large proportion of complex global system and are unable to produce inherent features and dynamics of climate at the local sub grid scale (Wigley *et al.* 1990). These are the coarse resolution climate models projected under increased global temperatures for large spatial scales. Whereas, finer spatial scales climate models are required for better management of resources at the basin level. The use of the GCM data for the regional level impact studies includes the following problems (Xu 1999):

- Impact studies demand higher resolution climate data but increase in scales both spatially and temporally leads to decrease in accuracy of GCM.
- Water balance computations mainly depend on ground surface variables, but GCMs simulate free tropospheric variables more accurately compared to surface variables.
- Variables like precipitation, evapotranspiration, runoff and soil moisture play a significant role in hydrologic regimes. However, these variables are predicted with low accuracy.

Therefore, to overcome the disadvantage of using GCM outputs, the downscaled GCM data is used for impact analysis at a regional level. Use of the regional climate models compared to global climate models have proved to be efficient while assessing the impact of climate change on hydrology at basin level (Chien *et al.* 2013, Kulkarni *et al.* 2014, Demaria *et al.* 2016).

IPCC introduced many global climate emission scenarios as mentioned in the Assessment Report (AR) from 1992 to 2007. The Special Report on Emission Scenarios (SRES) comprises four different socio-economic “story-lines”, viz. A1, A2, B1 and B2. These scenarios mainly focus on the economic development, industrialisation, fossil fuel utilisation, population growth and advancement in technological applications to explore human contribution to future climate change (Kripalani *et al.* 2007). However, Fifth Assessment Report (AR5) of IPCC in 2014 focuses on the emission trajectory and radioactive forcing rather than social-economic conditions. This approach was motivated by varying information requirements of policy makers as well as a growing interest to minimize the risk that encompasses reductions in emissions and adaptation strategy to reduce climate change consequences. Radioactive forcing is used to categorise different climate scenarios, defined as extra energy absorbed by the earth due to increase in greenhouse gases. More precisely, it is the difference in the energy balance that enters and leaves the atmosphere as compared to the pre-industrial state. The unit of radioactive forcing is expressed as watt per meter square (W/m^2). The developed scenarios are represented as Representative Concentration Pathways (RCPs): these define the projected trajectories of concentrations of greenhouse gases, pollutants and dynamic vegetation due to the anthropogenic activities over time and their radioactive forcing in 2100. In SRES scenarios, climate change evaluation is primarily based on population growth, economic, and technology development. However, in RCP scenario the projections are mainly based on the radioactive forcing instead of any predefined assumption as in the case of SRES scenarios because different socio-economic storylines may produce the same magnitude of radioactive forcing. RCP scenarios are categorised into four groups, viz. RCP2.6, RCP4.5, RCP6.0, and RCP8.5. Based on the forcing, RCP2.6 and 8.5 are considered as low and high emission scenarios respectively with RCP4.5 and 6.0 as intermediate emission scenarios. The values indicate the magnitude of forcing in W/m^2.

The climate model scenario projects an increase in both mean and extreme precipitation in Indian summer monsoon (Noble *et al.* 2015). Most reported impacts of climate change are attributed to warming and/or to shifts in precipitation patterns and increase in annual mean temperature trends (Field *et al.* 2014). In South Asia, inter-decadal variability and lack of monsoons are observed with a declining trend in seasonal mean rainfall regionally. It is also observed in the case of extreme rainfall events with some weak rainfall events in many parts of India (Noble *et al.* 2015). RCP projections proposed by IPCC AR5 also indicate the variations of precipitation in both space and time like magnitude of intensity, variability and frequency of extremes, with prominent positive and negative impact on water resources. Hence, it is essential to focus on the availability of water resources in the context of climate change for proper allocation of resources without affecting the nature and society.

1.3 Climate Change Impact under Uncertainty

The local and global pressures on natural resources are increasing because of external forces like high living standards, anthropogenic changes, land use and water management policies, etc. Streamflow is the prime element of water cycle which is influenced by many meteorological factors such as intensity, amount and duration of precipitation, temperature, evapotranspiration and relative humidity. Previous studies have assessed the effects of climate change on water resources using downscaled GCM simulations (Gosain *et al.* 2006, 2011, Roy and Mazumdar 2013, Kulkarni *et al.* 2014). The future water demands will be more uncertain in addition to the uncertainty developed due to changes in demography and climate (Yang *et al.* 2008). The effects of climate change which include seasonal variation in stream flow, changeover in extreme high and low flow events and deviation in ground water recharge can be simulated with a combination of hydrological models and global climate model database (Jha *et al.* 2004, Chien *et al.* 2013, Noble *et al.* 2015). Many studies have proved that the use of regional climate data for impact assessment is more reliable compared to GCM data (Chien *et al.* 2013, Kulkarni *et al.* 2014, Demaria *et al.* 2016). The climate models come with biases and uncertainty that vary from one model to another. The increase in skill and reliability of multi-model ensembles compared to single climate model projections has been demonstrated through various studies (Giorgi and Mearns 2003a, Tebaldi and Knutti 2007). The additional stress as a result of climate change on water resources provides clarity to water managers and policy makers for efficient water supply for future periods (Mondal and Mujumdar 2015).

Climate change impact on water resources includes projections of climate variables downscaled to a regional scale, which is modelled for uncertainty with respect to the observed climate. RCMs are the most plausible tools to project climate variables for future period on a regional scale. Then, the desired climate variables are used in the hydrological model in simulating the streamflow for future periods. In addition to these streamflow predictions, uncertainties related to RCMs and Hydrological models are to be addressed for better future projections. However, most of the studies have concentrated on the overall variations of water resources instead of temporal changes in the stream flow variability using GCM data. An attempt has been made here to simulate the magnitude and temporal variations of streamflow in a river basin using Regional Climate Model (RCM) data.

1.4 Hydrological Modelling for Impact Studies

Hydrologic models represent a part of the hydrologic cycle in simplified and conceptual way. These simulate all the natural processes related to water movement such as stream flow, evapotranspiration and evaporation, soil moisture, ground water recharge, sediment transport, growth of microorganisms in water bodies, sediment transport etc. The hydrologic processes include both time and space derivatives in the processes. The hydrologic models are categorized as distributed or lumped models, if they consider space derivatives (distributed) or not (lumped). On the assumption that some processes account for spatial variations are classified as semi distributed models.

Most of the available hydrologic models measure the peak discharge, hydrograph at specified locations in a catchment. The selection of the hydrological model specially depends on the assumptions and methods utilized in estimating diverse hydrological components, and their efficiency as to how they account for the dispensed techniques on spatial scales. Hydrologic models typically operate at a river basin or a watershed scale. They play a widespread function in offering an expertise of more than a few problems dealing with water resources and hydrologic extremes at river basin and watershed scales. The inputs required by using hydrologic fashions depend on the motive for which the model is built. A river float simulation version calls for the inputs such as precipitation, catchment characteristics which include the soil type, slope of the catchment, kind of plant life, type of land use, temperature, solar radiation groundwater contribution, and so forth. The typical output from this type of model includes the river flow at a place at some point of a length (such as a day, every week, or a month), and soil moisture and evapotranspiration all through the period and thus provides precious data for ascertaining the impacts of modifications in land use and climate.

1.5 Drought Indices under Climate Change

Droughts are the highest ranked natural hazards having severe impact on people and environment, associated with climatic and hydrological processes like precipitation, temperature, streamflow etc. Droughts usually result due to increase in low precipitation and high temperature events relative to average conditions. According to IPCC AR5, South Asia is about to experience lack of monsoons with a declining trend in seasonal mean rainfall and recurrent hot and cold temperature extremes (IPCC 2014). Drought is a persisting phenomenon of climate, which varies with space, time and intensity. It is one of the most severe problems affecting the sustainable usage of resources. It continuously develops inconsistent rainfall for the required period and is categorized as one of the most detrimental types of natural disasters over long periods. Efficient planning and decision making require information regarding the locations, pattern, severity and timing of the drought. This information enables the people for management of the risk brought on by drought. Identification and quantification of drought in a particular region by drought indices helps in reducing the impact of drought through early warning system. Many indices are developed to monitor the drought based on rainfall and many other indicators. Drought is classified mainly into four types: meteorological (shortage of precipitation); hydrological (evaporation of stored surface water); agricultural (reduction of soil moisture in root zone) and socio-economic (less water supply for socio-economic purposes) droughts (Wilhite and Glantz 1985). In recent periods, drought indices have been developed with a combination of different variables such as rainfall, temperature and evapotranspiration into a single number. Standardized Precipitation Index (SPI) (Thomas *et al.* 1993), Percent Normal, Palmer drought severity index (PDSI), the moisture anomaly index (*Z*-index) (Alley, 1984) and aridity index (Gore and Ray, 2002) are the most commonly used drought indices.

1.6 Effect of Climate and LULC Change on Hydrology

Economic growth and development of the human and ecosystem functions of the country mainly depend on natural resources, such as land and water. However these resources are subjected to immense pressure caused by urbanization and industrialization due to increase in human population. In addition to these, water systems have been affected by climate change in the form of variability of the temperature and rainfall both spatially and temporally, water balance changes, sea level rise etc. Hence, land use and climate variability are two important factors affecting water resources and sustainability of the ecosystems. In the Hydrological processes the parameters like evapotranspiration, infiltration and interception are mainly subjected to land use change based on varied surface and subsurface flows (Wang *et al.* 2014, Niraula *et al.* 2015).

As discussed earlier, climate change makes a significant impact on the hydrology of a river basin. The effect of both LULC and climate changes on the parameters of the hydrologic cycle is significant to make necessary decisions for proper utilization and management of water resources in future periods. Variations in water balance components like evapotranspiration, base flow, surface and sub-surface runoff spatially and temporally are important for management of the water resources. Irrigation system design and management, hydrologic water balance, crop yield simulation, planning and management of water resources and water loss optimization by improving the use of water in agriculture are the various areas developed based on these changes.

1.7 Climate Change Adaptation Policies

Based on IPCC 2014, the present stress on water resources is observed to intensify in the future period. Variations in temperature and precipitations lead to a 10% to 40% rise of streamflow in high latitudes and a loss of about 10% to 30% in mid-latitudes. In India, streamflow is the main water source for living and occupation. The effect of climate change needs to be monitored for effective utilization of water resources. The positive and negative impact of climate change has to modified by developing adaptation policies. Adaptation refers to the actions formulated to reduce vulnerability. Vulnerability refers to the ability to anticipate potential harm or damage. It includes factors such as absorb stress or effects or ability of a system to cope and to recover or "bounce back". Adaptation measures are of many forms based on the response and anticipation to climate change for ex: planned and spontaneous adaptation strategies. Among the various types of adaptations, some are categorized as long term such as reduction in the use of greenhouse gas emissions and to reduce the changes by decreasing the greenhouse concentrations in the atmosphere. Dams, dikes and levees are some flood control works suggested to mitigate natural events like floods and droughts. For agriculture, changes in crop management practices such as increased irrigation water, additional fertilizer, pest and disease control and change in location and cropping patterns are adaptive measures suggested to tackle climate change and its variability.

The effect on local water systems with respect to changes in weather conditions, temperature and precipitation, especially in areas like reservoirs, developed for multipurpose use of water, has been investigated (Wood *et al.* 1997, Simonovic and Li 2004, Raje and Mujumdar 2010). From the literature, it is apparent that the management of water in storage reservoirs reduces potential impact of adverse climate change on water resources. The main purpose of the reservoir is not only to serve the needs of people and animals but also to store excess water during high seasonal flows and to protect the downstream area from floods. Many scientific works have been carried out to illustrate the risk developed in the present reservoir operation practices during climate change (Yao and Georgakakos 2001). Reliability, Resilience and Vulnerability are the performance indices used to evaluate the effect of climate change for future scenarios and an adaptive policy is developed using Stochastic Dynamic Programming (SDP) methods.

1.8 Research Motivation and Problem Formulation

An extensive literature review (presented in chapter 2) revealed that, not many studies have been undertaken to estimate the impact of climate change on a river basin using ensemble climate data developed using multiple climate models and adaptation policies to mitigate the risk. Therefore, there is scope to reduce the effect of climate change on hydrology by developing proper adaptation policies for sustainable utilisation of resources. In this proposed research, an attempt has been made to study the impact of climate change on a river basin using ensemble climate data of different scenarios and to develop the adaptation policies for proper distribution of resources and help in reducing the effect of climate change.

Many studies have been successfully carried out to investigate the effect of varying climate on hydrology of different rivers and watersheds in the literature. Future projections of the water resources have been assessed and quantified using various GCMs all over India. Estimations of water resources in the river basins by using RCMs in place of GCMs and uncertainty modelling of climate model database portrays the necessity of high-resolution data in climate change studies. Considering the effect of LULC changes on water resources, there is a need to assess the combined effect of climate and LULC changes on river basins. Spatial and temporal variations of the parameters in the hydrological regime are simulated using a distributed rather than lumped hydrological model.

In the literature, it is seen that projected streamflow in the river basin tends to develop risk for the future periods. Based on the risk identified in the basin, adaptation strategies are developed for a reservoir system using stochastic dynamic programming tool. The adaptation policies developed are evaluated using the performance indices for the future scenarios and the best among them is selected for proper utilization of the water resources. The main aim of this study is to assess the impact of climate change on the river basins of India and to mitigate the risk by developing adaptation strategies. For this purpose, Impact analysis is carried out for watershed using uncertainty modelled ensemble climate model data and adaptation strategies have been developed to reduce the vulnerability.

Based on the above research studies, it is noticed that there is a need to analyse impact of climate change on various river basins with latest climate change scenarios (AR5) using regional climate model data. It has also found that necessity for the basin level climate change impact studies has grown to analyse the availability of water resources; water quality etc., in many rivers of India, as the water demand is increasing along with the increase in spatial and temporal changes of water availability. Hence, it is necessary to conduct hydro- meteorological drought studies for the future periods under variable climate conditions. In addition, changes in the LULC along with the climate change need to be studied for impacts on the water resources and ecosystems. The risk developed due to climate change need to be reduced by developing adaptation strategies for proper utilization of resources of the water resource system like Reservoirs. Hence, in the present research work it is proposed to study the impact of climate change on the water resources of water stressed rivers and to formulate adaptation policy for a multipurpose reservoir.

1.9 Objectives of the study

The main aim of the research work was to study the climate change impacts on Wardha and Krishna river basins using ensemble regional climate model database and well distributed hydrologic models and to suggest the adaptive strategies for managing the water resources of one of the reservoirs of the study area with the following steps.

1. To analyse the intra and inter annual streamflow variations of a sub basin using multiple climate models.
2. To analyse the spatial pattern of Reliability Ensemble Average (REA) climate model database for assessing meteorological drought using Standardized Precipitation Index (SPI) in a river basin.
3. To assess the hydrological drought and trend analysis of future streamflow projections using ensemble climate model database of a river basin using SWAT.
4. To simulate the impact of both climate and LULC changes on water balance components of a watershed.
5. To develop an adaptive policy for reservoir operation under climate change scenarios.

1.10 Organization of the thesis

This thesis consists of the chapter of introduction which presents the motivation for the study and objectives of the work. Literature review of the uncertainty in climate models, various hydrological models, impact assessment using climate model data in hydrological modelling, mitigation of the effect of climate change on water resources by developing adaptation strategies for future periods using various tools has been presented in second chapter. The overall methodology with the materials used in the present research study are given in third chapter. Chapter four describes the study area and database preparation for the research work. Model setup for simulating streamflow using uncertainty modelled climate model is presented in chapter five. Results and discussions of the present research work are given in sixth chapter. Chapter seven summarises the conclusions and suggests scope for further study.

Chapter – 2

Literature Review

2.1 General

To investigate the effect of climate and other factors on hydrologic regime, it is necessary to obtain the data for baseline conditions and forecast for future periods using long-term monitoring network. Monitoring networks are also necessary for fully assessing the hydrologic processes, which lead to changes in water resources and for calibrating and validating models used to simulate over a long time. Water is India's future and its spatial variation was assessed by Amarasinghe *et al.* (2005, 2007) as it is a big country with variable percapita demand over regions. They provided better idea about the usage of water, water supply and demand across the rivers of India. Analysis was carried out by dividing the area into 19 major river basins. Based on the results, future growth in other factors such as domestic, industrial and environmental water demand, and internal and international trade are the various factors affecting water supply and demand. Among 19 basins, Krishna River is a water scarce river with 20-40% of irrigation mainly depending on ground water. The degree of development in this basin is greater than 60%, which leads to depletion of water by 50-75% by 2050. Therefore, Krishna river basin was selected for assessing water availability under climate change scenarios.

In this chapter, literature available on climate change impacts on hydrology of a river basin using hydrological model and RCM database is presented. The literature required to develop adaptation strategies for a reservoir operating system to reduce the risk obtained due to climate change is described.

2.2 Climate Change and its Effects

India is a semi-arid country highly dependent on precipitation and even minute departures in the rainfall patterns may lead to natural disasters like droughts and floods affecting agriculture, ecosystems and economic sectors. The study and selection of climate variables plays a major role in climate change impact studies.

Xu (1999**)** has discussed the limitation of GCM's ability in simulating the streamflow at regional level; this can be obtained by downscaling to basin level. Author suggested that there be improvement of methodologies to develop new climate change scenarios, macro scale hydrological models to simulate hydrologic processes, and the necessity of uncertainty modelling for climate variables etc.

Bouwer *et al.* (2006**)** studied the effect of climate, land use and water consumption changes on the streamflow of Krishna river basin in peninsular India over a span of 100 years (1901-2000). Streamflow variations in the basin was low in the early period until 1960: later the decrease in streamflow was mainly due to reservoir construction and increased water consumption. Hence, the study emphasizes the need to consider water consumption, changes in LULC parameters, climate changes due to greenhouse gas, using climate models. Reduced peak streamflow and shortfalls in precipitation enhance the need to study severe events like droughts in the Krishna river basin.

Kjellström *et al.* (2010**)** analysed the performance statistics of RCMs using both weighted and unweighted ensemble means. The results show that weighted means variables are more close to actual observations than ensemble variables.

Lee and Bae (2015**)** assessed the availability of blue and green water over Asian Monsoon Region for three future periods compared with a reference period using VIC model. The climate data was obtained on zonal basis using Koppen climate classification method. The projections show an increase in annual average increase in green water and blue water in future period. The climate classification system in the thesis was based on the tropical climate zone. However, Asian continent impact studies need to consider other important estimates like high population, adaptable climate zones etc.

Mondal and Mujumdar (2015**)** encapsulated modern research on the estimation of the impact of climate change on hydrologic regime raising the mismatch issue between scale and physical processes. Changes in the availability of water, water quality and irrigation demands were mainly focused in these studies. The authors also proposed methodologies to reduce uncertainties in future scenarios of multi climate models developed due to human induced emissions. In addition to these, the most probable elements responsible for validation of the observed data were also discussed.

Schoof and Robeson (2016**)** scrutinized the historic and projected change in the precipitation and temperature extremes with a high emission scenario RCP 8.5. The authors discussed general definitions of extremes based on thresholds and percentiles, quantification of changes in extremes using statistical methods using extreme value theory and various downscaling methods to inspect regional climate with pros and cons of each method. Estimation of temperature extremes were carried out using quantile mapping method using fine resolution gridded daily data. The results project an increase in warm extremes with a decrease in cold extremes, but stated that the downscaling of GCM data removes the bias and produce substantial spatial variability within the relatively small sub-regions.

2.3 Regional Climate Models and their Uncertainty Modelling

The changing global climate alters the hydrological cycle, which in return causes variability in the frequency of extreme events, availability of water, water use for irrigation, and quality of freshwater resources (Simonovic and Li 2004). Furthermore, the hydrological changeability affects the productivity of natural and agricultural systems, designing of hydrological structures, demand and supply of water, as well as aquatic ecosystem. Change in climate has been modelled using GCMs by incorporating changes in atmosphere and anthropogenic activities for the historic and future periods. GCM simulates the climate variables at a coarser scale i.e. at continental and hemispherical scale; however, the regional impact analysis requires the variables at a finer scale. The downsides of the GCM outputs, such as decreasing capability at finer temporal as well as spatial scales and the inability to simulate the variables of hydrological importance, prevent direct involvement in hydrological studies (Xu 1999). In addition, the circulation pattern causing extreme hydrological events are also not captured adequately by GCM (Christensen and Lettenmaier 2007).

Therefore, in order to analyse the climate change impact, large-scale climatic variables should be linked to the hydrologic variables at regional scale (e.g. precipitation, runoff) for better planning and management. The method of modelling the hydrologic variables at a regional scale based on large-scale GCM outputs is known as downscaling. Dynamic and statistical downscaling techniques are the commonly accepted downscaling methodologies, in which the former projects the coarser resolution GCM outputs to a finer resolution by incorporating the physical laws, boundary conditions, and atmospheric processes (generally known as Regional Climate Model, RCM or Limited Area Model, LAM). On the other hand, statistical downscaling techniques establish statistical association between large-scale GCM variables and regional scale hydrological variables, forecast for future time steps and finally evaluate the consequences relative to the present climate. Hence, the following sub-sections review the literature related to the climate change impact investigation using dynamic and statistical downscaling techniques around the globe.

Giorgi and Mearns (1991**)** compared the empirical and GCM nested limited area modelling techniques and discussed the advantages, limitations, weakness, and viability of their use. They advocated that the implementation of the empirical techniques is quite easy; however, these techniques are incapable of representing mesoscale forcings that are more sensitive to future climatic conditions. Though the GCM nested limited area models are capable of encompassing a wide range of climate variability and atmospheric phenomena, they are computationally complex and expensive. Based on the strength and weakness of different modelling approaches, they suggested rapid improvement in both the techniques for better representation of regional response in the context of climate change.

Giorgi and Mearns (2003**)** proposed the use of multi model ensemble mean in probabilistic climate projections in the form of REA. The method overcomes the limitation of assuming that all simulations are likely equal with reliability based on the likelihood of simulations. The authors also state that REA acts as a simple and flexible tool to quantify climate change and relate uncertainty and reliability, as well as the probability of change.

The extreme precipitation over the UK was inspected by Fowler et al. (2005) using HadRM3H regional climate model. In spite of the deviations in spatial resolutions between the observed and modelled data, the RCM was able to simulate the extreme rainfall at various return periods and durations. Additionally, HadRM3H provides a better representation of spatial variability of extreme precipitation for shorter durations in complex orographic regions. Though the model overestimates the extreme in high altitude area and underestimates in ‘rain shadow ‘area, the authors suggested that RCM has the capability to capture the variability in the extreme precipitation under enhanced greenhouse conditions.

Tebaldi and Knutti (2007**)** focused on the combination of multi model ensembles like selection of metrics and complexity of performance of the model in suggesting the reliable model for future projections. It also quantifies the inter model dependencies and the representations of the models with some basic uncertainties. The authors suggested that uncertainties of the AOGCMs includes basic components and are standard across large model population. The uncertainties of the models depend on new challenges like emission scenarios, uncertainties due to social, economic and technical developments, as well as uncertainties in scenario based climate models and the ability to describe using reasonably efficient computational model. The uncertainties developed for regional studies are more compared to Global level studies.

Gosain *et al.* (2011) studied the application of Regional Climate Model (RCM) – PRECIS with IPCC AR4 emission scenario daily weather data provided by the Indian Institute of Tropical Meteorology (IITM) to evaluate the change in water availability of the Indian River systems in both space and time. The analysis of the results was carried out to evaluate the severity of Floods and Droughts and thus to identify the Hotspots.

Teutschbein and Seibert (2012**)** reviewed various simple and sophisticated bias correction methods for RCMs and their selection in correcting deviations of the models. The performance of raw data and bias corrected data was assessed and an improvement was observed in the streamflow using bias corrected data than uncorrected RCM data.

Chou *et al.* (2014**)** applied Eta RCM to two GCMs, the HadGEM2-ES and MICRO5 with climate forcing of RCP 4.5 and RCP 8.5 scenarios to generate four downscaling simulations of climate change. The downscaled simulations were assessed for climate change over South America. Both the models identified reduction in the precipitation in the end of the century. The low and high emission RCP scenarios and the use of different GCMs produces different error behaviours necessitating experiment to include more possibilities and uncertainties in the evaluation of impacts of climate change.

Kulkarni *et al.* (2014**)** investigated future changes in the water balance components of Krishna river basin using RCM (PRECIS) data in SWAT. The simulations were carried out for the control and two future scenarios without change in LULC data. The results showed that the future annual discharge, base flow and surface runoff show increase in values over the present scenario. The limitation in this study was that model simulations were carried out considering future climate changes keeping the same LULC.

2.4 Hydrological Modelling and Impact Studies

Water resource management studies, flood control and drought mitigations, planning and design of water conservancy projects, hydrologic response to climate change and so on rely on hydrologic models. The calibration of the hydrological models is based on trial and error method and auto-calibration method. Optimization algorithms are also developed for individual models for parameterization and uncertainty modelling. Various hydrologic models and their suitability for impact studies are reviewed in the sections that follow:

The simulation biases observed in the simulated streamflow from the hydrologic models were addressed by Hashino *et al.* (2006). Simulations biases tend to reduce the forecasting ability of the model and restrict the operational usefulness. In this study, the authors have evaluated the quality of probabilistic forecasts by three bias correction methods using a distribution-oriented verification approach. It was found that forecasting quality improved by elimination of unconditional biases with increase in potential skill.

Chien *et al.* 2013 modelled the potential impact of a river basin through the coupling of hydrologic models and GCM projections. They demonstrated spatial and temporal variations of the future stream flow using multi-site calibration and validation using SWAT. Future projections show a decrease in annual and intra annual streamflow variability in all the watersheds. The results from the study provide basic knowledge for developing the adaptation strategies focused on reducing the impact on climate change on aquatic resources and ecosystems.

Narsimlu *et al.* 2013 conducted a study on climate change effects on water resources of Upper Sind river basin, India using SWAT. Uncertainty and sensitivity analysis of SWAT model was carried using Sequential Uncertainty Fitting algorithm (SUFI-2). Sensitive parameters obtained from SUFI-2 were used for calibration and validation of the model. The performance of the SWAT model was evaluated by comparing the simulated streamflow with the observed values during calibration and validation. Accuracy of the model performance was examined by the coefficient of determination (R^2) and Nash Sutcliff Efficiency (NSE), p-factor and d-factor. The results obtained reveal that average streamflow increases as both surface runoff and base flow increases by the end of the century.

Roy and Mazumdar (2013**)** has made an effort to assess the river runoff in the flood prone systems of Eastern and North Eastern river basins of India using HEC-HMS model. The analysis was carried out in the continuous time slices data for the period 2010-2040, 2041-2070 for A2, A1B and B2 scenarios based on PRECIS model with the baseline 1961-1990 without sulphur cycle. The climate vulnerable scale of river runoff of three scenarios shows that A2 and B2 scenarios are more vulnerable than A1B scenario. The analysis was carried out for virtual water availability, water footprint, green water availability, water sequestration by estimated water availability.

Meenu *et al.* (2013**)** studied the hydrologic impact of climate change over Tunga-Bhadra river basin, India. Prior to hydrological modelling, precipitation and maximum and minimum temperature at daily time scale were downscaled using linear regression based statistical downscaling model (SDSM). The future projection of the large-scale climate variables were obtained from the Hadley Centre Coupled Model version 3 under A2 and B2 scenarios for three future periods, viz. 2011-2040, 2041-2070, and 2071-2099. Authors used Hydrologic Engineering Center‘s Hydrologic Modelling System version 3.4 (HEC-HMS 3.4) to assess the potential climate change effect over the basin. The water balance evaluation under climate change suggested increase in rainfall and runoff with declining rate of actual evapotranspiration loss for both the scenarios. However, the highest change was observed in case of B2 scenario.

Abbaspour *et al.* (2015**)** attempted to design and calibrate an uncertainty modelled hydrological model SWAT to investigate the various components of water resources under climate change. Components were simulated with monthly time levels at monthly time scales. The study made a persistent and detailed examination of integrated system behaviour through physically based data driven simulations of large scale and high-resolution water resources models. Availability of data, calibration and uncertainty modelling procedures were clearly explained in this study.

Uniyal *et al.* (2015**)** stated that increasing human population and the impact of urbanization lead to detrimental consequences for natural resources like land and water. Additionally, the growing population has a direct impact on water demand, causing water scarcity; this factor would enable one to assess the climate change impact on water resources to ensure better water management in future.

Demaria *et al.* (2016**)** analysed the change and trend in streamflow of 124 basins in Northeast and Midwest of US using VIC model. Future climate projections from 16 GCMS were obtained for regional scale using statistical methods both spatially and temporally. Uncertainty in the climate models could be reduced by the performance of the climate model in reproducing the observed and future simulations similar to the ensemble mean. From the results, it was observed that uncertainty in downscaled GCM data is not reduced due to coarse resolution; therefore, the use of RCM data needs to be enhanced for obtaining details of future streamflow. They predicted that underestimation of streamflow values was mainly due to the structural biases in hydrological models and uncertainty in the bias correction- temporal disaggregation of climate data.

2.5 Drought Analysis under Climate Change

The severity of climate change which is explained using extreme events like floods, droughts etc., are observed during impact analysis. The risk developed by these events needs to be monitored to avoid the implications of climate change. From the literature, India is a semi-arid country prone to rainfall deficit in the future, leading to the possibility of drought conditions. Among the various types of droughts, meteorological drought and hydrological drought have been analysed under climate change. High dependencies of various activities such as urban development, water supply, hydropower generation on surface water resources increases the significance of hydrologic component in analysis of drought in an area. Mishra and Singh (2010) inferred that reduction in water supplies, water quality deterioration, limited water for irrigation leading to crop failure, minimized power generation, disturbance to riparian habitats, reduction in recreation activities and diversity of economic and social activities depend on hydrologic drought. Quantification of droughts through various indices are discussed in the following sections.

The spatio and temporal variability of meteorological drought in arid and semi-arid parts in India was computed by Patel *et al.* (2007) using SPI. The seasonal drought patterns have been quantified effectively using SPI at 3-month time scale. Further, this 3-month SPI was interpolated to depict spatial patterns of meteorological drought and its severity during typical drought and wet years.

Shukla and Wood (2008**)** applied the Standardized Runoff Index (SRI) for assessing the effect of climate anomalies on present hydrologic conditions governed by land surface physical processes. The authors reviewed the advantages and disadvantages of SRI. They have concluded that SRI lags in verifying the runoff throughout area as it reflects the customary uncertainties of models. Reliability of the SRI value depends on the calibration of the model. They also suggested that multi period SRI plays a significant role in drought research, monitoring and management communities.

Vidal and Wade (2009**)** computed SPI to assess the drought patterns of 183 hydrologic areas using bias corrected high resolution gridded precipitation data over the United Kingdom. The climate data were obtained from 6 GCMs under two emissions scenarios. Variations of streamflow obtained from two scenarios with time necessitated the utilization of multi model statistics when assessing the uncertainty in future drought indices to be used in long term water resources planning.

Karavitis *et al.* (2011**)** applied the SPI in Greece to analyse the drought based on drought, duration, magnitude and spatial extent. SPI has the ability to identify the starting and ending of the drought event. Hence, it enables the engineers towards planning of drought contingency by providing drought alert mechanisms. SPI was calculated for four different time scales using data from 46 precipitation stations. The calculated SPI index is shown spatially to forecast the variations over various regions in Greece.

Tabari *et al.* (2013**)** concentrated on quantifying the hydrologic drought using SDI for overlapping periods of 3,6,9 and 12 months at 14 hydrometric stations in Iran from 1975-2009. The ability of the data was examined by various distributions of probability and the best fit was found to be log normal distribution for long term of streamflow data. It was observed from the results that all stations suffered from extreme drought conditions during the study period.

Ojha *et al.* (2012) addressed the limitation of uncertainty in preserving temporal correlations, frequencies and intensity distributions, which avoid the direct use of GCM data in Hydrological modelling studies. Precipitation based drought index SPI was used to predict frequencies and occurrences of extreme events across India for a period of 48 years using nested bias corrected and raw climate data of 17 GCMs. It was concluded that nested bias corrected GCM data projects similar to observed data and an increase in drought events have been observed in west central, peninsular and central north east regions of India.

Van Loon and Laaha (2015**)** focused on the drought severity due to change in climate and catchment characteristics on 44 catchment areas with long-term hydro meteorological data and information on a large number of physiographic catchment characteristics. The authors estimated the possibility of drought using variable threshold level method where various statistical tools were applied to analyse the droughts. From the observations they concluded that global scale droughts are more related to climate than catchment characteristics, but at regional level, the spatial variations of drought severity are highly dependent on terrestrial hydrological processes.

2.6 Adaptation Strategies Based on Impact Studies

The study of climate change globally and regionally will act as an endeavour to assess and have preparedness to overcome deleterious effects of environmental change. Modelled streamflow plays a major role in these studies. Thus, the changes in the stream flow have been propagated from climate change scenario in hydrological models and are used to infer the effects on availability of resources in the broadest sense. Reservoirs play a dominant role in continuous supply of water satisfying the municipal, industrial, agricultural and environmental needs. Hence, the reservoir operating systems are to be modelled in meeting the substantial demands under climate change.

Cole *et al.* (1991**)** inspected seasonal and daily rainfall in the UK based on different GCM assessments of 40 years data. Sequence of runoff and evaporation losses are generated on that basis of climate variables. Further, yield versus storage graphs for future periods are generated with yield and storage values proportional to historic annual runoff. Systematic fall in the yield from existing storages were observed towards future periods. The results recommend optimal planning of reservoir operating system.

Raje and Mujumdar (2010**)** derived adaptive policies for the Hirakud reservoir performance for future scenarios over changing climate. For this study, the monsoon streamflow is downscaled using three GCMs for two future time slices and then analysed the performance of annual hydropower generation by four indices of reliability with respect to reservoir functions i.e., hydropower, irrigation and flood control, resiliency, vulnerability and deficit ratio were taken into considerations with respect to hydropower for projected hydrologic scenarios. Performance of the reservoir was examined with standard operating policy using current rule curves, which showed an increase in deficit ratio and vulnerability, and a decrease in reliability with respect to hydropower and irrigation. Hence, Stochastic Dynamic Programming (SDP) was used to develop adaptive policies for optimal monthly operation of reservoir. The results show that increase in hydropower reliability and generation for future scenarios can be maintained by sacrificing reliability in irrigation and flood control. Revision of the reservoir rules for flood control was suggested due to increasing probability of droughts in future climate change projections.

Li *et al.* (2010) focused on performance of reservoir operation subjected to future climate change under flood state situated in Northern America Pirarie watershed. Raje and Mujumdar 2010 has analyzed the performance of reservoir under uncertainty in hydrologic impacts of climate change and developed adaptive policies for possible future scenarios with a case study of Hirakud reservoir on Mahanadi River in Orissa, India.

Eum *et al.* (2010**)** calculated the optimal water releases for future periods under droughts using stochastic dynamic programming model combined with hedging rule. This model helps in mitigating the impact of drought in operating reservoir with good water supply probability. Emergency operating policy and Normal operating policy were developed based on the Aggregate drought index. Limitations of the proposed methodology of the releases can be reduced by introducing the hydrologic state variable in SSDP model, which can distinguish the probabilities of scenario conditioned on the selected hydrologic state variable. Applicability of the reliable streamflow drought index will also help in quantifying the optimal water releases.

Turner and Galelli (2016**)** developed and demonstrated the use of R package named 'reservoir', designed for rapid and easy routing of runoff data through storages. The uncertainties of the data are modelled using SDP in releasing the runoff without affecting the performance of the reservoir. It comprises tools for designing the capacity, release policy optimization and evaluation of performance, which enables the users in establishing reservoirs to meet the water needs of people and crops.

Ehsani *et al.* (2017**)** proposed a neural network based general reservoir operation to overcome the harmful observations of dam under climate change at regional scale. It is an automated model, which adapts to climate change and adjusts water storage levels based on the timing and magnitude of inflows. The authors also developed an indicator called Effective Degree of Regulation (EDR) by dams on water resources. Effective operating policies showed an increase in EDR, especially in dry months of year. The results of EDR indicate the need to increase the size and number of dams in addition to modifying their operations and thereby reducing the vulnerability of water resources systems to future uncertainties.

2.7 Critical Appraisal

Climate change is an emerging element to be considered for quantifying its effect on the hydrologic components of a river basin. Planning and management of water resources depends on the future climate and flow simulations of hydrologic model. Climate change impact analysis depends on

(i) Availability of regional climate data
(ii) Selection of suitable hydrological model
(iii) Uncertainty modelling of climate data and hydrological model
(iv) Analysis of the climate and hydrology for future scenarios
(v) Development of adaptation policies for mitigation and management of impact effects.

From the literature, it is observed that use of the RCMs compared to GCMs have proved to be efficient while assessing the impact of climate change on hydrology at basin level (Chien *et al.*

2013, Kulkarni *et al.* 2014, Demaria *et al.* 2016). SWAT model was proposed being a physically distributed model and is applicable to simulate various hydrological parameters with the efficiency of preserving the basin characteristics through sensitive analysis and uncertainty modelling using SUFI-2 algorithm (Gosain *et al.* 2006, Abbaspour *et al.* 2015, Yang *et al.* 2008, Meenu *et al.* 2013, Uniyal *et al.* 2015). Future simulations have been interpreted for inter and intra annual variations, trend analysis and drought studies. Drought indices proposed for both meteorology (Patel *et al.* 2007, Vidal and Wade 2009, Ojha *et al.* 2012) and streamflow (Tabari *et al.* 2013) are used for analysing the droughts in the Krishna basin. In addition to climate change, LULC is incorporated to determine the water balance components of an agricultural watershed. Many studies proved that application of SDP for the reservoir operation system has proved to be a powerful tool for developing the operating policies as it considers uncertainty in the inflows (Li *et al.* 2010, Raje and Mujumdar 2010, Eum *et al.* 2010, Turner and Galelli 2016). Hence, SWAT model is adopted to simulate the future projections using uncertainty modelled REA climate data to assess the impacts of climate change on water resources of river basin. SPI and SDI are selected to evaluate the drought indices in the basin. SDP proposed by Turner and Galelli 2016 is adopted for developing the operating rules of the reservoir system under climate change. The detailed methodology and application of the models are explained in the following chapters.

Chapter – 3

Methodology

3.1 Introduction

The overall methodology of the research work is shown in Figure 3.1. Hydrologic modelling mainly depends on interacting factors of the hydrologic cycle such as soils, topography, vegetation cover, climate, water bodies,…etc. Hydrologic models are evolved from simple rational models relating to rainfall and runoff to more advanced models integrating more complex system components. SWAT model is one among the complex models which simulates the water and sediments in large scale basins under varied soil types, land uses and management conditions. Geospatial data DEM, LULC and soil maps are required to set up SWAT model. The streamflow data collected at different gauge stations are used in the calibration process. The observed daily meteorological data like precipitation, minimum and maximum temperatures are used in the SWAT model to simulate the streamflow at each sub basin outlet. Model simulated streamflow is calibrated with observed streamflow in SWAT-CUP using SUFI-2 algorithm. In order to predict the future streamflow under climate change, multiple climate models are selected. Bias in the climate model data is reduced using non-parametric quantile mapping method. Thus, future streamflow of the basin is simulated using bias corrected climate data and is further analysed for the variations in streamflow both on monthly and annual basis.

Uncertainty in the climate model database compared to IMD data is reduced using the REA method (Figure 3.2). REA data is further bias corrected using the Quantile mapping method.

Standardized Precipitation Index (SPI) using the bias corrected REA data quantifies climatological drought of the basin. Bias corrected REA data is also used in the calibrated and validated SWAT model for future streamflow simulations. Future projections of the stream flow are analysed for the drought-based impact studies using Streamflow Drought Index (SDI).

An agricultural watershed is selected to assess the combined impact of LULC and climate change. Adaptation strategies are developed for a reservoir using stochastic dynamic programming method considering the releases for the water supply (Figure 3.3). Evaluation of the adaptation strategies are quantified using performance indices like Reliability, Resilience and Vulnerability.

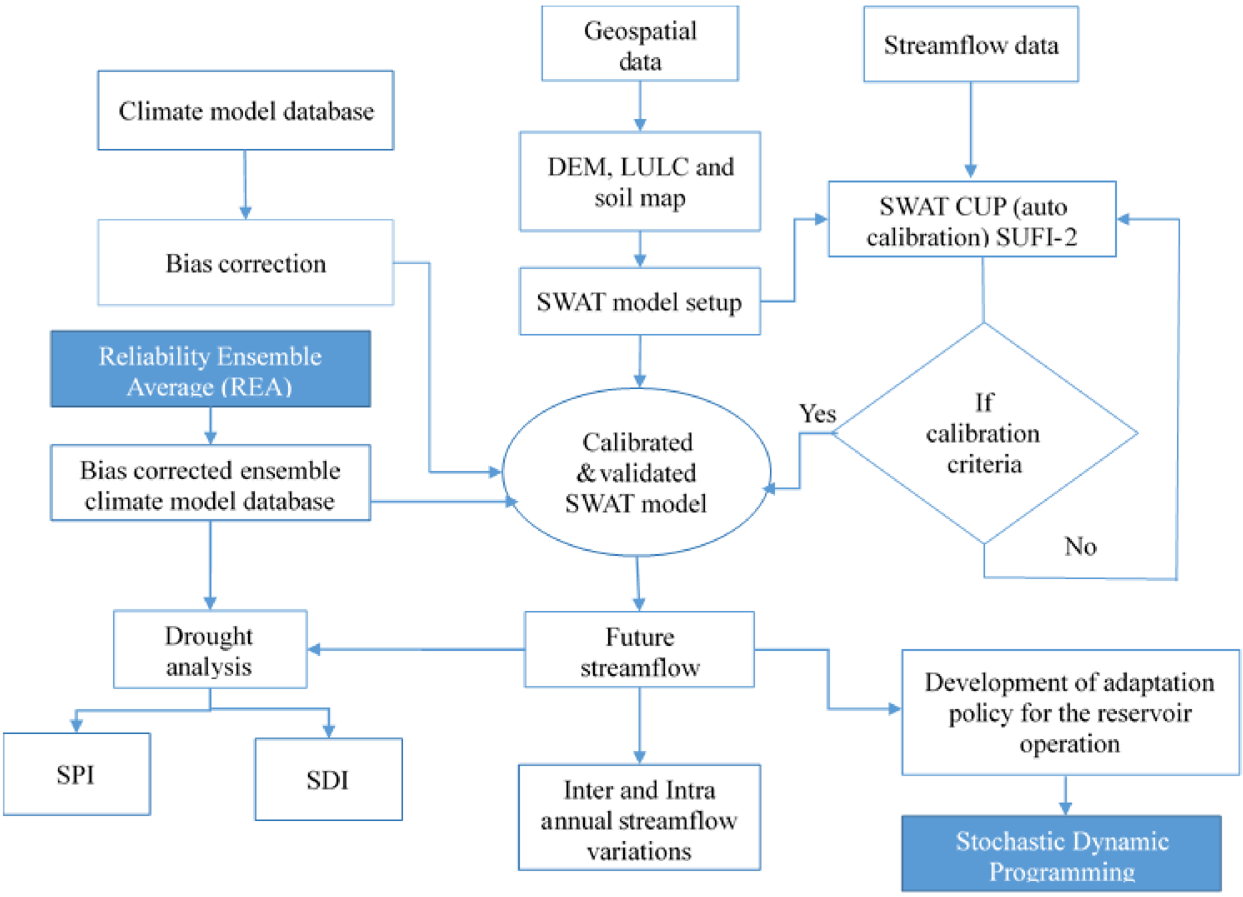


Figure 3.1 Overall Methodology of the Research work

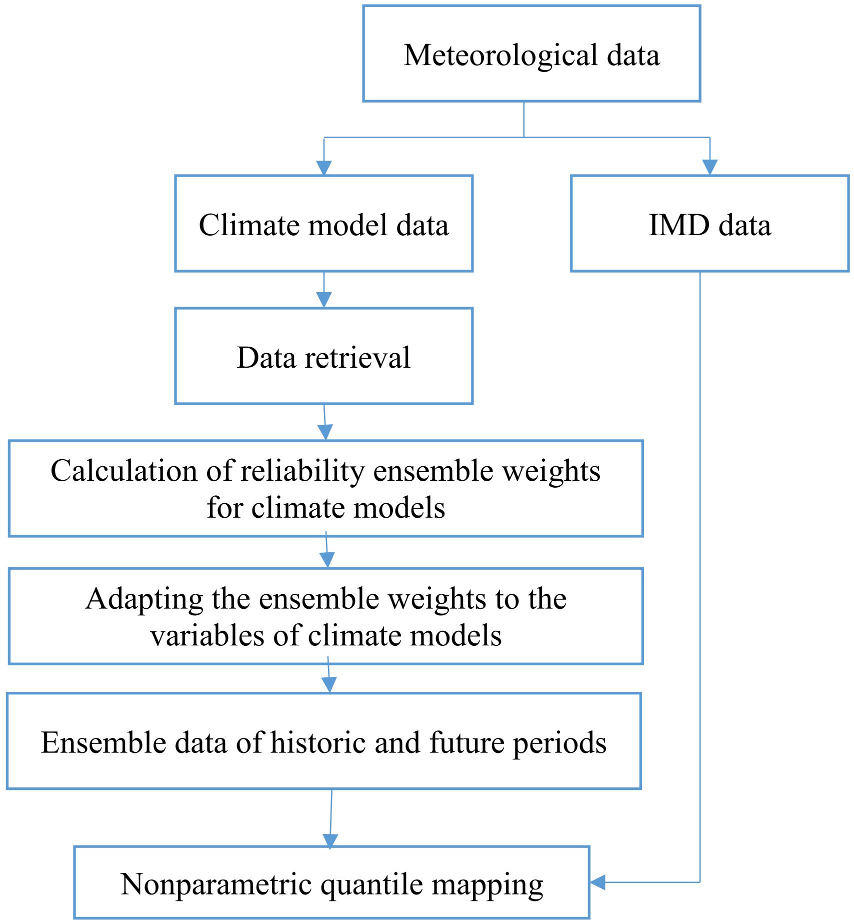


Figure 3.2 Flowchart for Reliability Ensemble Average Method

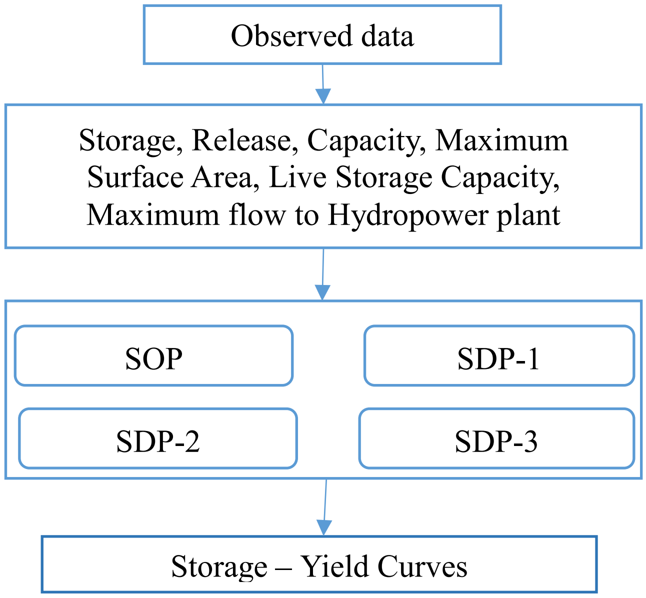


Figure 3.3 Flowchart for Stochastic Dynamic Programming approach for Reservoir operation

3.2 Materials

Based on the literature review and objectives discussed, a distributed hydrological model SWAT for the simulation of all-natural processes related to the movement of water such as the flow of the water in a stream, evaporation and evapotranspiration, groundwater recharge, soil moisture, sediment transport, chemical transport, growth of microorganisms in water bodies, etc, is selected. Impact analysis of the river basin is carried out at the sub basin level. SWAT model is developed for all the study areas using geospatial data DEM, LULC, Soil and slope maps and meteorological data such as daily precipitation, maximum and minimum temperatures. The detailed information about sources of data collected is given in Table 3.1. Data is processed and used based on the particular objective for different study areas.

Table 3.1 Data used for the research study

DATA	DESCRIPTION	SOURCE
Digital Elevation Model	30m*30m grid DEM used to delineate the boundary of the watershed and analyse the drainage pattern of the Terrain.	Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER) of NASA.
Land Use Land Cover (LULC)	Water base Land use data contains crop specific digital layers of 400m resolution, suitable for use in GIS	http://www.waterbase.org/
	Decadal LULC for 1985, 1995, 2005 of 100m resolution.	https://daac.ornl.gov/VEGETATION/guides/Decadal_LULC_India.html
Soil data	Soil Map of scale 1:2,50,000	http://www.waterbase.org/
Weather data	Precipitation and Temperature: 0.5 km*0.5km regridded data	Indian Meteorological Department, Pune, India.
Hydrological Data	Gauge data at 20 stations	Central Water Commission, Ministry of Water Resources, GOI
Climate Model Data	Regional Climate Model data of 0.5 km*0.5km obtained for 4 Global Climate Models	ftp://cccr.tropmet.res.in/
Reservoir data	Inflow, Release and Storage details of Nagarjuna sagar for the period (1970-2013)	Through personal contact (11-08-2016 by email) from AE, Nagarjuna sagar dam, Andhra Pradesh, India.

Aster DEMs were used for all the study areas. LULC obtained from water base of 400m resolution was used for impact analysis where, LULC of 100m resolution is used for assessing the impact at watershed level. Accuracy of all these geospatial datasets were verified by SWAT group (website: http://swat.tamu.edu/software/links/india-dataset/). The meteorological data is checked for missing values. Regional climate model data is obtained from COordinated Regional Climate Downscaling Experiment (CORDEX) which is of 50km x 50km resolution simulated under RCP 4.5and RCP 8.5 scenarios. Based on the availability of climate data, five models were selected for the impact studies (Table 3.2). RCP 4.5 is a scenario with stabilized radiative forcing of 4.5 W m^{-2}i.e. approximately 650 ppm CO_2-equivalent, which considers the long-term, global emissions of greenhouse gases on short-lived species. Thomson *et al.* (2011) suggested that RCP4.5 scenario in climate models investigates the remote future response of climate system by stabilizing the anthropogenic components of radiative forcing. RCP 8.5 is characterized as high greenhouse gas emissions scenario over time with increased concentration levels of greenhouse gases (Riahi *et al.* 2011). Climate model data possess bias when compared with observed data.

Table 3.2 List of climate models

Accronym	**Full Name**	**Modelling Centre**
ACCESS	Australian Community Climate and Earth System Simulator.	Commonwealth Scientific and Industrial Research Organization and Bureau of Meteorology, Australia
CCSM4	Community Climate System Model	National Center for Atmospheric Research
CNRM_CM5	Centre National de Recherché Meteorologiques	Centre National de Recherches Meteorologiques, Centre Europeen de Recherche et de Formation Avancee en Calcul Scientifique
NorESM 1	Norwegian Earth System Model 1	Bjerknes Centre for Climate Research, Norwegian Meteorological Institute
MPI-ESM-LR	Max Plank Institute Earth System Model at Base Resolution	Max Planck Institute for Meteorology

3.2.1 Non-parametric Quantile Mapping Method

The significant bias developed from system model errors caused by inexact conception, spatial averaging and discretization within the grid cells is reduced by using bias correction rules applied to the climate variables.

Non-parametric quantile mapping using empirical quantiles bias correction method has been proposed by Gudmundsson *et al.* 2012, and this has been adopted for precipitation data bias correction. The transformation used for bias correction of the model data with the observed data is given in equation 3.1.

$$P_o = F_o^{-1}(F_m(P_m)) \tag{3.1}$$

Where, P_o and P_m are the observed and model precipitations and F_m is the CDF of P_m and F_o^{-1} is the inverse CDF (or quantile function) corresponding to P_o. The empirical cumulative distribution function of model and observed data estimated is applied for simulated climate model data. The quantile plot comparing uncorrected and corrected precipitation data of a grid point is shown in Figure 3.4.

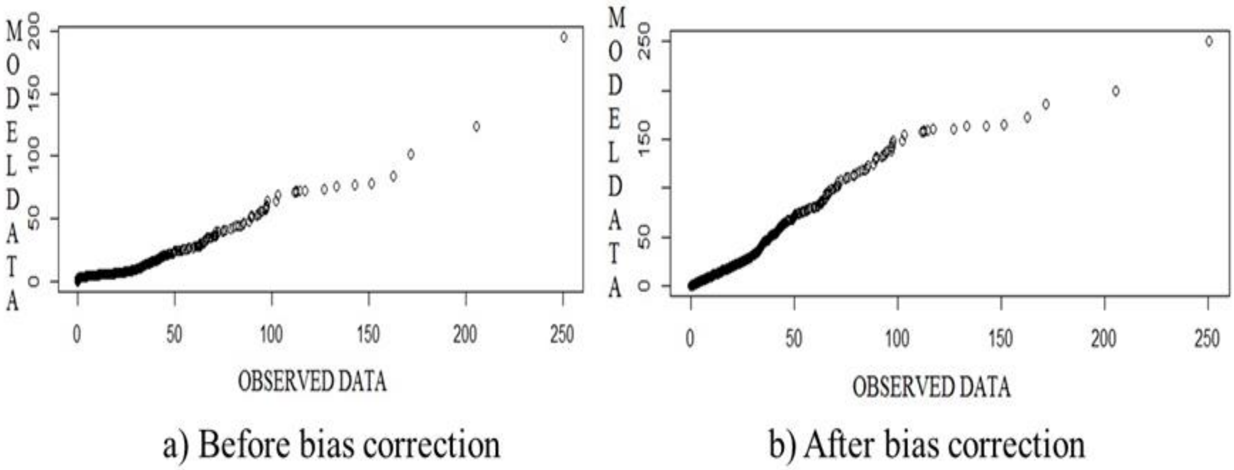


Figure 3.4 Nonparametric Quantile mapping of Precipitation Data for a Grid Point.

Temperatures (*TMP*) have been corrected using the additive term based on the difference between the observed and control run data (Lenderlink et al. 2007)

$$\mathrm{TMP}_{\mathrm{c(his)}} = \mathrm{TMP}_{\mathrm{his}} + (\mathrm{MMTMP}_{\mathrm{obs}} - \mathrm{MMTMP}_{\mathrm{his}}) \tag{3.2}$$

$$TMP_{c(fu)} = TMP_{fu} + (MMTMP_{obs} - MMTMP_{his}) \tag{3.3}$$

Where $TMP_{c(his)}$ is historic temperature corrected, $TMP_{c(fu)}$ is future temperature corrected, TMP_{his} is temperature historic, TMP_{fu} is temperature future, $MMTMP_{obs}$ is observed mean monthly temperature and $MMTMP_{his}$ is historic mean monthly temperature.

3.2.2 Reliability Ensemble Averaging

In 2003 Giorgi and Mearns developed a probability based REA method which enables the best estimate and reliable climate model data with a small range of uncertainty. The uncertainty occurred from ensemble inter models is inscribed taking into account performance and convergence criteria. This method was used to evaluate the exceedance probability of multiple climate model variables based on a threshold. REA analysis was performed for climate variables like precipitation and surface air temperature change using different General Circulation Models over 10 sub – continental scales. Based on comparative studies with other methods the authors inferred that REA is a simple and flexible tool for assessment studies that integrates the ensemble model projections. REA measures the model uncertainty in the form of model performance and model convergence and assign weight to each model based on their ability to capture the observed climate and convergence of the simulated changes across models to minimize the model uncertainty before modelling of hydrological processes. Moreover, REA allows a reduction in uncertainty range in the simulated series by minimizing the influence of outlier and poorly performing models; hence, it enables to measure the reliability of the simulated series by fulfilling the model performance and convergence criteria. For this purpose, the climate models are assigned separate weights based on different criteria, instead of equal weightage.

For this study, REA is quantified with an algorithm developed by Chandra *et al.* (2015) for variables like precipitation, minimum and maximum temperatures. REA is associated with two reliability criteria “model performance” i.e. ability of the model to capture the original series and “model convergence” i.e. convergence of the model simulation for a given forcing scenario (Giorgi and Mearns 2003). A similar approach is adopted in the present study to quantify the model uncertainty in the form of model weighting and applied to atmospheric variables of RCMs, scenarios, and different grid points to obtain a weighted projected time series for use in hydrologic modelling. Model performance is evaluated based on errors obtained from the deviation of Cumulative Distribution Function (CDF) between RCM simulated and original series; while model convergence is calculated with respect to weighted mean, CDF is obtained from multiple RCM future simulations. Moreover, the convergence criterion measures the agreement of a model ‘s future projection with respect to the other models. In REA, initial weights (Eq. 3.5) are obtained based on the ability of the RCMs to simulate historical observations in terms of root mean square error (RMSE) (Eq. 3.4), which defines the performance criteria.

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}(Observed_i - RCM_i)\right]^{1/2} \quad (3.4)$$

$$w_{int} = \frac{\left(1/_{RMSE_i}\right)}{\left(\sum_{i=1}^{n} 1/_{RMSE_i}\right)} \quad (3.5)$$

The following are the steps used to quantify the reliability of the climate model and to obtain the reliability ensemble mean:

- Divide the total range of RCM variable data into 10 equal intervals of CDF with respect to the observed time series data and compute RMSE. Inverse values of RMSE are considered as the proportional weights and the sum of the weights of all RCMs is equal to one. Higher weights are assigned for better performing models.
- Model convergence criteria is performed by considering the weights obtained from model performance criteria as initial weight for their respective RCMs.
- The product of the initial weight (w_{int}) and corresponding CDF of the future simulated i^{th} RCM (F_{RCMi}) is taken as the weighted mean CDF (F_{wm})

  $F_{wm} = \sum_i W_{int(i)} \times F_{RCM_i}$
- The same procedure is repeated as step-1 but the RMSE is calculated with respect to the weighted CDF and future projection of RCM weights is used in the next iteration for the respective RCMs and a new weighted CDF with different weights is computed.
- Repeat the steps 2 to 4 until the same weight repeats and complete the model convergence criteria.

This procedure was adapted for all grid points and 3 meteorological variables namely precipitation, minimum and maximum temperatures under RCP 4.5 and 8.5 scenarios in the study area, because of the varied nature of RCMs for different grids and atmospheric variables. Ensemble average of the climate variables for a particular grid which was obtained based on reliability is the weighted sum of the product of corresponding final weights with the respective meteorological variables. Thus, ensemble weighted average of each hydrological variable is given as input to the distributed hydrological model for each grid instead of giving each RCM input separately.

The minimum and maximum temperatures of the climate model data projects values similar to the observed data. REA precipitation possesses further bias which is reduced by adopting the non-parametric quantile mapping method as described in the previous section.

3.2.3 SWAT Model

SWAT model works on a daily time step continuous simulating model for a long period. The model is a computationally efficient, physical based model and capable of simulating high-level spatial details by dividing the watershed into smaller sub-watersheds (Arnold *et al*. 2012). The Hydrological Response Units (HRUs) are the percentages of sub-watershed area comprising homogeneous land use, management, and soil characteristics. SWAT model allows users to estimate the anticipated scenarios of a watershed by using different climate data and LULC patterns as inputs. In addition, it is capable of assessing the variability in stream flow by considering the future projected climate variables. SWAT model requires daily meteorological data i.e., either from a measured data set or generated by a weather generator model. The water balance equation, which governs the hydrological components of SWAT model, is as follows:

$$SW_{ti} = SW_O + \sum_{i=1}^{t}(R_{dayi} - Q_{surfi} - E_{ai} - W_{seepi} - Q_{gwi}) \tag{3.6}$$

Where SW_{ti} is soil water content at the end of the day (mm H_2O),

SW_o is the amount of initial soil water content on day i (mm H_2O),

t is the time in days, R_{dayi} is the amount of precipitation on day i (mm H_2O),

$Q_{sur\,f\,i}$ is the amount of surface runoff on day i (mm H_2O),

E_{ai} is the amount of evapotranspiration on day i (mm H_2O),

W_{seepi} is the amount of water entering the vadose zone from the soil profile on day i (mm H_2O) and

Q_{gwi} is the amount of return flow on day i(mm H_2O).

3.2.4 Calibration and Uncertainty Analysis using SUFI-2

Evaluation of the model calibration and validation is carried out through sensitive analysis and uncertainty analysis. As SWAT model comprises a large number of input parameters, calibration and validation of the model is highly complex, challenging and is a very rigorous process. SWAT-CUP (SWAT Calibration Uncertainty Procedures) is a dynamic SWAT edit program provided to handle all SWAT parameters including different soil layers and management rotation operations, precipitation data etc., is used for calibration and validation of model. SWAT-CUP contains various techniques like MCMC (Markov chain Monte Carlo), GLUE (Generalized Likelihood Uncertainty Estimation), Parasol (Parameter Solution), and SUFI-2. Among all the techniques of SWAT-CUP, Yang *et al.* 2008 and Khoi and Thom 2014 suggest that SUFI-2 needs a minimum number of model simulations to attain high quality calibration and uncertainty results. Overall uncertainty in the output of Hydrologic response is quantified using the uncertainties developed due to parameter ranges using 95 PPU P-factor, R-factor, Nash Sutcliff Efficiency (NSE), Coefficient of correlation (R^2) etc. P-factor is the percentage of measured data falling into the 95 PPU confidence interval, whereas R-factor is the average breadth of the 95 PPU band divided by the standard deviation of the measured data.

For the present study, the performance of model was evaluated using R^2 and NSE at monthly temporal scale. R^2 varies from 0 to 1 and NSE varies from negative infinity to 1. The values of R^2 and NSE nearer to one indicate better agreement between simulated and observed values. NSE is highly sensitive to estimation errors for high values (i.e., peak flow values). R^2 and NSE values have been computed as:

$$\boldsymbol{R^2 = \frac{n\sum Q_{obsi}\, Q_{simi} - (\sum Q_{obsi})(\sum Q_{simi})}{\sqrt{n(\sum Q_{obsi}^2) - (\sum Q_{obsi})^2}\sqrt{n(\sum Q_{simi}^2) - (\sum Q_{simi})^2}}} \tag{3.7}$$

$$\boldsymbol{NSE = 1 - \left[\frac{\sum_i^n (Q_{obsi} - Q_{simi})^2}{\sum_i^n (Q_{obsi} - Q_{mean})^2}\right]} \tag{3.8}$$

where, n is the total number of observations, Q_{obsi} and Q_{simi} are the observed and simulated discharges at i^{th} observation, respectively, Q_{mean} is the mean of observed data over the simulation period.

The overall methodology of the work is shown in Figure 3.1. The geospatial data like DEM, LULC and soil maps are required to set up SWAT model. Observed streamflow data of different gauge stations are used in calibration process. The observed daily meteorological data like precipitation, minimum and maximum temperatures are used in SWAT model to simulate the streamflow at each sub basin outlet. Model simulated streamflow is calibrated with observed streamflow in SWAT-CUP using SUFI-2 algorithm. In order to predict the future streamflow under climate change, multiple climate models are selected. Bias in the climate model data is reduced using non-parametric quantile mapping method. Thus, future streamflow of the basin is simulated using bias corrected climate data and is further analysed for variations in streamflow both monthly and annually. Uncertainty of the climate model database compared to IMD data is reduced using the REA method. REA data is further bias corrected using Quantile mapping method. Standardized Precipitation Index (SPI) using bias corrected REA data quantifies climatological drought of the basin. Bias corrected REA data is also used in the calibrated and validated SWAT model for simulations of the future streamflow. Future projections of the streamflow are analysed for drought-based impact studies using Streamflow Drought Index (SDI). From the impact studies, an agricultural watershed is selected to assess the combined impact of LULC and climate change. The adaptation strategies are developed for a reservoir using stochastic dynamic programming method considering the releases for water supply. Evaluation of the adaptation strategies is quantified using performance indices like Reliability, Resilience and Vulnerability.

3.2.5 Inter and Intra Annual Streamflow Variations

The variations in the streamflow are obtained using inter and intra annual Coefficient of Variation (*CV*). Inter annual variability of a sub basin is calculated using the following equation (Lenderlink et al., 2007):

$$\boldsymbol{CV_{inter}} = \frac{\boldsymbol{STD\ (Q_y)}}{\boldsymbol{\overline{Q_y}}} \tag{3.9}$$

Where Q_y is yearly streamflow, $\overline{Q_y}$ and $STD\ (Q_y)$ are the mean and standard deviation of annual streamflow.

CV_{intra} is used to quantify the intra annual variability of predicted stream flow using the following equation (Lenderlink et al. 2007):

$$\boldsymbol{CV_{intra} = 1/N \sum_{i=1}^{N} \left(\frac{STD(Q_m)}{\overline{Q_m}}\right)_i} \tag{3.10}$$

Where Q_m is monthly streamflow, $\overline{Q_m}$ and STD (Q_m) are the mean and standard deviation of monthly streamflow in a year, and i is the year number. CV_{intra} is Mean of *CV* for N-years in a sub-basin, where N=20 for this study. Overall, Intra annual variability and Inter annual variability of streamflow of a watershed is the mean of CV_{intra} and CV_{inter} of all sub-basins.

3.2.6 Standardized Precipitation Index (SPI)

Based on the previous studies, a notable increase in temperature is observed in future projections than past centuries (Jones and Moberg 2003) leading to drastic effect on the severity of droughts. It is also stated that change in precipitation in addition to temperature rise has serious effect on the drying rate of the land (Abramopoulos *et al.* 1988). Rebetez *et al.* (2009) showed that cultivation and natural systems in Europe are afflicted because of high temperature rise, evaporation and water stress. Lower levels of precipitation are an important factor which leads to increase in the severity of drought in a location. Precipitation will be insufficient to meet the demands of human activities and environment with the continuation of this phenomena for a season or over longer period. Other important factors to be considered in characterizing the drought are Temperature, wind and relative humidity. Monitoring of drought also needs to be specific with application, as it varies in various sectors. Based on the type, droughts are classified into meteorological, agricultural and hydrological. These differ with duration, intensity and spatial coverage from one another. The most common drought indices used to quantify, analyze and monitor the drought events are Palmer Drought Severity Index (PDSI) (Alley 1984) and Standardized Precipitation Index (SPI) (Thomas *et al.* 1993).

SPI is a normalized index representing the probability of occurrence of an observed rainfall amount compared to rainfall at a certain geographical location over a reference period.
Steps involved for SPI calculation are

- Fit a gamma distribution to the time series of precipitation values for each timescale of interest. Compute the parameters of the distribution.
- Compute the value of cumulative distribution function (CDF) [G(x)] corresponding to each value of precipitation (x).
- SPI value of precipitation is the value of standard normal deviate corresponding to the value of CDF [G(x)].

SPI was used to evaluate the deficit in precipitation for different time scales, which cast the availability of different water resources due to impact of drought.

3.2.7 Streamflow Drought Index (SDI)

Significant declination in the availability of water in all forms appearing in the land phase of the hydrological cycle is categorized as hydrological drought. Streamflow, lake and reservoir level and ground water level are the various forms of hydrological variables. Among all these variables, streamflow is the most important variable that reflects the quantity of water in terms of surface water resources. Hence, a hydrological drought event related to streamflow deficit with respect to normal conditions. SDI developed by Tabari *et al.* (2013) is used to evaluate the drought. Hydrological year is from June to May of every next year, and four overlapping time periods are utilized within each hydrological year: June to August (3 month), June to November (6 month), June to February (9 month), and June to May (12 month) drought.

$$\boldsymbol{V_{i,k} = \sum_{j=1}^{3k} Q_{i,j} \quad i = 1, 2, 3, \dots, 12 \quad k = 1, 2, 3, 4} \tag{3.11}$$

where, $Q_{i,j}$= Streamflow for the $_j$th month in $_i$th Hydrological Year, $V_{i,k}$ = cumulative streamflow volume for the i-th hydrological year and the k-th reference period, k=1 for June - August, k=2 for June - November, k=3 for June - February and k=4 for June – May.

$$\boldsymbol{SDI_{i,k} = \frac{V_{i,k} - \bar{V}}{S_k} \quad i = 1,2,3,\dots \quad k = 1,2,3,4} \tag{3.12}$$

Where $\bar{V}$ and S_k are the mean and standard deviation of the cumulative streamflow values of reference period k as these are estimated over a long period of time.

Positive SDI values indicate Wet conditions; Negative SDI values indicate Dry conditions. SPI and SDI were categorized based on the classification given in Table 3.3

Table 3.3 Event classification based on SPI value (Thomas *et al.* 1993)

SPI Value	**Category**	**Probability (%)**
≥ 2.00	Extremely wet	2.3
1.50 to 1.99	Severely wet	4.4
1.00 to 1.49	Moderately wet	9.2
0 to 0.99	Mild wet	34.1
0 to -0.99	Mild Drought	34.1
-1.00 to -1.49	Moderate Drought	9.2
-1.50 to -1.99	Severe Drought	4.4
-2 or less	Extreme Drought	2.3

3.2.8 Mann Kendall Trend Test

The statistically significant trends in the annual streamflow were determined using the Mann - Kendall (M-K) tau non-parametric test for each basin. For a probability value of less than or equal to 0.10 i.e. when Kendall's tau value equals zero, the trend was considered to be statistically significant. The degree of correspondence between two variables x and y where x variable is time and y variable are streamflow was measured using Kendall's tau. If τ=1, then the data shows perfect positive correlation; if τ= -1, then the data exhibits perfect negative correlation and τ= 0 shows no correlation between the pairs. Thus, the positive value of τ represents an increase in trend and negative value of τ represents a decrease in trend. Sen's method was used to estimate the magnitude of the trend (Hamed and Rao 1998, Mann 2016).

3.2.9 Reservoir Operation under Climate Change.

Reservoir system operation for various purposes require optimizing the use of water over time. The design of the storage capacity of a reservoir is a continuing problem in water resources management. The value of releasing water in any period need to be compared to the value of stored water. Release policy decisions are necessary to optimize the release decisions. Two functions such as deterministic Dynamic Programming (DP) and Stochastic Dynamic

Programming (SDP) are available for release policy design. In the present study, releases are estimated for the standard operating and adaptive policy using SDP. Standard Operating Policy aims to meet target at all times, unless constrained by available water in reservoir plus incoming flows. SDP is an extension of the dynamic programming algorithm in which the reservoir inflows are random variables described by probability distributions. Such a stochastic description of inflow helps in computing the expected benefits attributable to each release decisions. Let Q_t represents the inflow vector into the reservoir during any time period *t.* S_t represents the storage vector for period t, R_t the release vector for period t and $e_t(S_t , S_{t+1})$ is the evaporation loss in period t. The continuity equation used to make the decision is based on the reservoir-storage mass balance (Faber and Stedinger 2001) in Eq 3.13.

$$S_{t+1} = S_t + Q_t - R_t - e_t(S_t, S_{t+1}) \tag{3.13}$$

The state of the system in each stage *t* can be described by the reservoir storage S_t and often some variable that represents the hydrologic state of the river basin. At each stage and state, a release of water R_t is chosen which maximizes the sum of the current benefit of that release $B_t(R_t)$ and the future benefit $\boldsymbol{f_{t+1}(S_{t+1})}$, which depends on the resultant storage $\boldsymbol{S_{t+1}}$ in the following period, assuming the system is operated optimally from that point onward. The model uses a backward recursive starting from a year sufficiently distant in future to arrive at a steady state operating policy on a monthly basis. Neglecting streamflow uncertainty and for known inflow values Q_t the functional equation is evaluated using Eq 3.14 (Faber and Stedinger 2001).

$$f_t(S_t) = \max_{\boldsymbol{R_t}} \underset{\boldsymbol{Q_t}}{\boldsymbol{E}} \{\boldsymbol{B_t}(\boldsymbol{S_t}, \boldsymbol{Q_t}, \boldsymbol{R_t}) + \propto \boldsymbol{f_{t+1}}(\boldsymbol{S_{t+1}})\} \qquad \forall \boldsymbol{S_t} \; \boldsymbol{and} \; \boldsymbol{t} \in \{\boldsymbol{1}, \ldots\ldots, \boldsymbol{T}\} \tag{3.14}$$

where T being the final period in the model, $\boldsymbol{B_t}(.)$ the benefit function for period *t* and α be the discount factor. The transition probabilities provide the information on inflow characteristics in order to make a decision on the release for a given time step. The SDP adopted in the present study uses the release policy decisions made to optimize the release decisions to minimize the sum of penalty costs given in Eq (3.15). Eq (3.16) is used to compute the reservoir storage capacity with minimum releases. Penalty costs are function of the volume delivered relative to the demand.

$$\mathbf{C_t = [1\text{-}(R_t / D)]^{\tau}} \tag{3.15}$$

where D = Demand or target release τ = penalty cost exponent (τ = 2 Academic purpose)

Backward recursive equation (Faber and Stedinger 2001).

$$\boldsymbol{f_t}(\boldsymbol{S_t}, \boldsymbol{Q_t}) = \min_{\boldsymbol{R_t}} \left\{ \boldsymbol{C_t}(\boldsymbol{S_t}, \boldsymbol{Q_t}, \boldsymbol{R_t}) + \underset{\boldsymbol{Q_{t+1}} | \boldsymbol{Q_t}}{\boldsymbol{E}} [\boldsymbol{f_{t+1}}(\boldsymbol{S_{t+1}}, \boldsymbol{Q_{t+1}})] \right\} \quad \forall \boldsymbol{S_t}, \boldsymbol{Q_t} \; \boldsymbol{and} \; \boldsymbol{t} \in \{\boldsymbol{1}, \ldots\ldots, \boldsymbol{T}\} \tag{3.16}$$

The release decision R_t is selected to minimize the current period cost $C_t(S_t,\ Q_t, R_t)$ plus future cost expectation $f_{t+1}(S_{t+1}, Q_{t+1})$, which depends on the resultant state of the system at time step t+1.

The performance Indices for the proposed releases are calculated using the Reliability, Resilience and Vulnerability functions (McMahon *et al.* 2006). Reliability represents the probability of no failure. It is classified into Time based and volumetric reliabilities.

Time based reliability $(\boldsymbol{R_t})$: $\boldsymbol{R_t} = \left(\frac{\boldsymbol{N_s}}{\boldsymbol{N}}\right) \quad \boldsymbol{0} < \boldsymbol{R_t} \leq \boldsymbol{1}$ (3.17)

where $\boldsymbol{N_s}$= number of intervals with the target demand; $\boldsymbol{N}$ = total number of intervals.

Volumetric reliability $(\boldsymbol{R_v})$: $\boldsymbol{R_v} = \boldsymbol{1} - \left(\frac{\sum_{i=1}^{N}(D_i - D_i^{'})}{\sum_{i=1}^{N} D_i}\right);\ \boldsymbol{0} < \boldsymbol{R_v} \leq \boldsymbol{1}$ (3.18)

where $\boldsymbol{D_i}$= Target demand during ith period; $\boldsymbol{D_i^{'}}$ = Actual volume supplied during the ith period; N = Number of time intervals in the simulation.

Resilience $(\boldsymbol{\varphi})$: Conditional probability of a recovery from the failure set in single time step.

$$\boldsymbol{\varphi} = \frac{f_s}{f_d}\ ;\ \boldsymbol{f_d} \neq \boldsymbol{0} \tag{3.19}$$

where $\boldsymbol{f_s}$ = Number of individual continuous sequences of failure periods; $\boldsymbol{f_d}$ = Total duration of all the failures.

Vulnerability (ή): Measure of likely damage in a failure event, which refers to the likely magnitude of failure.

$$ή = \frac{\sum_{j=1}^{f_s}(\max s_j)}{f_s} \tag{3.20}$$

where s_j= Volumetric shortfall during jth continuous failure sequence; $\boldsymbol{f_s}$ = Number of continuous failure sequences.

3.3 Closure

In this chapter, methodology, data required, bias correction and uncertainty analysis techniques for processing climate model database, description of hydrological models for simulation of streamflow in a river basin, and analysis techniques for impact assessment have been explained. Flowcharts are given for the impact assessment on water resources; developing ensemble data from multi model runoff. Development of adaptation strategies based on the performance indices for the future projected streamflow has been discussed.

Chapter – 4

Study Area and Database

4.1 General

Different study areas in India have been selected to investigate the proposed research methodology. The study areas include Wardha, a sub basin of Godavari river, for analysing the Inter and Intra annual stream flow variations for future periods, Krishna river basin for analysing the drought conditions, impacts on water resources, Munneru an agricultural watershed in the Lower Krishna basin, was chosen to assess the variation of water balance components spatially under combined changes of climate and LULC. Assessment of performance indices has been carried out for Nagarjuna sagar dam in Krishna river basin using Stochastic Dynamic Programming (SDP).

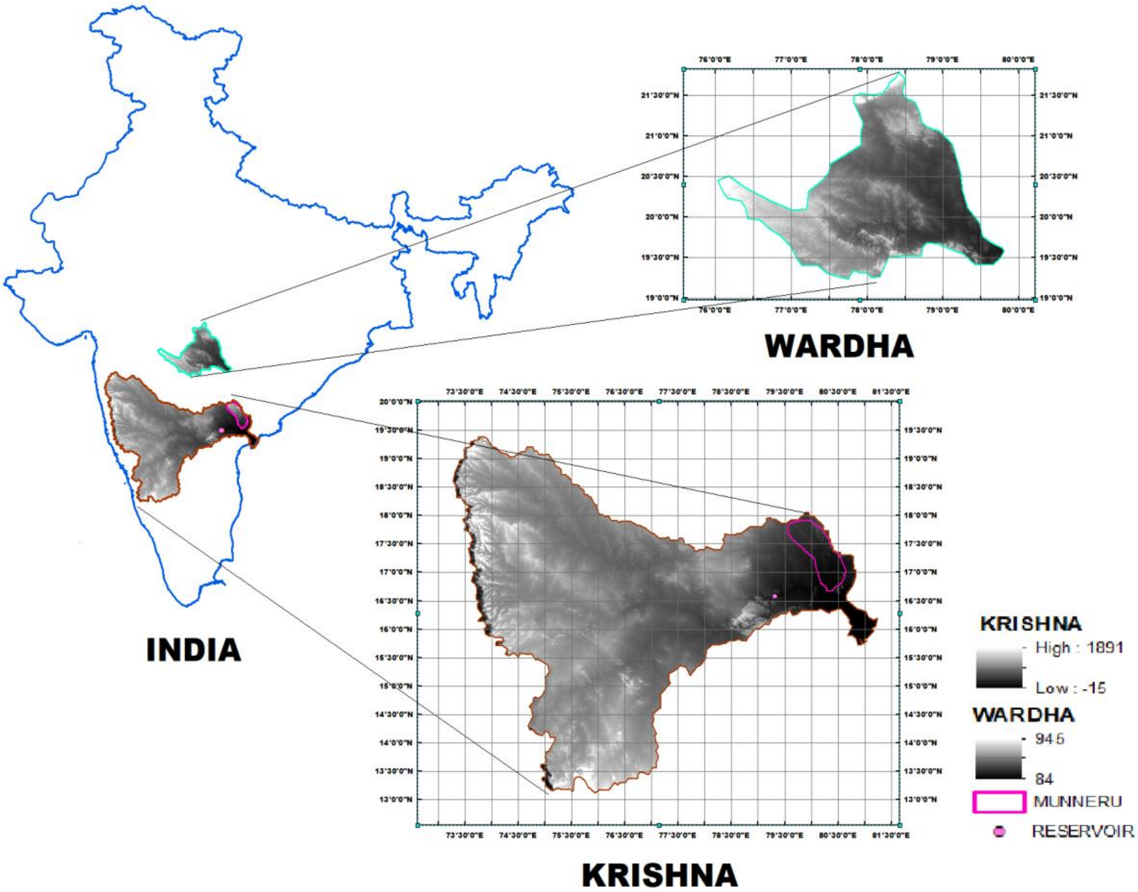


Figure 4.1 Location of the study area

The location map of study areas is shown in Figure 4.1. The geospatial, hydrological data and meteorological data of the basins were obtained from WRIS portal[1]. A detailed explanation of all study areas is provided in the following sections.

4.2 Wardha Sub Basin

Wardha region is a sub basin of Godavari with a spatial extent of latitude 19° 18ˈ N and 21° 58ˈN and longitude of 77° 20ˈE and 79° 45ˈ E (Figure 4.1). The drainage area of Wardha sub basin is around 15.31% of the Godavari basin (Godavari Basin 2014). The sub basin conveys the combined water of the Penganga and Wardha rivers to Pranahitha, the largest tributary of Godavari basin. It flows along the entire Northern and Western border from the Mutai plateau of the Satpura range of Wardha district, India. The sub basin includes 14 districts consisting of around 8,440 villages with a total population of 3,23,21,974 according to 2011-census data (Godavari Basin 2014). The streamflow carried by the river serves as the principal source of

[1] http://www.india-wris.nrsc.gov.in/wrpinfo/index.php?title=Main_Page

water and has witnessed large-scale interventions and problems related to such interventions. Hence, Wardha sub basin was selected to analyse streamflow variations in the future periods using Regional Climate Model database. Wardha sub-basin is divided into 43 watersheds with a total drainage area of 46237.65 sq.km. The terrain of the sub basin is full of undulations like ridges and valleys, with the surface marked by a medium density forest cover. The sub-basin experiences an average annual rainfall of approximately 1,055 mm. The average minimum and maximum temperatures of the Wardha sub basin are 9.4°C to 46°C respectively.

Geospatial data required for hydrological modelling includes DEM, Soil, LULC and slope map. In Figure 4.1 Wardha basin is projected with 30m gridded DEM obtained from ASTER where the highest and lowest elevation of the basin are 945m and 84m respectively. Figure 4.2 presents drainage pattern with available gauge station in the basin. LULC of the basin (Figure 4.3) contains 10 classes with maximum area under cultivation. Classification of the soil classes is mainly 3 as shown in Figure 4.4. Slope classes are categorized into 5 classes based on the DEM, as shown in Figure 4.5.

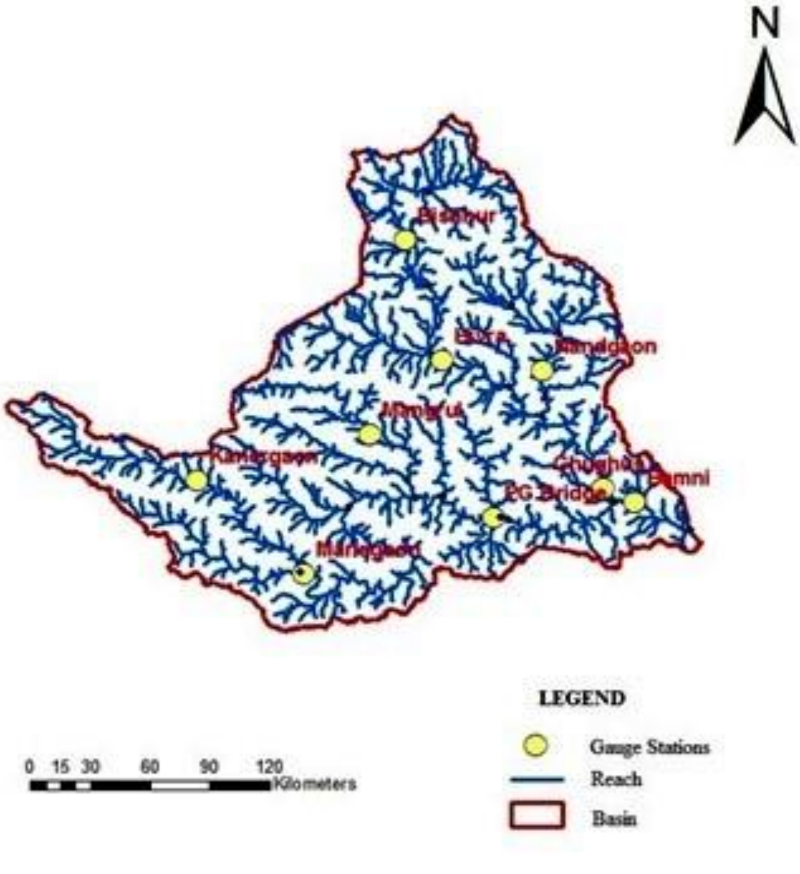


Figure 4.2 Drainage pattern and Gauge stations of Wardha basin

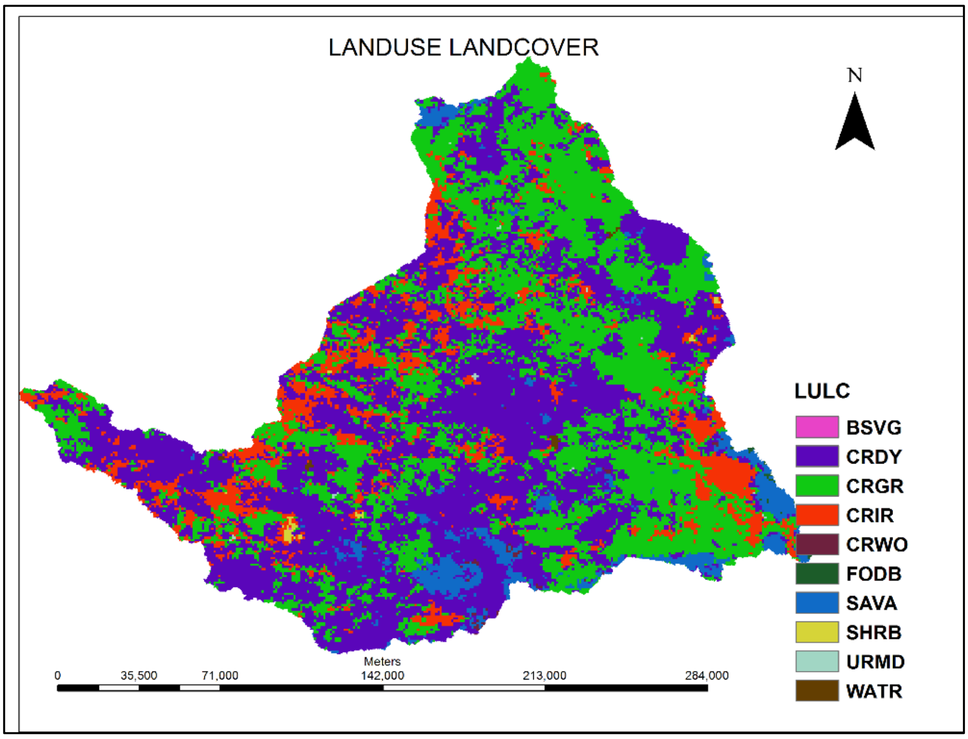


Figure 4.3 LULC map of the Wardha basin (www.waterbase.org)

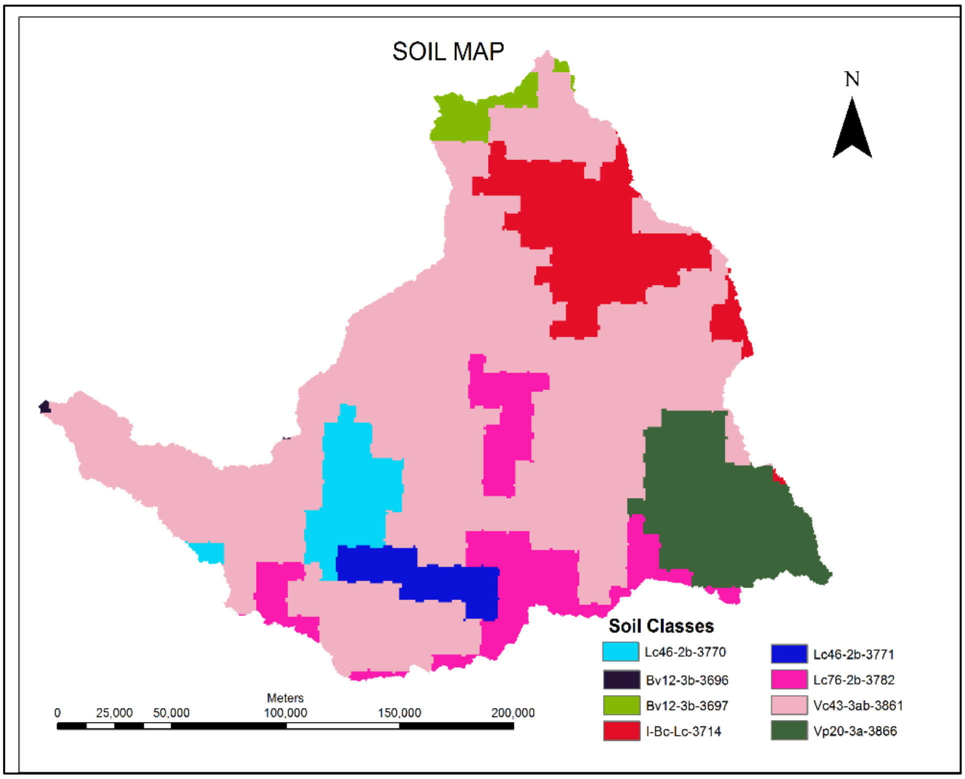


Figure 4.4 Soil map of the Wardha basin (www.waterbase.org)

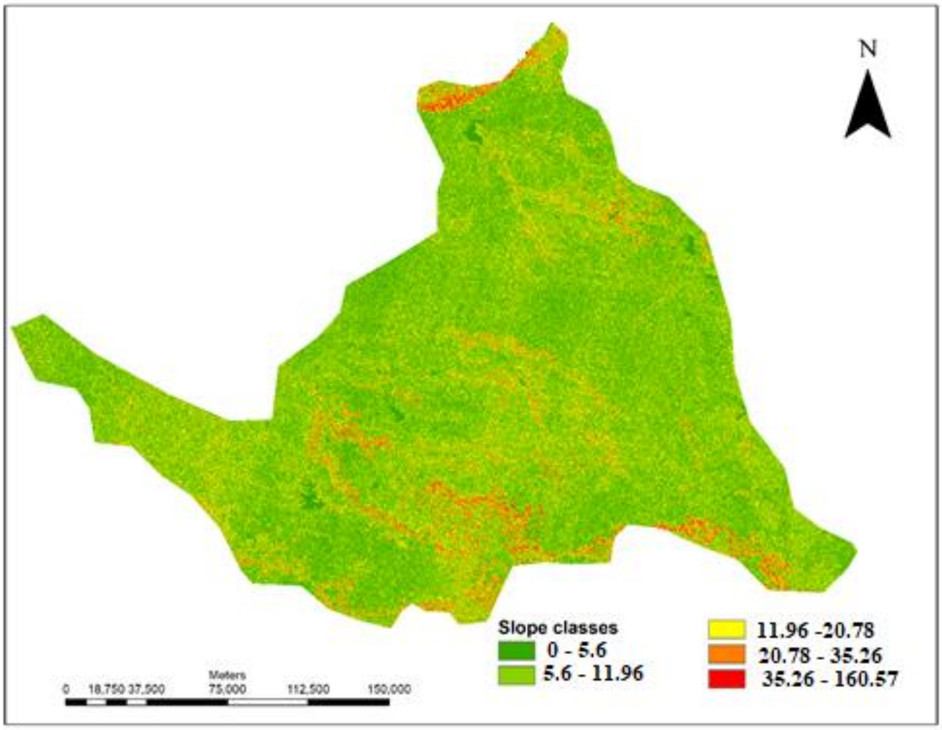


Figure 4.5 Slope map of the Wardha basin

Observed meteorological data required for the study area was retrieved for 27 grid points for the period 1975 to 2003 as given in Figure 4.1. Regional climate model database of 27 grid points for five climate models under RCP 4.5 and RCP 8.5 scenarios for the period 1975 to 2099 was retrieved using a Graphical User Interface as shown in Figure 4.6 using R - Programming Language. The RCM simulated temperature and precipitation are to be bias corrected before being used in the hydrological model as they are subjected to significant biases from system model errors caused by inexact conception, spatial averaging and discretization within the grid cells.

Observed streamflow data obtained from the CWC was checked for missing data and gauge stations with no or limited missing data for a continuous period of 20 years for calibration of the hydrological modelling. Streamflow data from 1984 to 1996 and 1997 to 2003 period have been used in calibrating and validating the model respectively by excluding the spin up period for analysis.

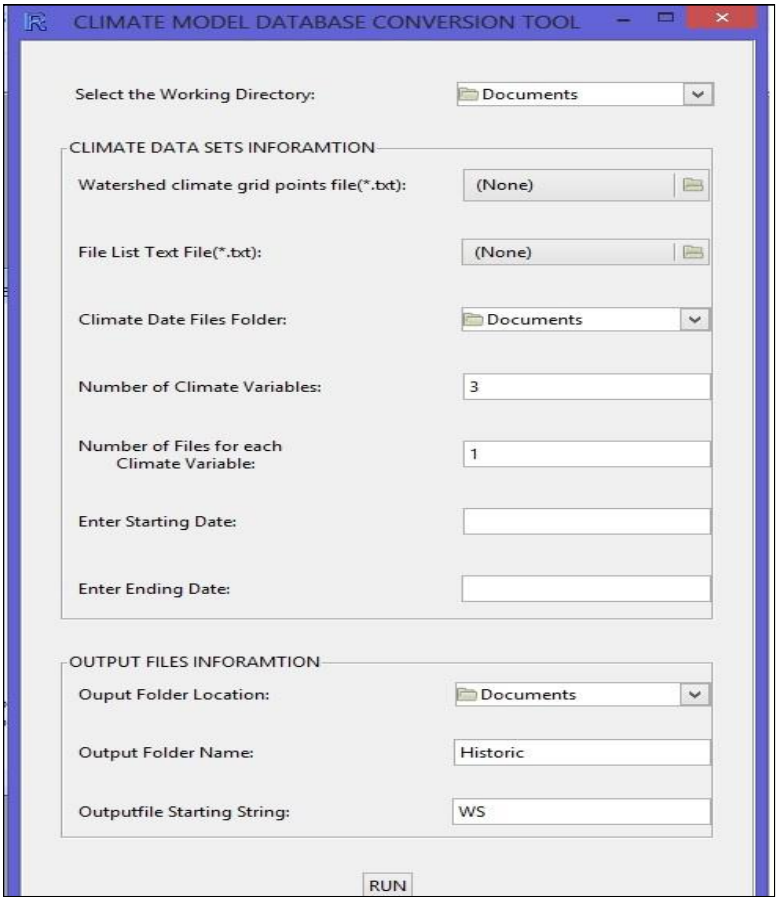


Figure 4.6 Interface to retrieve the climate variables for the latitude and longitude

4.3 Krishna River Basin

The Krishna river basin is the fourth biggest with a total area of 258948 km^2, located in the four states Karnataka (43.8%), Andhra Pradesh, Telangana (29.81%) and Maharashtra (26.36%), India as shown in Figure 4.1. The basin lies between 3°10' to 19°22' North latitudes. It consists of several tributaries among which Ghatprabha, Malprabha and Tungabadhra are right joining while Bhima, Musi, and Munneru are left joining principal tributaries. There are seven subbasins in Krishna basin - Bhima Upper, Bhima Lower, Krishna Upper, Krishna Middle, Krishna Lower, Tungabadhra Upper and Tungabadhra Lower. Climate of the basin is tropical, with the average annual Precipitation of 960 mm and minimum and maximum temperatures of the basin being 20.73˚C and 32.2˚C. The basin receives an annual average precipitation i.e. maximum value of 2000 mm at the Western Ghats region, with values ranging from 300mm to 1000mm in the delta region. The DEM (Figure 4.7) projects the minimum, maximum and mean elevations of the basin as 18m, 1903m, and 518m. Approximately 50.47% of the total area falls under 500m to 750m elevation zone. The climate data includes maximum temperature (T_{max}), minimum temperature (T_{min}) and precipitation with the spatial resolution of 0.5°x0.5° for 132 grid points. Streamflow has been characterized by low flows during March to May and high flows in August to November with around 47 Hydro – Meteorological stations on the basin. The streamflow data obtained from the hydro meteorological stations shows some missing values. Due to the missing stream flow data in many stations, only 14 out of 47 stations data were used for calibration and validation of the model. Land use information of Krishna basin comprises 14 categories as shown in Figure 4.8 with Agriculture (72.56%) as the dominant category. Figure 4.9 presents the soil map, which is dominated by fine texture soil. Laterite and lateritic soils, red soils, alluvium, black soils, mixed soils (red and black, red and yellow, etc) and alkaline and saline soils are important soil types found in the basin. The slope map of Krishna river basin is developed based on the percentage rise with 5 classes as shown in Figure 4.10.

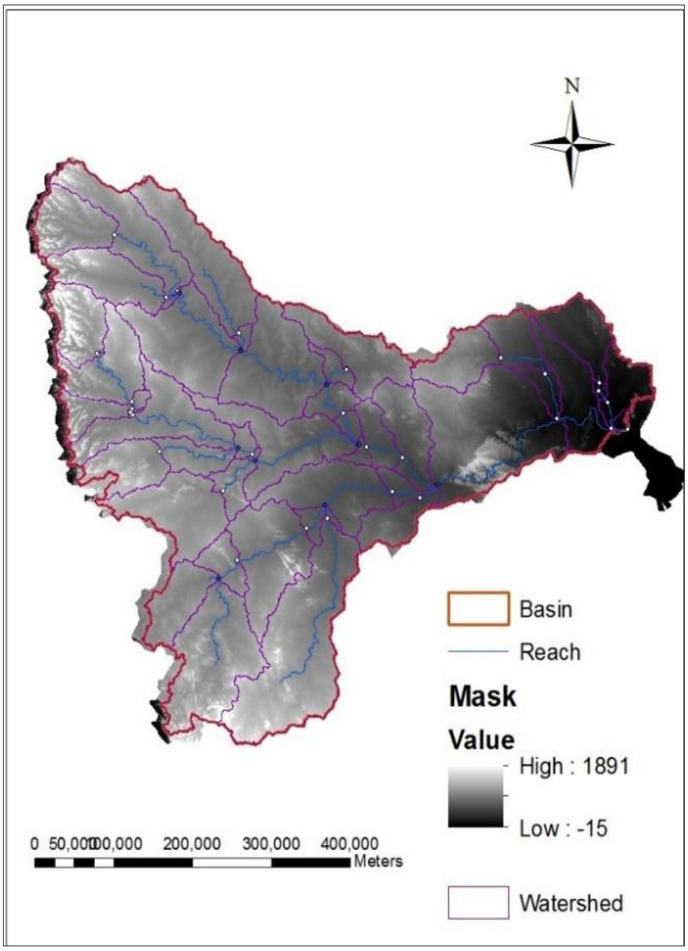


Figure 4.7 DEM of the Krishna river basin with delineated stream and sub watersheds.

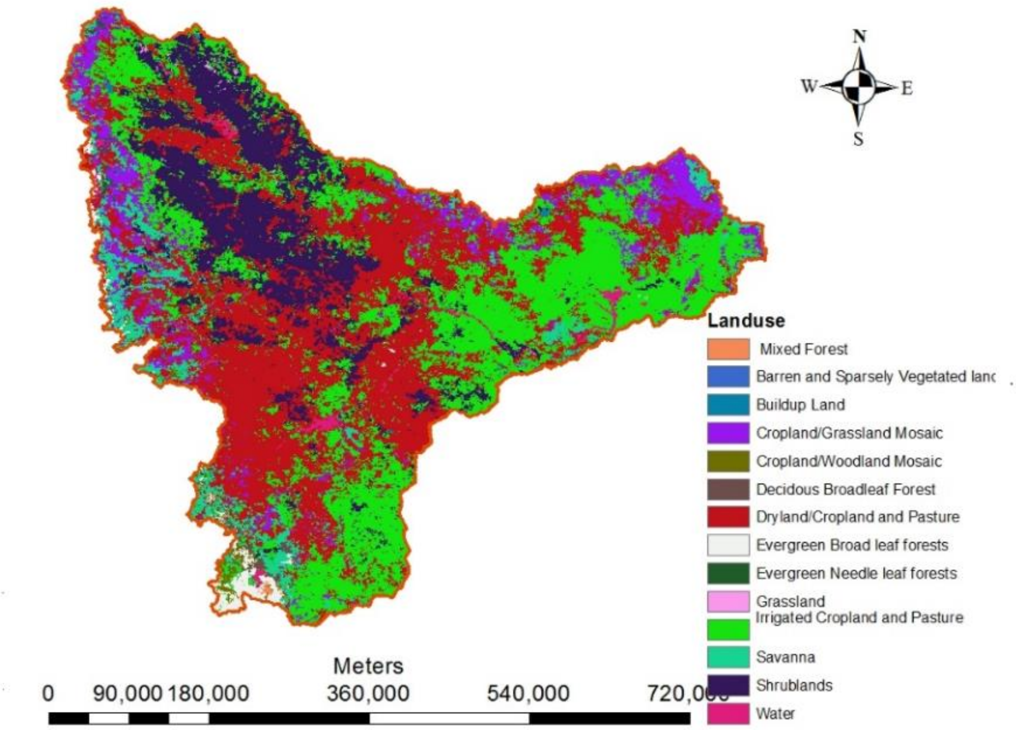


Figure 4.8 LULC map of the Krishna river basin

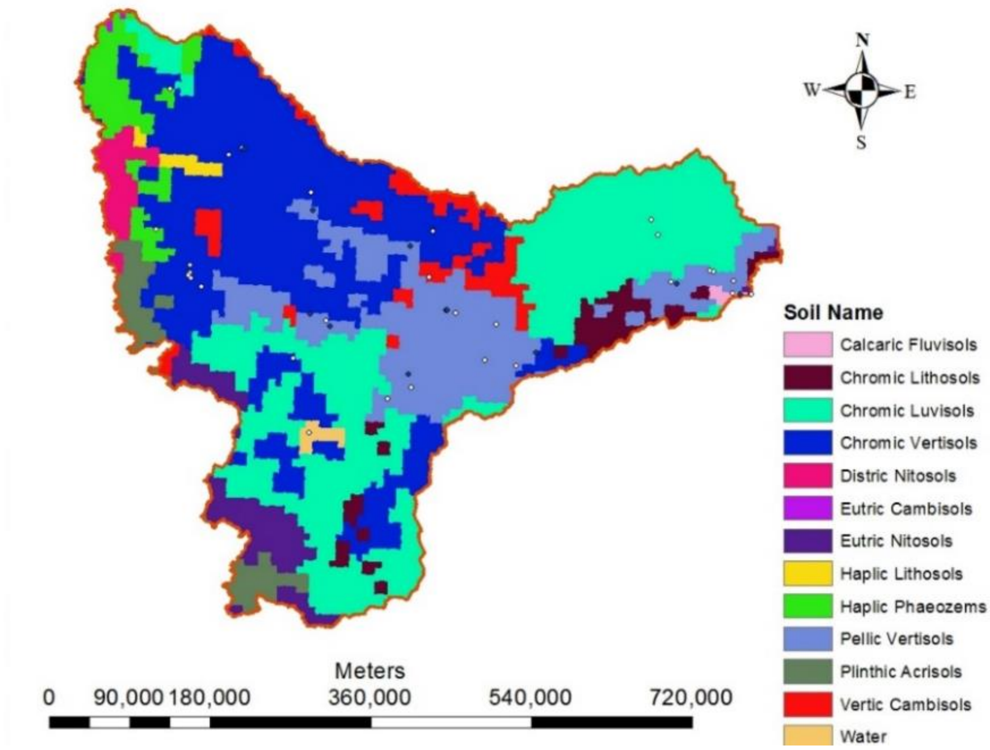


Figure 4.9 Soil map of the Krishna river basin

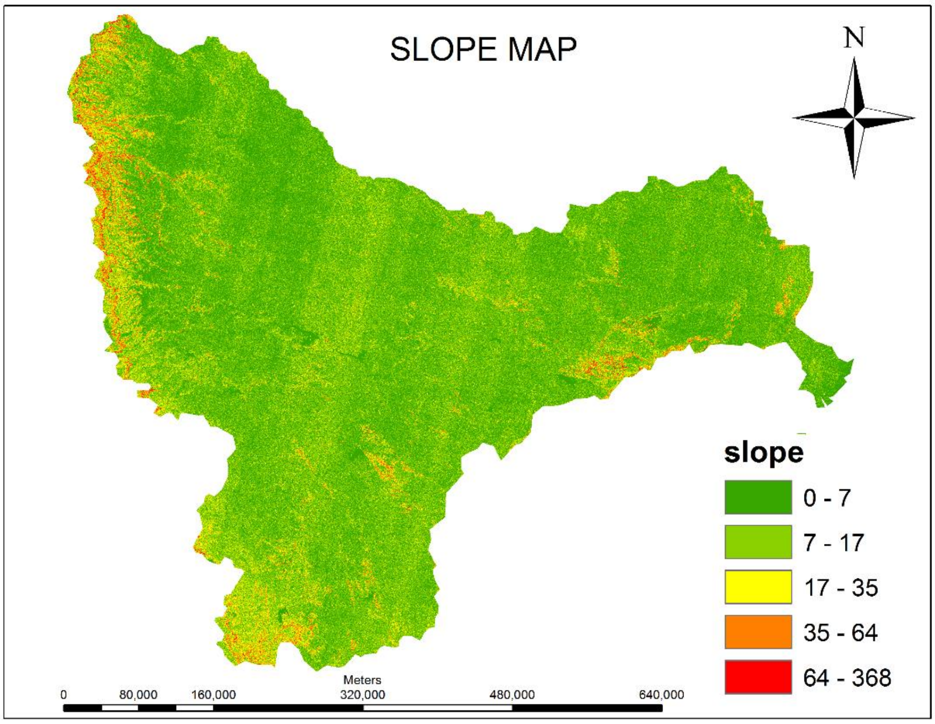


Figure 4.10 Slope map of the Krishna river basin

The total population of the Krishna river basin was 74.2 million as per 2011 census. Around 68% of the population in the basin lives in rural area with agriculture as the main source of livelihood (Sarma *et al.* 2011). Around 77% of the total geographical area of the basin is cultivable area with the main crops being rice, corn, cotton, sorghum, millet, sugar cane and a variety of horticulture crops. Increase in population results in high consumption of water for domestic and industrial purposes leading to stress on water resources of the basin. The major projects developed in all the states provoke interstate conflicts on water rights. According to (Biggs *et al.* 2007) the basin is under water stress due to consumption of more water than is available. They also suggest that it is essential to assess the monthly changes of climate parameters and their effect on the runoff for framing a water allocation policy for future use.

The observed meteorological data is retrieved for 132 grid points of 50 km x 50km resolution over the basin. Instead of using multiple climate model data, uncertainty modelled ensemble mean of the multi climate models is used for impact assessment of climate change on future streamflow projections.

4.4 Munneru Watershed

Lower Krishna basin consists of Paleru, Munneru and Musi river basins with the maximum area in Andhra Pradesh. Munneru is the left bank major tributary of the basin with a length of 195km, lying between latitudes 16°43'N to 17°52'N and longitudes 79°20'E to 80°35'E (Figure 4.11). It covers a catchment area of 10,409 km^2. The average temperature and precipitation of the watershed is 28°C/month and 988.64 mm/year between 1970 and 2005. The river plays a major role in providing water for irrigation and for domestic purposes. The decreasing trend in the annual runoff has been observed from 1991 due to changes in LULC and climate (Figure 4.12).

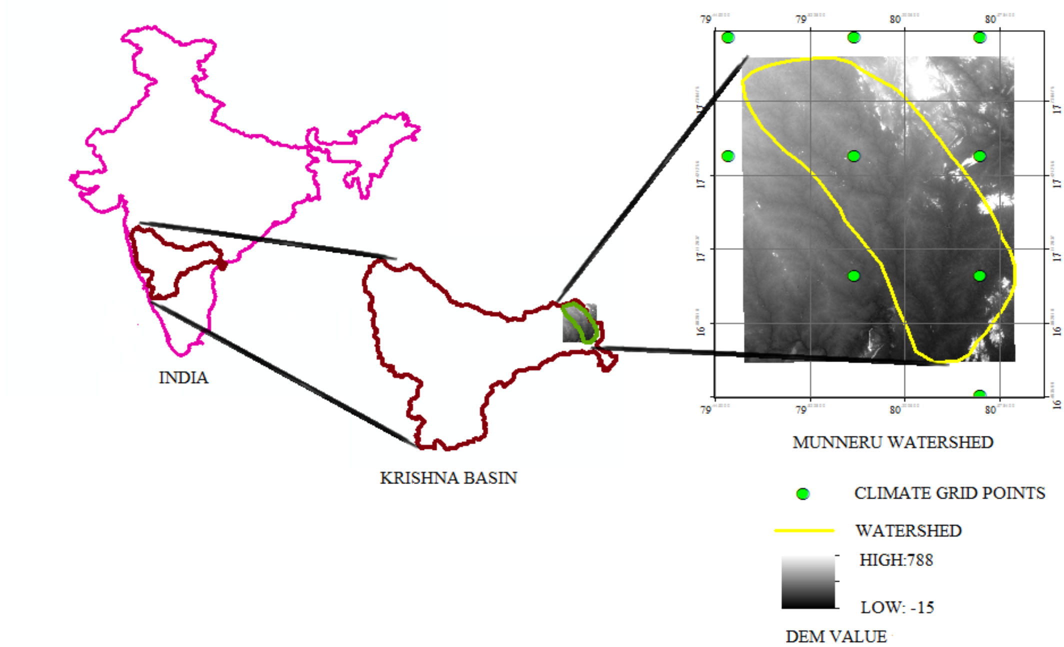


Figure 4.11 Location of the Munneru watershed with DEM

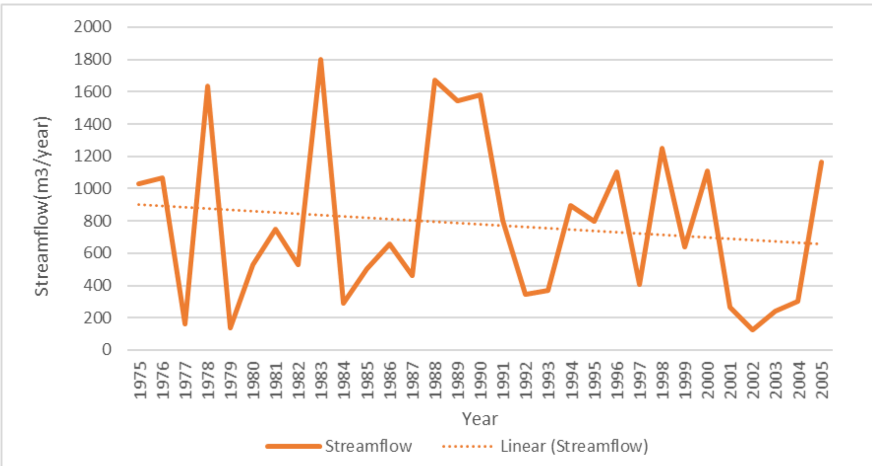


Figure 4.12 Observed annual streamflow at Keesara gauge station in Munneru watershed

In order to assess the combined effect of climate and LULC of watershed, multi temporal LULC maps of 100m resolution have been used. The decadal LULC maps (Figure 4.13 a,b,c) for 1985, 1995 and 2005 were used to detect changes in land use classification. Figure 4.13 (e, f) represent the change in the land use from 1985 – 1995 and 1995-2005. Land use of the watershed is mainly dominated by the cropland/irrigated land which is the main factor for Evapotranspiration. Conversion of barrenland to urbanland, cropland/woodland to the cropland / dryland are the major changes from 1985-1995. On the other hand, during 1995-2005 limited changes were observed compared to 1985-1995. LULC change from two decades is considered in simulating the water balance components of the study area. REA climate model data for 9 climate grid points of the Munneru watershed (Figure 4.11) have been used for the hydrological modelling and further analysis.

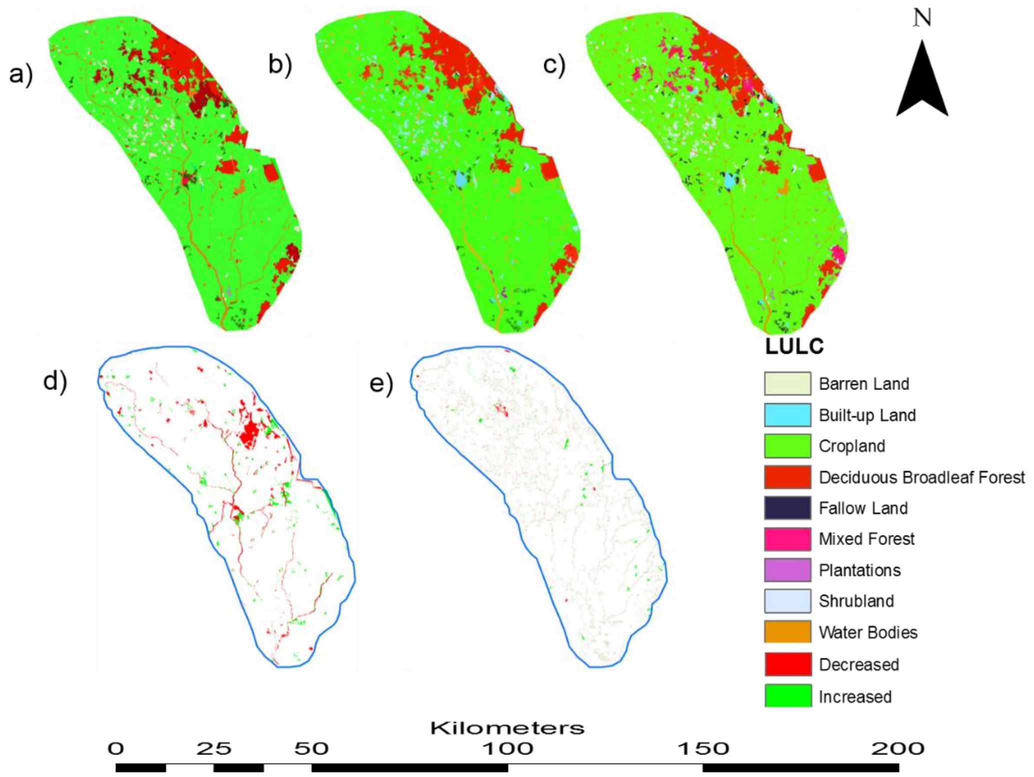


Figure 4.13 Decadal land use maps of the watershed a)1985 b)1995 c)2005 (https://daac.ornl.gov/VEGETATION/guides/Decadal_LULC_India.html). Change in the land use classes between d) 1985-1995 and e) 1995-2005.

4.5 Nagarjuna Sagar Dam

Nagarjunasagar dam is located in the Middle Krishna sub basin and situated downstream of Srisailam reservoir in Andhra Pradesh. It is a multipurpose project, comprising dam and two main canals, one each on either flank of the river. The catchment area at the dam is 215,193 km2; the annual rainfall in the catchment is 889 mm, the maximum observed flood is 30,050 cumec, and the design flood (return period 1,000 year) is 58,340 cumec. When the Nagarjunasagar reservoir is full, its backwater extends up to the Srisailam dam and covers an area of 285 sq. km. A view of Nagarjunasagar dam can be seen in Figure 4.14. Besides providing irrigation facilities to 22 lakh acres, the project was formulated to generate about 810 MW of hydropower. Subsequently, power units were constructed below the head sluices of right and left canal (Jawaharlal & Lalbahadur) for generating 150MW of power, increasing the total power generation to 960 MW. The project is conceived mainly to convert rain fed cultivation to irrigation agriculture in the districts of Nalgonda, Khammam, Krishna and west Godavari on left command and Guntur and Prakasham on right command. Table 4.1 presents the salient features of dam. The daily inflow and outflow of the reservoir obtained is verified for the missing values and the continuous data is considered for further analysis. The daily data was converted into monthly data based on the purpose of the study. Future streamflows simulated in the ArcSWATwere used for the designing of adaptation strategies.

Figure 4.14 A view of Nagarjuna Sagar dam

Table 4.1 Salient features of the Nagarjuna Sagar dam.

Location	
Latitude	$16^{\circ}84'$N
Longitude	$79^{\circ}19'$E
	It is about 2.4km away from Nandikonda village of Peddavoora Mandal, Nalgonda District, Andhrapradesh.
Hydrology	
Catchment area at dam site	83087 Sq. Miles (2,15,195 Sq.Kms.)
Design Flood	58,340 Cumec
Reservoir	
Full Reservoir Level	590.00 ft. (179.95 m)
Maximum Water Level	594.00 ft. (181.10 m)
MDD Level	510.00 ft. (161.58 m)
Gross storage capacity at El. +590.00 ft.	312.045 TMC
Dead storage capacity at El. +510.00 ft.	131.669 TMC
Live storage capacity	180.376 TMC
Water spread area	285 Sq.Kms

4.6 Closure

Wardha and Krishna river basins are chosen as the major study areas based on the availability of the spatial and meteorological data. Further, Munneru an agricultural watershed and Nagarjuna sagar dam are selected for impact assessment. The required geo database and meteorological data is prepared using ArcGIS and meteorological data in the required format to be used in ArcSWAT.

Chapter – 5

Model Setup

In order to study the hydrologic parameters with climate change, a physical based hydrologic model is required. Hence, SWAT model is calibrated and validated for all the study areas to simulate stream flow for the future periods.

5.1 Wardha basin

The DEM, soil and land use GIS layers are the inputs that influence SWAT model. The watershed has been divided into 43 sub basins and 549 HRUs based on uniqueness of land use, soil type and slope. The daily climate data observed from IMD including precipitation, maximum and minimum air temperature from 1980 to 2005 have been used to drive the model with a spin up period of 4 years. Stream flow data from 1984 to 1996 and 1997 to 2003 period have been used in calibrating and validating the model respectively by excluding the spin up period for analysis. The sensitivity of the parameters was measured using t-test, and the p-values of the global sensitive analysis. T-test values with large absolute values were more sensitive than lower ones, where p-value closer to zero had more significance. The Goodness of fit of the model was evaluated using R^2 and NSE. The best set of parameters with maximum R^2 and NSE obtained from SUFI-2 calibration period were used to drive SWAT for the historic period of 1975 to 2003 and future period of 2020 to 2099.

5.1.1 Calibration and Validation of SWAT Model

Table 5.1 presents details and fitted values of parameters applied for sensitivity analysis. Sensitivity analysis results project that few among the 17 parameters considered sensitive are applicable to the surface runoff, ground water, channel routing and soil properties. In this study, based on the t-test of the global sensitive analysis, CN2 (SCS runoff curve number), ALPHA_BF (Base flow alpha factor (days)), GW_DELAY (Groundwater delay (days)), ESCO (Soil evaporation compensation factor), EPCO (Plant uptake compensation factor) and SOL_AWC (Available water capacity of the soil layer) are the most sensitive parameters in the basin.

Table 5.1Best-fit parameters obtained from calibration of the model and their parameter significance.

Parameter	Nandgaon	Ghughus	Bamini
	Fitted value	**Fitted value**	**Fitted value**
R_CN2	**-0.2170**	**-0.1091**	-0.1403
V_ALPHA_BF	**-0.5944**	0.1170	**-0.5947**
V_GW_DELAY	278.7875	**29.1203**	**136.7822**
V_GWQMN	-17.8561	1.0609	-71.5096
V_GW_REVAP	0.1889	0.2427	0.1889
V_ESCO	**0.9764**	0.754	**0.678**
R_SOL_K	0.8688	0.2567	0.1547
V_ALPHA_BNK	0.1529	0.6611	0.1892
R_SOL_AWC	**-0.0816**	**0.1375**	0.0812
V_REVAPMN	4.7024	2.5232	5.0656
R_SOL_BD	0.4520	0.0927	0.4007
R_OV_N	-0.0516	-0.1331	-0.0465
V_CH_K2	68.1581	64.7485	81.7966
V_EPCO	**-0.6815**	-0.3766	**-0.6815**
R_HRU_SLP	0.1099	0.1225	0.1897
V_CH_N2	-0.0568	0.0565	0.0565
R_SLSUBBSN	0.1893	0.1893	0.1676

CN2: SCS runoff curve number ; ALPHA_BF: Baseflow alpha factor (days); GW_DELAY: Groundwater delay time(days); GWQMN: Threshold depth of water in the shallow aquifer required for returnflow to ocuur (mm); GW_REVAP: Groundwater "revap" coefficient; ESCO : Soil evaporation compensation factor; SOL_K: Saturated hydraulic conductivity in main channel alluvium (mm/hr); ALPHA_BNK: Baseflow alpha factor for bank storage (days); SOL_AWC: Available water capacity of the soil layer (mm); REVAPMN: Threshold depth of water in the shallow aquifer for "revap" or percolation to the deep aquifer to occur(mm); SOL_BD: Moist Bulk density (Mg/m^3); OV_N: Manning's "n" value for overland flow;

CH_K2: Effective hydraulic conductivity in main channel alluvium (mm/hr); EPCO: Plant uptake compensation factor; HRU_SLP: Average slope steepness; CH_N2:Mannings "n" value for the main channel; SLSUBBSN: Average slope length. WhereV__ represents that existing parameter value is to be replaced by the given value and R__ represents that existing parameter value to be multiplied by one plus a given value. Bold values represent the sensitive parameters.

The best parameters obtained from SUFI-2 iterations with optimum R^2 and NSE were adopted in SWAT. Bias corrected precipitation; maximum and minimum temperatures of RCMs were inputs to SWAT to simulate future stream flow. Quantification of the predicted stream flow and its variability of future periods have been carried out by dividing the total period into four twenty-year periods i.e., 2020 to 2039, 2040 to 2059, 2060 to 2079 and 2080 to 2099 at Bamini gauge station, which is the outlet of Wardha sub-basin. The monthly-simulated stream flow from SWAT model is compared with the observed stream flow during the calibration at three-gauge stations - Bamini, Ghughus and Nandgaon. The model was calibrated for the period 1984-1996 (Figure 5.1) and validated for the remaining 7 years of the dataset, i.e., 1997-2003 (Figure 5.2).

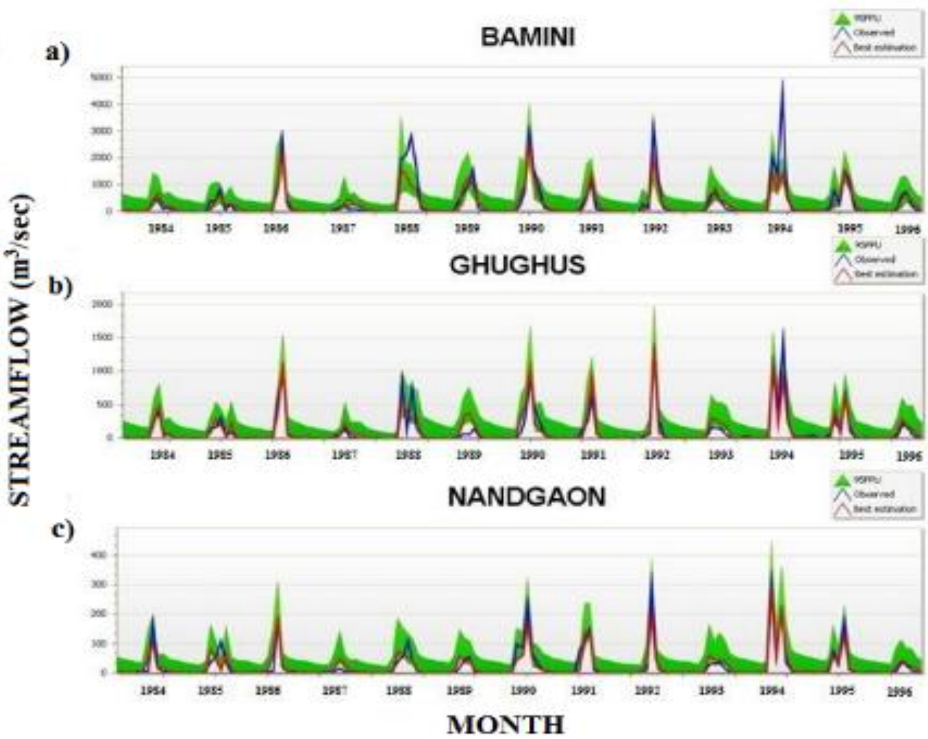


Figure 5.1 Best estimation and 95ppu of the Model for the calibration period.

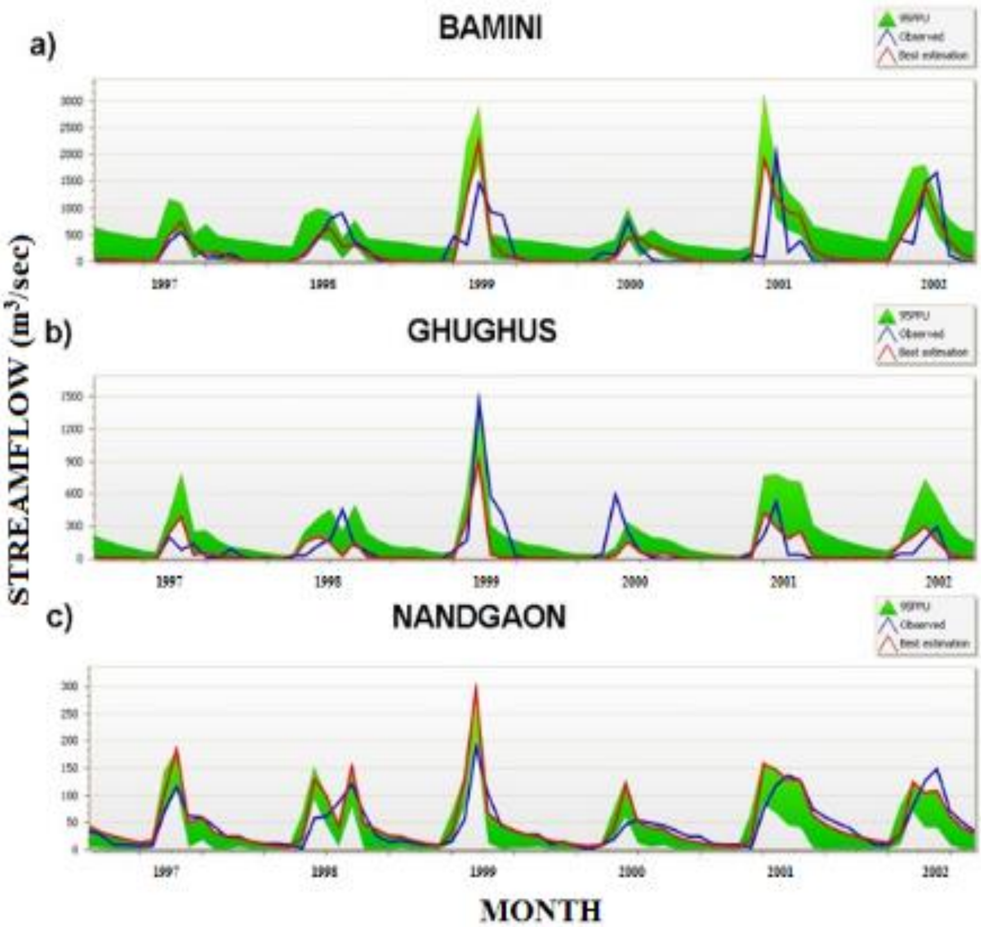


Figure 5.2 Best estimation and 95ppu of the Model for the validation period.

The 95% Prediction Uncertainty band represents 2.5% and 97.5% levels of the cumulative distribution of output variables. From Figure 5.1a, calibration results explain that the model is unable to predict the observed peak values in years 1986,1988,1989,1990, 1992, and 1994. For the validation period the model under predicted stream flow values (Figure 5.2a) in the basin from 200 to 2002. Similarly, under prediction of the model was observed in the Nandgaon gauge station and over prediction at the Ghughus gauge station during calibration and validation periods. From Figures 5.1&5.2, it is seen that the observed values of stream flow at the base flow part does not come under 95PPU band. The reason may be the constraint in simulating the Ground water flow of SWAT (Narsimlu *et.al* 2013). The variations of stream flow in calibration and validation periods at three-gauge stations with the monthly precipitation on the secondary axis are shown in the Figure 5.3 and 5.4.

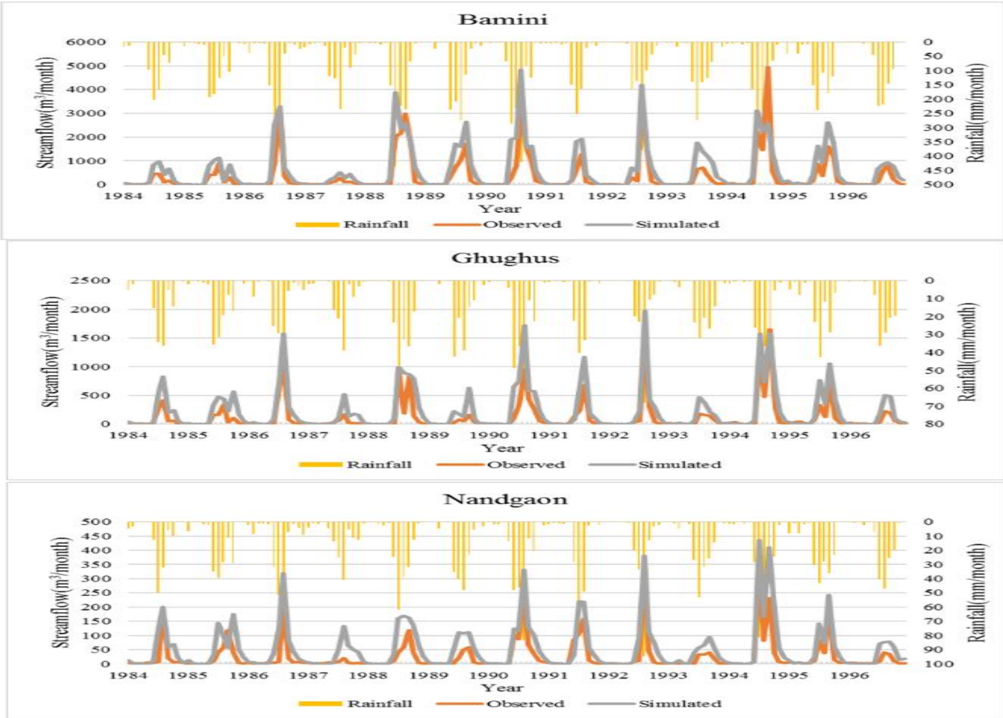


Figure 5.3 Monthly stream flow variations for the calibration period with Rainfall on the secondary axis

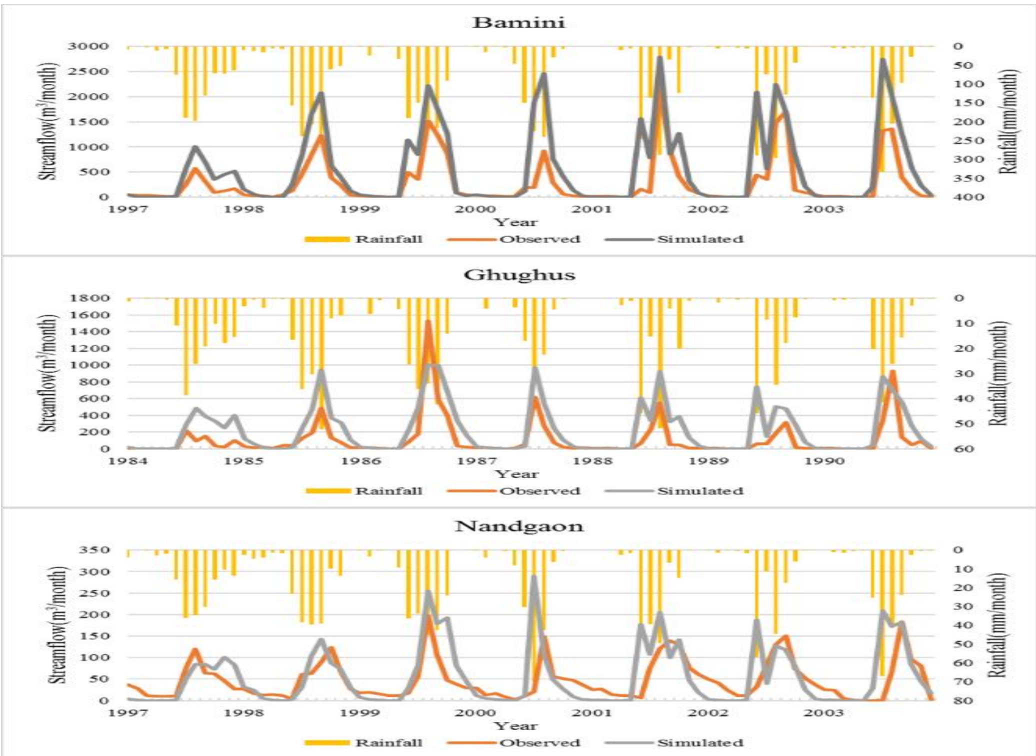


Figure 5.4 Monthly stream flow variations for the validation period with Rainfall on the secondary axis.

Table 5.2 presents R^2 and NSE of three-gauge stations using SUFI-2 Algorithm. NSE value greater than 0.75 is considered to be good and 0.36 as satisfactory (Nash and Sutcliffe 1970). The lower performance of the model during the validation period may be due to a mix of errors from observed and simulated stream flow, climate data, and changes in LULC. The mean monthly variations of the stream flow simulated using climate models for the historic period reveal that all the climate models underestimate the flows (Figure 5.5). Stream flow has been simulated using CCSM, MPIESM and NORESM models which are in similar pattern with the observed data with a decreased percentage change of around 21%, 42% and 40% respectively. It shows the range of uncertainty among the climate models for the Historic period, where CNRM and ACCESS models simulate peak stream flow values in the months of July and September, respectively. Simulated stream flow of climate models over predicts for the non-monsoon period and under predicts for monsoon season. Simulations using bias corrected climate model data show underestimation for July, August, September and October months, while the rest of the months are overestimated.

Table 5.2 Statistical parameters showing the efficiency of the Model

Gauge Station	Calibration		Validation	
	R^2	NSE	R^2	NSE
Bamini	0.78	0.74	0.7	0.50
Ghughus	0.84	0.84	0.51	0.50
Nandgaon	0.87	0.85	0.76	0.54

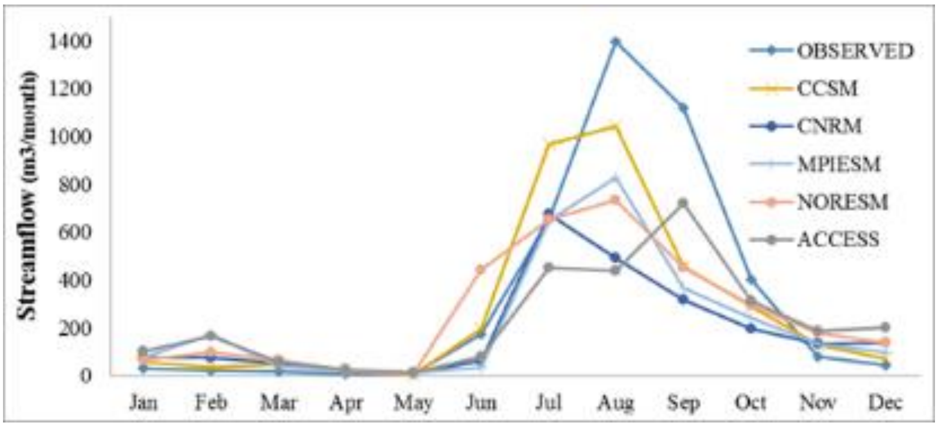


Figure 5.5 Mean Monthly variations of the stream flow for the Historic period.

5.2 Krishna basin

The geospatial and meteorological data shown in Table3.1 was used for model set up. SUFI-2 algorithm was adopted for the sensitivity and uncertainty analysis of SWAT model. 15 parameters were selected and used for the calibration process. The optimum range of the parameters obtained for calibration of the watershed with identical initial parameter ranges are shown in Table 5.3. For example, the initial range of ESCO (Soil Evaporation Compensation Factor) is 0.4 to 0.8, but the final range is 0.94, 0.55, 0.83, 0.46 and 0.62 for gauge stations Huvinhedgi, Narsingapur, Yadgir, Damercherla, and Keesara. Table 5.4 presents the R^2 and NSE values obtained of 5-gauge stations during the calibration and validation periods.

Table 5.3Parameter ranges of the five gauge stations for calibration and validation

S.No	Parameter	Initial	Final	Huvinhedgi	Narsingpur	Yadgir	Damercherla	Keesara
1	R__CN2.mgt	-0.20	0.20	-0.19	0.03	0.05	-0.17	0.17
2	V__ALPHA_BF.gw	0	1.00	0.20	0.96	0.95	0.16	0.26
3	V__GW_DELAY.gw	0	500	275	45	427	414	352
4	V__GWQMN.gw	0	5000	1.24	1.75	1.70	1050	1100
5	V__GW_REVAP.gw	0.02	0.20	0.19	0.19	0.17	0.16	0.14
6	R__SOL_K(..).sol	0.14	0.99	0.99	0.37	0.66	0.55	0.72
7	R__SOL_AWC(..).sol	-0.15	0.60	0.04	0.55	0.29	0.34	0.42
8	R__SOL_BD(..).sol	0.05	0.70	0.69	0.12	0.67	0.61	0.58
9	V__ALPHA_BNK.rte	0.00	1.00	0.60	0.40	0.43	0.36	0.65
10	V__CH_N2.rte	-0.09	0.09	0.09	0.11	0.08	0.07	0.04
11	V__CH_K2.rte	18.72	103.96	88.36	86.75	47.45	48.42	53.26
12	V__ESCO.hru	0	1.00	0.94	0.55	0.83	0.46	0.62
13	R__EPCO.hru	0	1.00	0.30	0.59	0.16	0.51	0.48
14	R__SLSUBBSN.hru	-0.12	0.30	0.13	0.09	-0.05	0.25	0.06

Table 5.4 Goodness of fit parameters for calibration and validation periods

Gauge Station	Calibration			Validation		
	R^2	NSE	PBias	R^2	NSE	PBias
Huvinhedgi	0.62	0.62	-13.5	0.42	0.42	79.8
Narsingapur	0.62	0.52	-41.9	0.5	0.47	-73.5
Yadgir	0.86	0.58	-27.1	0.4	0.32	-88.5
Damercherla	0.8	0.75	-8.35	0.58	0.43	-57.8
Keesara	0.68	0.62	-12.4	0.52	0.48	65.4

The performance of the model may be low due to combination of errors in Geospatial data including land use, soil map and climate data as well as error between the observed and simulated stream flow. However, when the R^2 and NSE values for the Calibration ranged from 0.52 to 0.86 and 0.32 to 0.58, the performance of the model was classified as good and satisfactory for the calibration and validation periods.

Comparison of observed mean monthly stream flow and those produced by SWAT driven by REA data at three gauge stations (Figure 5.6) ie., Huvinhedgi outlet of the Upper Bhima, Lower Bhima and Upper Krishna, Mantralayam outlet of the Upper, Lower Tungabadhra, and Pondugala the outlet of the Krishna river basin was carried out. The observed stream flows in July and August show more variation when compared to the simulated stream flow at Huvinhedgi, whereas at Mantralayam, other than in June and July, the model projects similar stream flows. Pondhugula gauge station at the downstream of Huvinhedgi and Mantralayam gauge stations shows similar pattern in the mean monthly stream flow with Maximum flows in the months of August, September and October. The errors in the mean monthly stream flow may be due to non-consideration of the reservoirs and the land use changes in Krishna river basin.

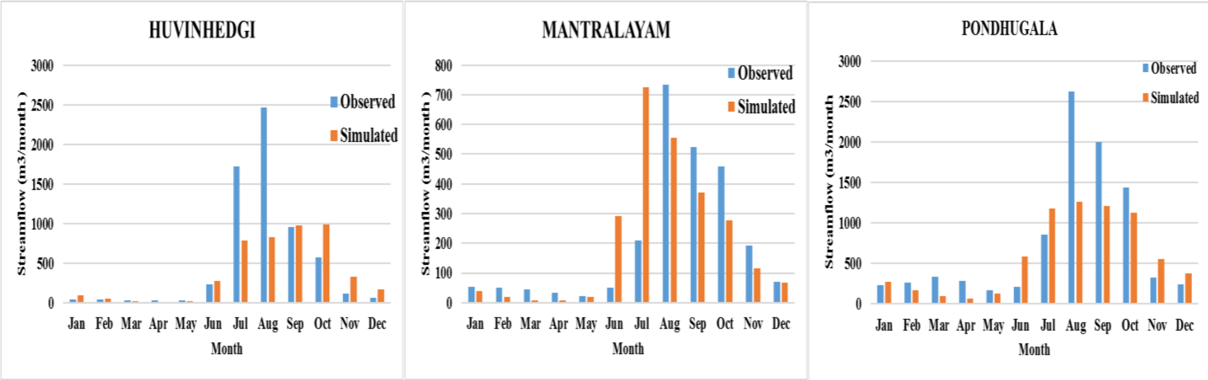


Figure 5.6 Observed and simulated mean monthly stream flow from SWAT for the historic period (1975 – 2005) at three-gauge stations.

5.3 Effect of Climate and LULC Change on Munneru Watershed

Human consumptive use of surface water resources, reduction in surface water base flows due to over abstraction of ground water and fewer releases to ocean are main factors for vulnerability of Krishna basin (Amarasinghe et al. 2007). It is also suggested that hydrological changes anywhere in the basin affects the lower Krishna adversely in terms of decrease in the total water availability and spatial redistribution of water during times of drought. Lower Krishna basin is the most densely populated part of the Krishna basin with three rivers Musi, Palleru and Munneru contributing to waterflow in the basin. Increase in domestic and industrial needs of urban areas and land use patterns are met with resources of the basin. The spatial variations of water balance components under climate and LULC change were evaluated. The bias corrected REA data and decadal change LULC were induced in calibrated and validated SWAT model to assess the variations of Water balance components spatially in the sub basin of Lower Krishna as shown in Figure 4.11. The SWAT model is calibrated and validated with the measured stream flow at Keesara gauge station using SUFI 2 algorithm in SWAT CUP.

The climate model for the future period i.e. until 2040 was used to simulate the variations in the water balance components in addition to land use change. The river plays a major role in providing sources for irrigation and domestic purposes. Decreasing trend in the annual runoff has been observed since 1991 due to changes in LU/LC and climate (Figure 4.12). The daily streamflow data from 1976 to 2005 at the Keesara gauging station were collected from CWC Hyderabad. The decadal variations in the land use were obtained from the LULC maps of the 1985, 1995, 2005 and changes (Figure 4.13) considered in the hydrological model SWAT.

5.3.1 Detection of LULC Change Over Time

Land use pattern of the watershed shown in Figure 4.13 indicates considerable change from 1985 to 1995 and insignificant changes between 1995 and 2005. The change in the land use classes of the study area between the decades are shown in Figure 5.7. It projects maximum change in the first two LULC maps. Urban land of the watershed in 1995 almost doubled i.e. to 91.6km^2 from 42.89km^2, whereas the Cropland/Dryland increased to 10.03km^2 from 1km^2 compared to the land use of 1985. Cropland / Woodland of the 1995 land use map reduced from 382.0259km^{2}to 280.42km^2. The remaining LULC projects fewer changes in 2005 compared to 1995 except Grassland.

5.3.2 Calibration and Validation of the SWAT

SUFI-2 optimizing technique was used to identify sensitive parameters, and to carry out calibration and validation of the model. The most sensitive parameters with their ranges and fitted values are shown in Table 5.5. Curve Number (CN2), Threshold depth of water in the shallow aquifer for "revap" to occur in mm (REVAPMN) and Base flow alpha factor (ALPHA_BF) identified as the sensitive parameters based on the p-value and t-stat. The R^2 and NSE obtained from the best simulation during the calibration is 0.81 and 0.79 whereas 0.75 and 0.72 were the values obtained during validation period. The 95 PPU plot of the observed and simulated stream flow with a certain range of uncertainty for the calibration and validation periods are shown in Figure 5.8. The mean monthly variations of the stream flow at the Keesara gauge station for the Historic periods (Figure 5.9) show a good correlation with Baseline period.

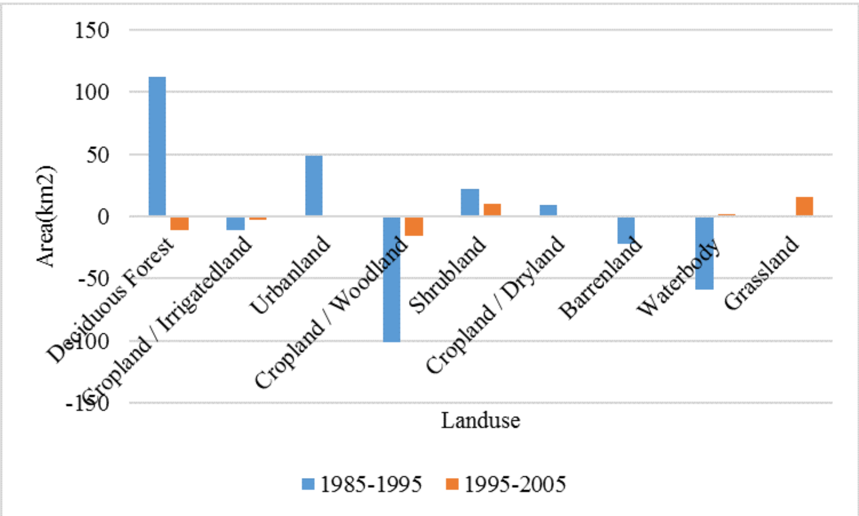


Figure 5.7 Decadal relative change (percentage) in the land use type of the watershed

Table 5.5 Sensitive parameters with the optimum values

Parameter_Name	Fitted_Value	Min_value	Max_value
R__CN2.mgt	0.035	0	0.2
V__ALPHA_BF.gw	0.925	0	1
V__GW_DELAY.gw	82.5	30	450
V__GWQMN.gw	687.5	500	2000
V__ESCO.hru	0.585	0.5	0.7
V__EPCO.hru	0.705	0.6	0.8
V__REVAPMN.gw	92.5	0	100

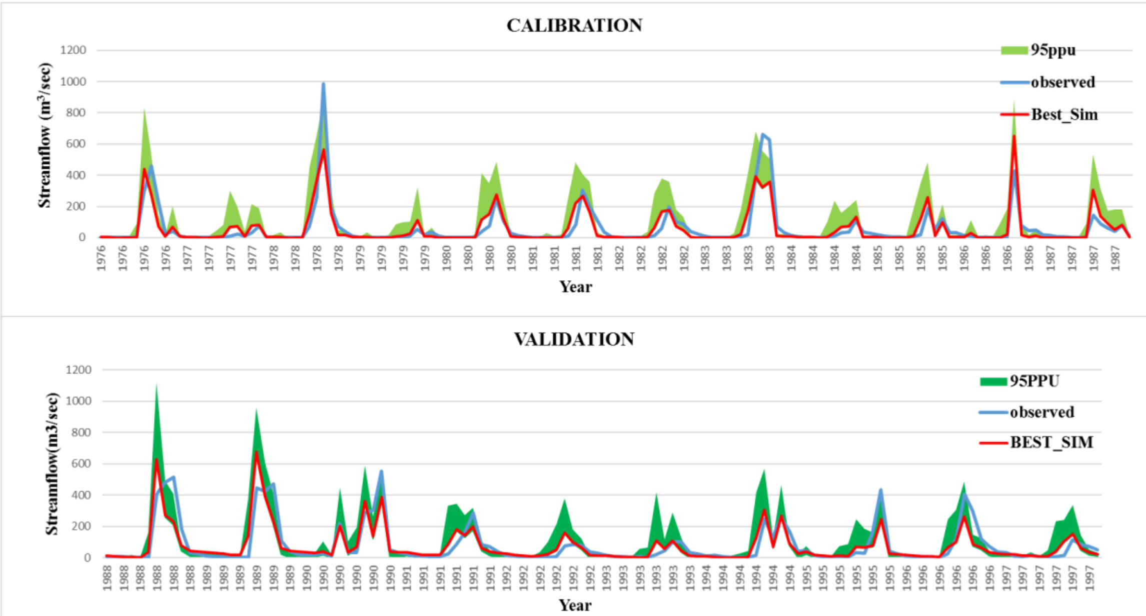


Figure 5.8 Calibration and Validation of the Monthly stream flow with 95PPU

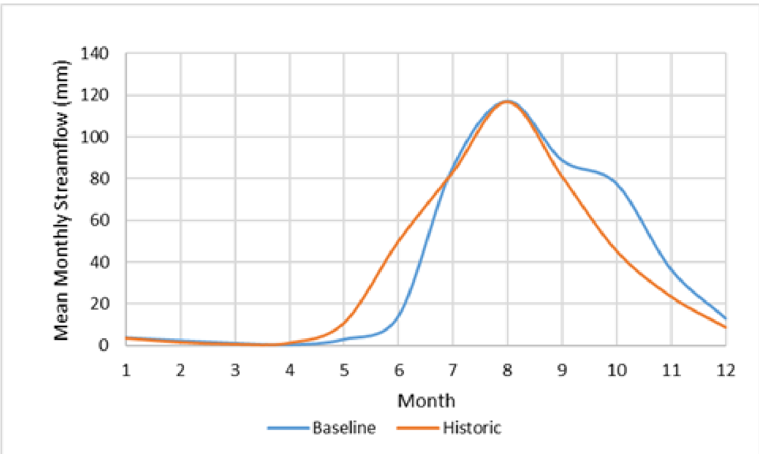


Figure 5.9 Monthly Stream flow variations for the Baseline and Historic periods.

5.4 Closure

In this chapter, climate change impact on the stream flow of Wardha, a subbasin of Godavari river, was analysed using multi climate model database of two scenarios using SWAT. Effect of the uncertainty modelled ensemble climate model on Krishna River with respect to Drought analysis was investigated. The results of LULC and climate change on an agricultural watershed has also been discussed in this chapter.

Chapter – 6

Results and Discussion

6.1 General

While climate model database is processed for bias correction and uncertainty, ensemble-using REA is applied to different basins to evaluate its effect on the water resources using SWAT model as described in chapter 3. The results are used to develop adaptation policies for reservoir operation system using stochastic dynamic programming for future projections.

6.2 Inter and Intra Annual Streamflow Variations in Wardha Basin

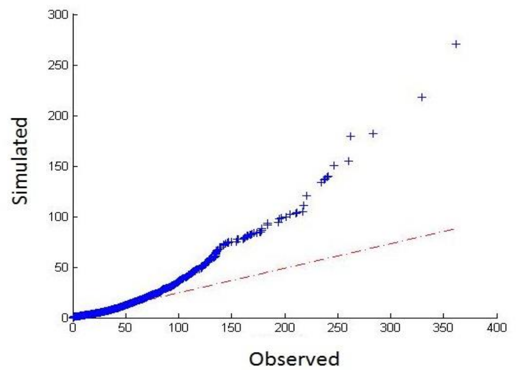
Regional differences in meteorological conditions, pollutant sources, water management, physiographic setting and interaction with local scale land use are the causes for variations in hydrologic components. Decrease in mean precipitation in the sub-tropical regions is predicted due to increase in the mean temperature. Increase in temperature and change in precipitation patterns are the most commonly predicted issues regarding variations in the hydrologic parameters in future. The effects of climate change include seasonal variation in stream flow, changeover in extreme high and low flow events and deviation in ground water recharge (Jha et al. 2004; IPCC 2014). Streamflow, precipitation, temperature, ground water recharge are important water balance components affecting the management of resources. Hence, inter and intra annual variations of streamflow and other water balance components in Wardha basin (Figure 4.1) for the historic and future periods are analyzed using multiple climate model database under RCP 4.5 and RCP 8.5 scenarios.

Climate data from multiple models (Table 4.2) are retrieved using the methodology given in Chapter 3 and bias corrected using non-parametric quantile mapping method. Figure 6.1 presents the quantile plot comparing uncorrected and corrected precipitation data of a grid point in the basin. The same procedure of bias correction is applied for all the climate models at 32 grid points.

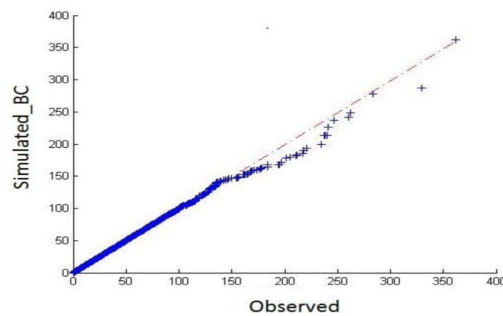
The efficiency of the bias corrected precipitation data using non-parametric quantile mapping is expressed in terms of monthly average precipitation (mm) as shown in Figure 6.2. It shows that four out of five climate models i.e., CCSM4, CNRM, MPIESM, NORESM simulations are similar to observed precipitation data with 50% of the data ranging between 800mm to 1200mm. Climate model data for future period is bias corrected using the fitted distribution parameters obtained by the bias corrected climate models for the historic period of each grid.

6.2.1 Streamflow of future period

Five climate models under RCP 4.5 and four climate models under RCP 8.5 scenarios were used to simulate the Future streamflow between 2020 and 2099. Analysis of the future predictions of the streamflow is carried out by dividing the period 2020-2099 into four 20year periods: Future1 (2020-2039), Future 2(2040-2059), Future 3(2060-2079) and Future 4(2080-2099) which were then compared with the Historic period (1984-2003). Absolute values of the streamflow of nine climate models for all future periods present high values under RCP 8.5 than RCP 4.5 as shown in Figure 6.3. Future 2 period projects the maximum streamflow compared to historic period under RCP 4.5 scenario i.e., 1101.14m^3/month where all Models under RCP 8.5 scenario project highest maximum streamflow i.e. around 4000m^3/month for all future periods. Shift in the peak flows were also observed in the climate models for Future periods (Figure 6.3) from August to July under RCP 4.5 scenario.



a) Before bias correction



After bias correction

Figure 6.1 Nonparametric Quantile mapping of Precipitation data for a grid point

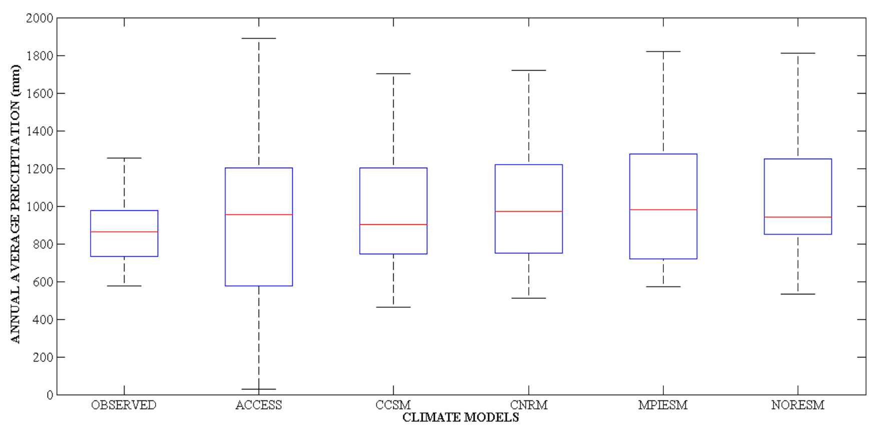


Figure 6.2 Changes in the annual average precipitation of climate models compared to observed precipitation.

The variations in the stream flow for future periods are studied using two parameters i.e., Inter and Intra annual coefficients of variations (chapter 3) between the Historic and Future periods (Table 6.1 & 6.2). The coefficient of variation is a measure of the sample that describes the quantity of variability with respect to the mean. For example, inter annual variabilities of the observed data and ACCESS data for historic period are 0.46 and 0.37 respectively, which reveals that monthly variation in streamflow is lower in ACCESS model as compared to the observed data.

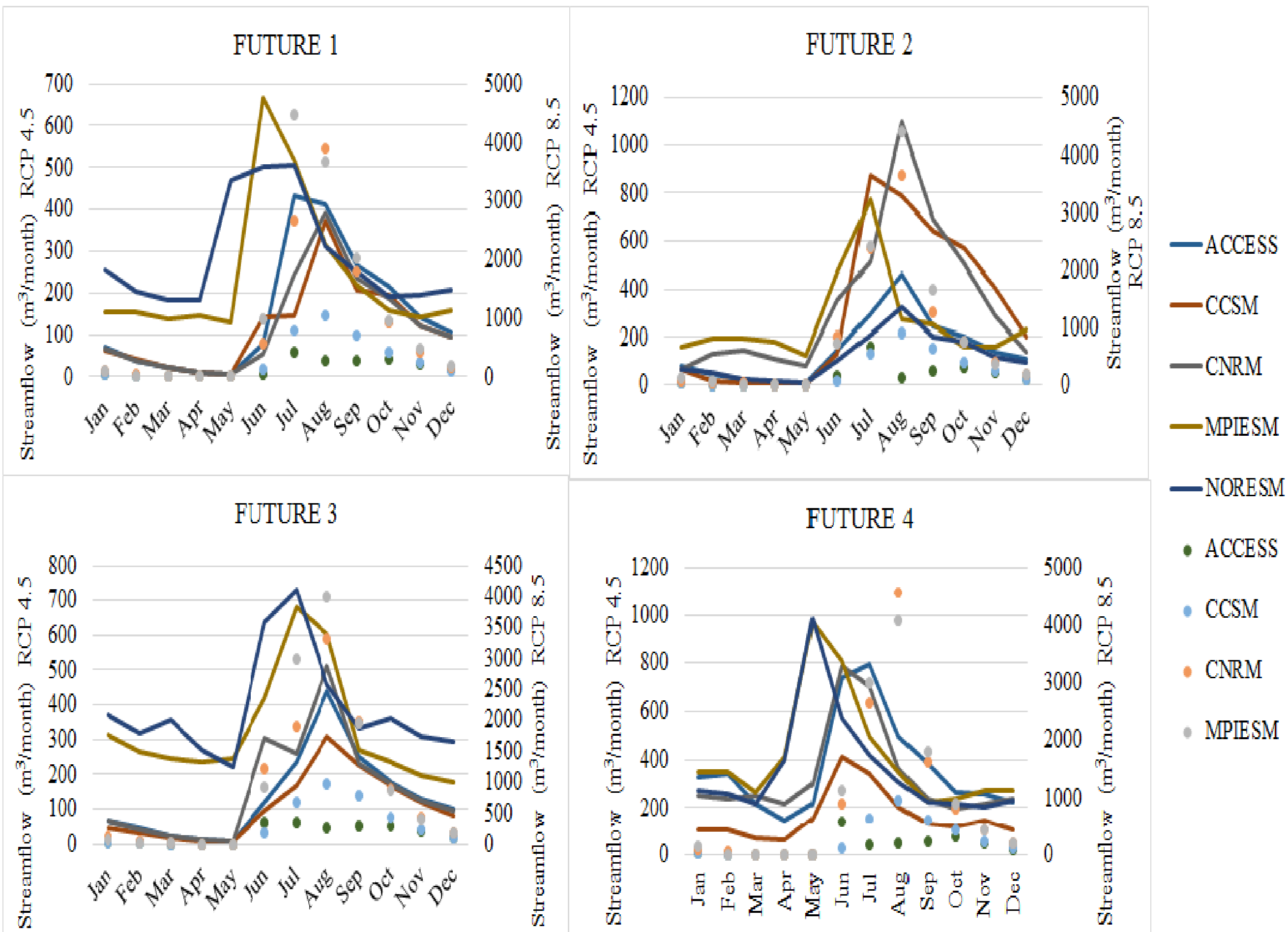


Figure 6. 3 Simulated streamflow changes using 5 models under RCP 4.5 (solid line) and 4 models under RCP 8.5 (scatter plot) from 2020-2099

Table 6. 1 The inter-annual variability of the streamflow in Wardha river for the Historic and Future periods.

Year	Observed	RCP 4.5					RCP 8.5			
		ACCESS	CCSM	CNRM	MPIESM	NORESM	ACCESS	CCSM	CNRM	MPIESM
1985-2003	0.46	0.37	0.49	0.68	0.493	0.35	--	--	--	--
2020-2039		0.40	0.38	0.44	0.35	0.38	0.65	0.47	0.36	0.65
2040-2059		0.26	1.16	0.38	0.42	0.36	1.01	0.50	0.47	0.36
2060-2079		0.40	0.44	0.49	0.38	0.43	0.96	0.50	0.40	0.29
2080-2099		0.63	0.768	0.41	0.31	0.31	1.22	0.53	0.60	0.56

Table 6. 2 The intra-annual variability of the streamflow in Wardha river for the Historic and Future periods.

Year	Observed	RCP 4.5					RCP 8.5			
		ACCESS	CCSM	CNRM	MPIESM	NORESM	ACCESS	CCSM	CNRM	MPIESM
1985-2003	1.32	1.09	0.99	0.98	0.89	0.80	--	--	--	--
2020-2039		1.09	1.14	1.08	1.00	0.79	1.38	1.46	1.54	1.59
2040-2059		1.16	1.12	1.04	0.95	0.83	1.48	1.35	1.57	1.60
2060-2079		1.03	1.03	1.18	0.93	0.74	1.45	1.46	1.45	1.62
2080-2099		0.81	0.91	0.95	0.87	1.01	1.50	1.39	1.6	1.57

Most of the Inter annual variations of the streamflow in Wardha river show increase in future under RCP 8.5 scenario and produce decreased values for intra annual variations (Table 6.1 & 6.2). The changes in precipitation in terms of frequency and magnitude and LULC characteristics are the main factors, which affect streamflow. However, in this study LULC was kept constant throughout the simulations for the historic and future periods. Increase in inter and intra annual variability values may be due to changes in minimum and maximum values of the streamflow simulated using climate models.

Figures 6.4 & 6.5 illustrate Inter annual variability of streamflow showing the range of minimum, median and maximum values for one Historic and four Future periods. Among the five models, two models i.e., ACCESS and NORESM project lower variations in the Historic period. Maximum inter annual variation of value greater than 1 is observed in CCSM (4.5) and ACCESS (8.5) for Future 2 period representing higher values of annual average streamflow in Future period 2 compared to other three periods.

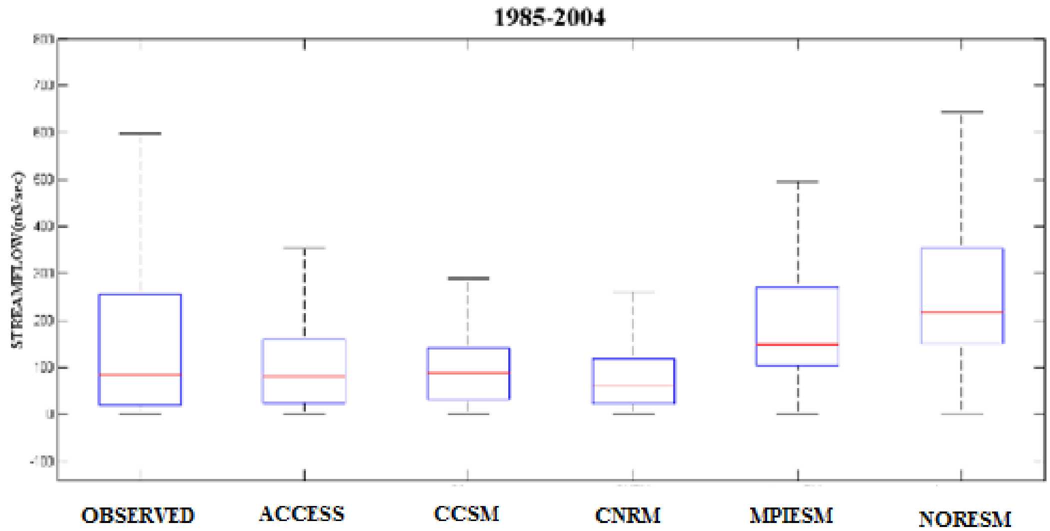


Figure 6.4 Changes in the mean, minimum and maximum inter annual streamflow values of climate models for Historic period

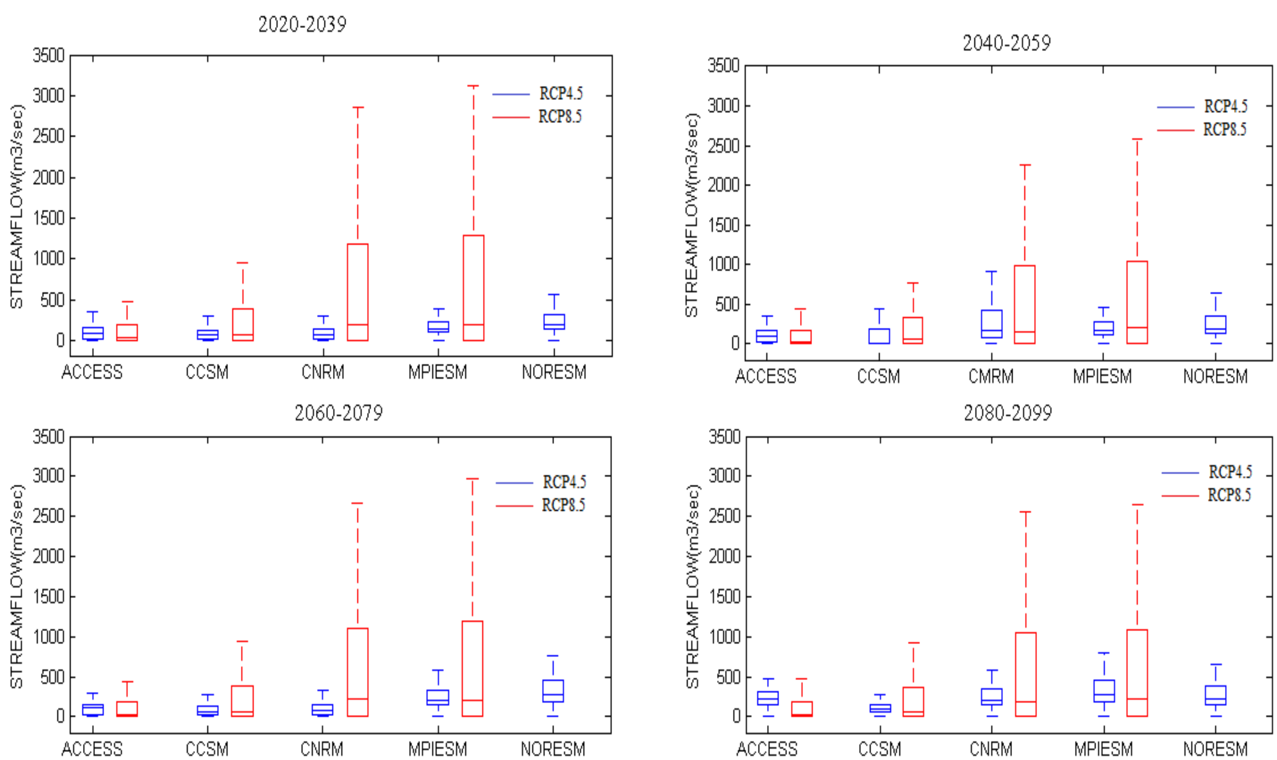


Figure 6.5 Changes in the mean, minimum and maximum inter annual streamflow values of climate models a) Future1 b) Future 2 c) Future 3 d) Future 4

Majority of the intra annual streamflow values i.e. around 78%, have values greater than 1 projecting the maximum variations in monthly streamflow values for future periods. Figures 6.6 to 6.11 represent variations of the monthly streamflow values from June to November for historic and future periods. Lower *CV* values produced in Future 4 period (Table 6.2) explain minimum variation of streamflow in five models under RCP 4.5 scenario. Maximum value of greater than 1 for the historic and future periods is justified as the high values show more variations in the monthly streamflow and low values fewer variations. Monthly variations of streamflow for the historic period (Figure 6.6) illustrate the shift in peak monthly flows i.e., from August to June for CCSM and CNRM models.

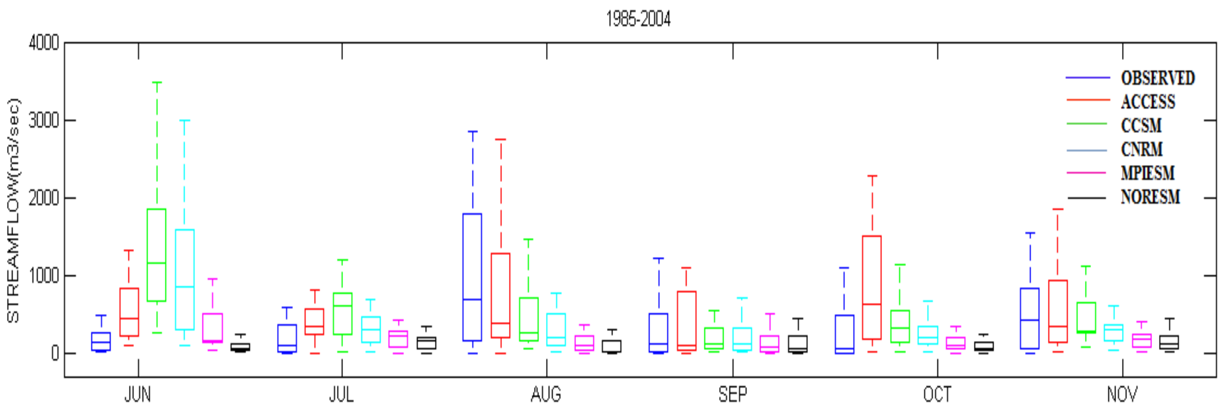


Figure 6.6 Monthly variations of streamflow of five climate models for Historic period

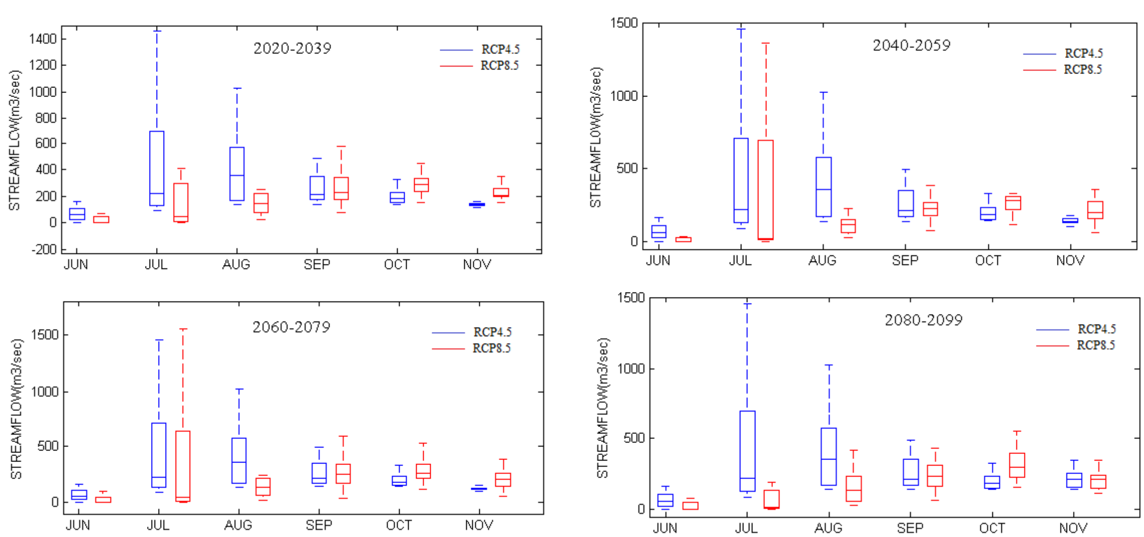


Figure 6.7 Monthly variations of streamflow of two scenarios for four future periods of ACCESS model

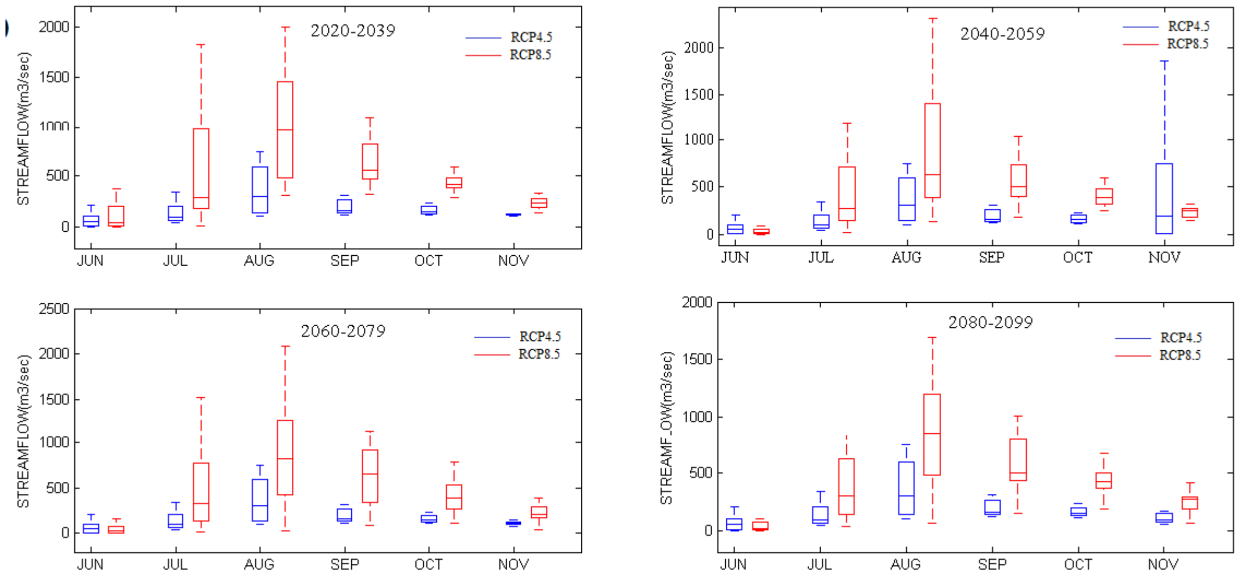


Figure 6.8 Monthly variations of streamflow of two scenarios for four future periods of CCSM model

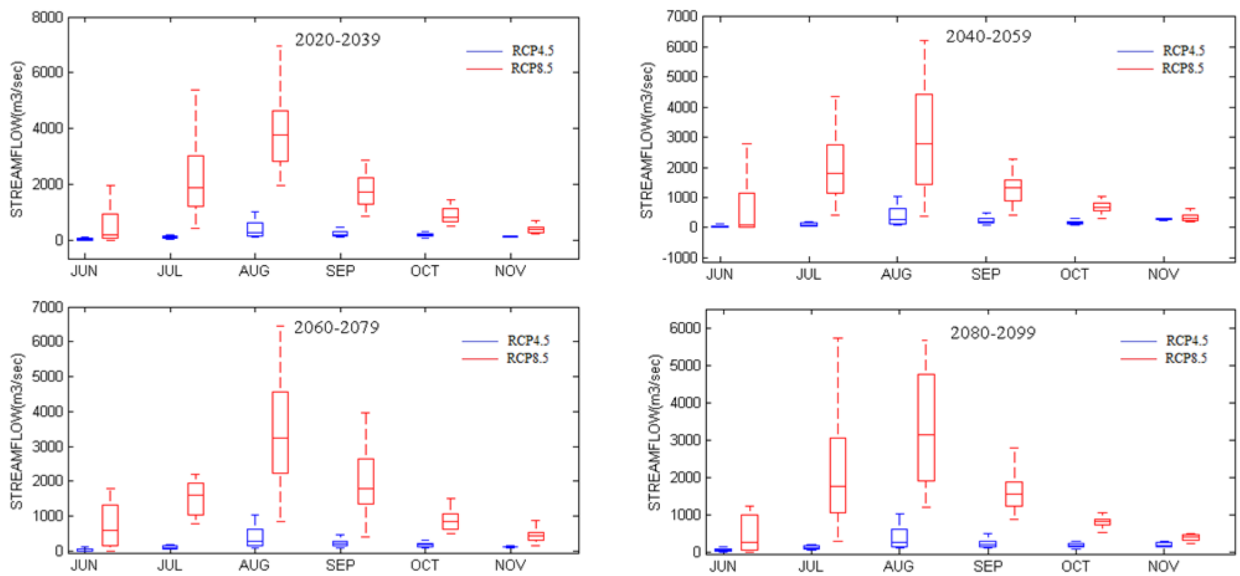


Figure 6.9 Monthly variations of streamflow of two scenarios for four future periods of CNRM Model

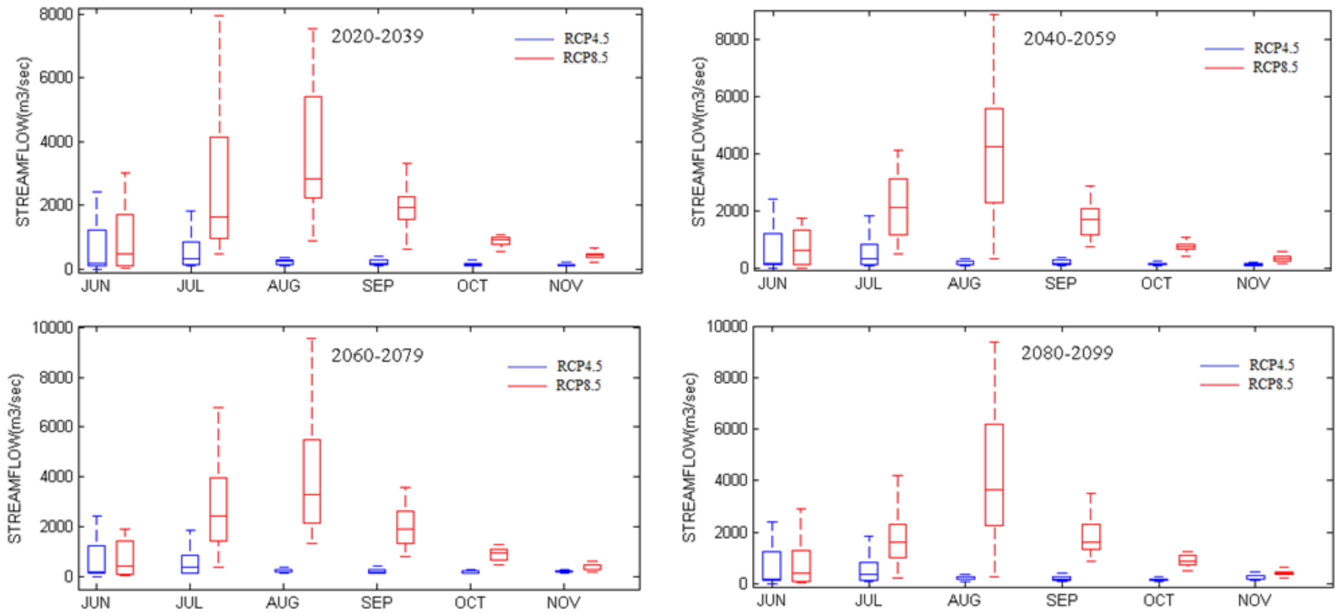


Figure 6.10 Monthly variations of streamflow of two scenarios for four future periods of MPIESM Model

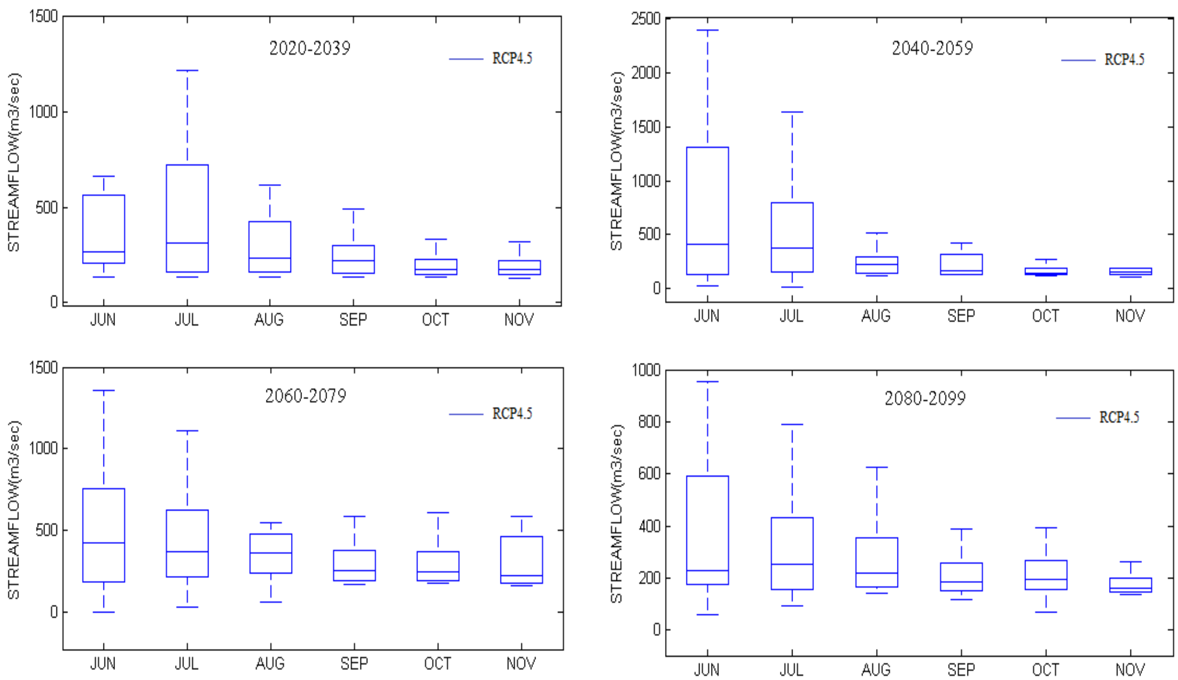


Figure 6.11Monthly variations of streamflow using NORESM for four future periods.

Figure 6.7 shows monthly variations of the streamflow for ACCESS model under RCP 4.5 and RCP 8.5 scenarios. Streamflow values exhibit peak values in July with highest values using RCP 4.5 and low values in RCP 8.5 scenario compared to other models. Maximum variations in streamflow are projected in CNRM and MPIESM models between RCP 4.5 and RCP 8.5 scenarios with a similar trend. Figure 6.11 shows the shift in peak streamflow from August to June for all future periods compared to historic period.

The analyses of the annual and monthly streamflow variations suggest that RCP 4.5 scenario produces lower variations of streamflow under decreased precipitation and increased temperature without considering changes in LULC. Among the five models, ACCESS and CCSM under predict while the other three models CNRM, MPIESM and NORESM predict high streamflow variations. The results from this study suggest decrease in the variations with varying climate change. Consideration of LULC change may lead to decrease in the variation. Uncertainty in the streamflow variations can be reduced by considering the ensemble model data for better management and mitigation of the impact of climate change on watershed.

In addition to the streamflow variability, the effect of climate change on water balance components has been analysed. Figure 6.12 emphasizes variations in four water balance components (Evapotranspiration (ET), Base flow, Surface Runoff and Ground water recharge) annually for the Historic period. It reveals that decrease in the temperature leads to increase in the surface runoff in the basin. NORESM model projects similar results whereas other models CCSM, CNRM and MPIESM show 50% decrease in components compared with observed data. Water balance components of climate models under RCP 4.5 (Figure 6.13) and RCP 8.5 (Figure 6.14) are shown for all Future periods. The maximum values of Evapotranspiration and Base flow with a reduced Surface runoff and Ground water recharge in Figure 6.13 explain increase in temperature when the pattern of rainfall is similar in Future periods. Changes in the water balance components may be altered with consideration of changes in land use and land cover with time.

Figure 6.14 illustrates the variations in the water balance components projecting maximum streamflow values by CNRM and MPIESM models compared to other two models. It explains how RCP 8.5 scenario changes with increase in rainfall and decrease in temperatures in the basin. ACCESS and CCSM results project low streamflow values with high values of ET and Base flow and project increase in temperature values.

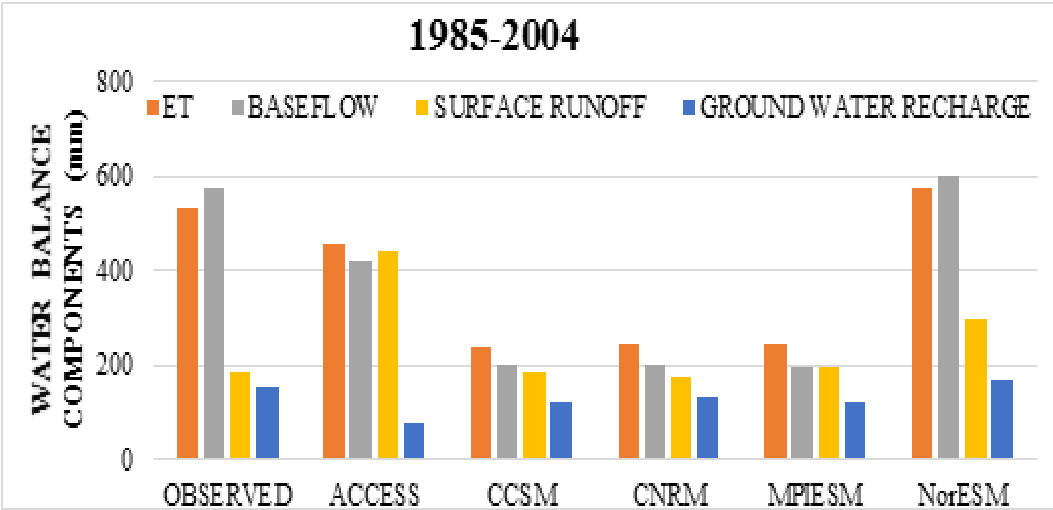


Figure 6.12 Water balance component's values of different climate models for Historic period.

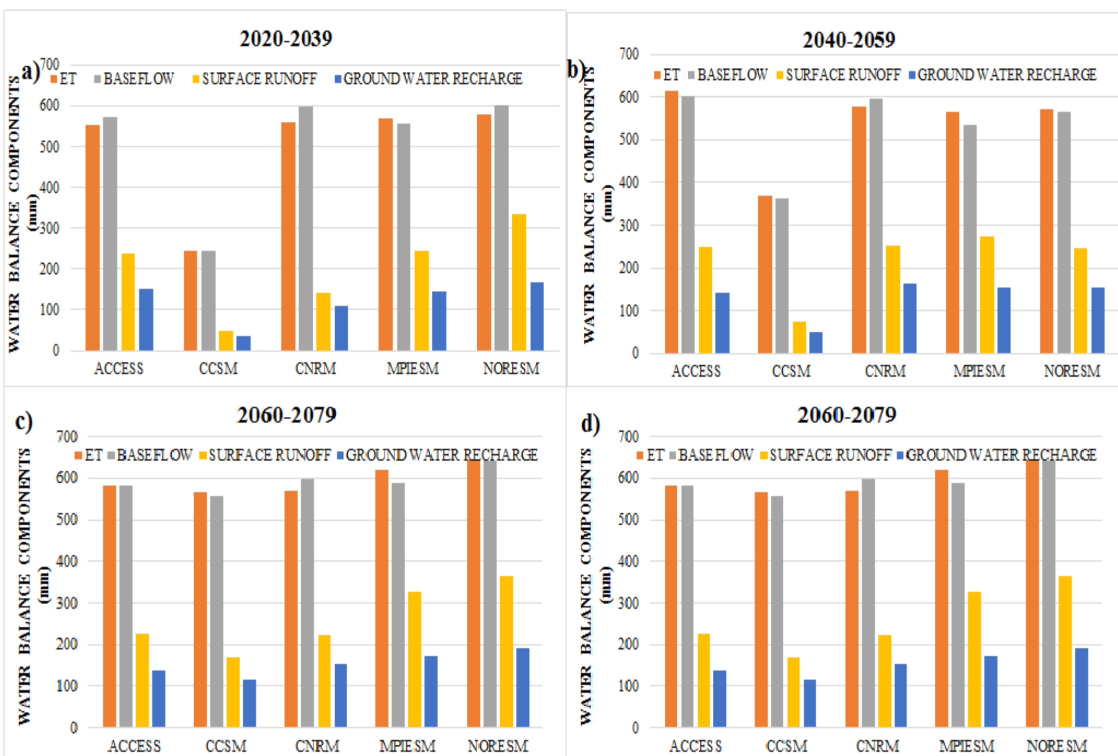


Figure 6.13 Water balance component's values of different climate models under RCP 4.5 scenario for four Future periods.

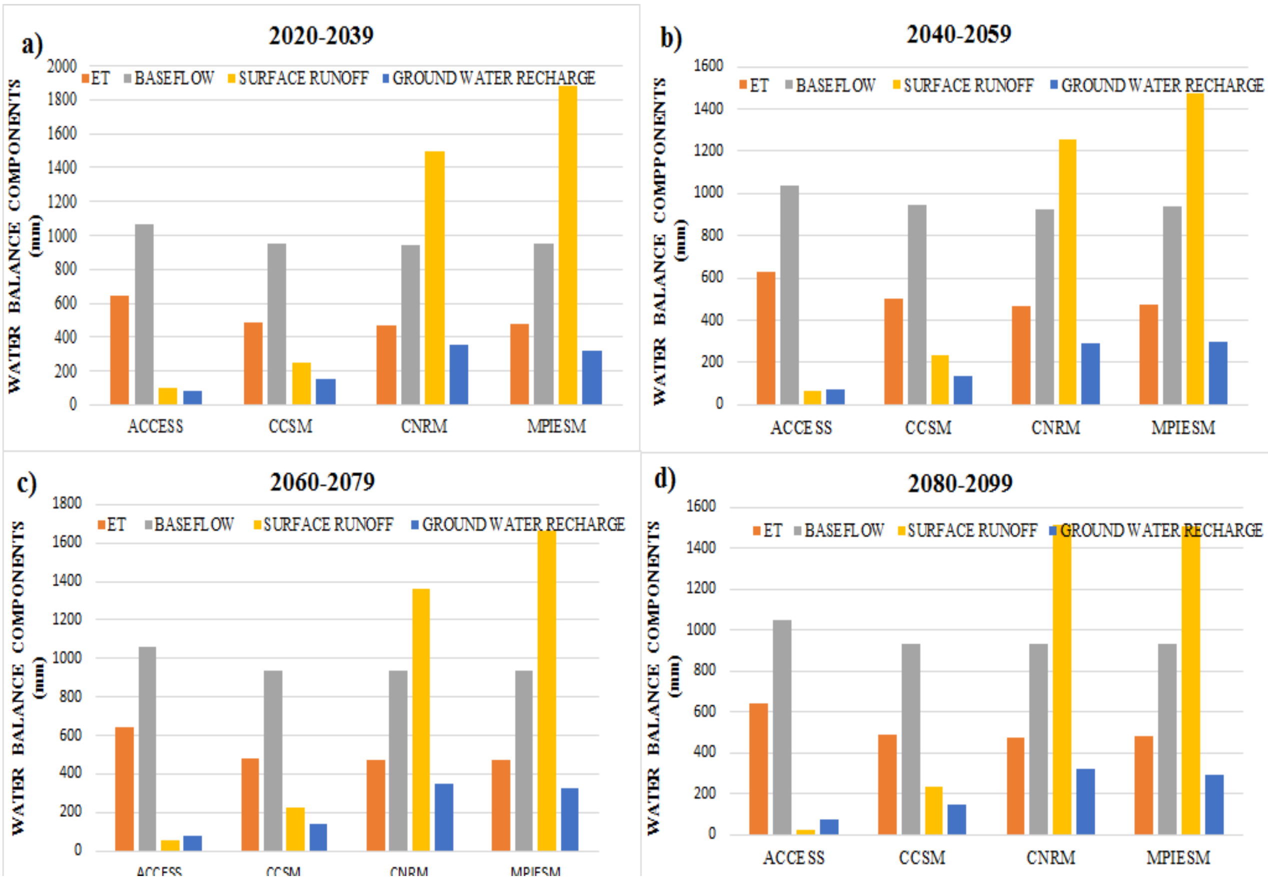


Figure 6.14 Water balance component's values of different climate models under RCP 8.5 scenario for four Future periods.

Overall, it can be inferred from the above results that variations in water balance components in the basin is mainly due to changes in temperature and precipitation values. Changes in the hydrology of the basin can be balanced by encouraging efficient resource management techniques and adaptation approaches.

6.3 Future projections of streamflow under changing climate

The basic objective of this study was to predict streamflow variations and to assess the climate change impact at sub basin level in Krishna river basin (Figure 4.1). Based on the availability of data, spatial and temporal variations of the climate parameters and streamflow were analysed without considering any manmade structures such as dams, diversions, etc. Though, many studies have been employed to estimate the impact on water resources using various GCM and RCM data, the need for uncertainty reduction in multi models is described in the literature (Chapter 2). Therefore, uncertainty was modelled using REA and bias corrected climate data was used in calibrated and validated SWAT model to project future streamflows. The climate model data obtained from five RCMs of RCP 4.5 and 4 models of RCP 8.5 scenarios were used in developing REA of the models. The REA precipitation as well as minimum and maximum temperature data were used to simulate the streamflow for future to assess the impact of climate change. The annual and seasonal variations of the climate parameters and streamflow were analyzed for the period from 1975 to 2100. Trend analysis of the streamflow in the basin at sub basin level was carried out using Man-Kendall trend test for all the future periods.

6.3.1 Future projections of REA climate data

Comparison of the observed and simulated REA precipitation as well as maximum and minimum temperatures before and after bias correction was carried out. Results suggest that the observed and simulated REA temperature values are in good agreement where the precipitation data projects the same results after reducing the biases using Q-Q mapping. The climate parameters obtained are for the period 1975-2099. The analysis was carried out by dividing the total period into four of 25 years as Historic (1980-2004), Future1 (2020-2044), Future2 (2045-2069) and Future3 (2070-2094). The annual average precipitation in (mm/year) for the Historic and Future periods of two scenarios are shown in Figure 6.15. The annual average variations of precipitation show an increase in Western part of the basin in Future 1 and lower values for Future2 period under RCP 4.5. Decrease of 36% in annual average precipitation is observed in Future1, 10% increase in Future2 and 60% decrease in Future3 periods under RCP8.5 scenario. Daily minimum and maximum temperatures within the basin show average higher values with an increase of 6 °C in future periods compared to the historic period. Future2 period projects higher temperature values compared to other two future periods.

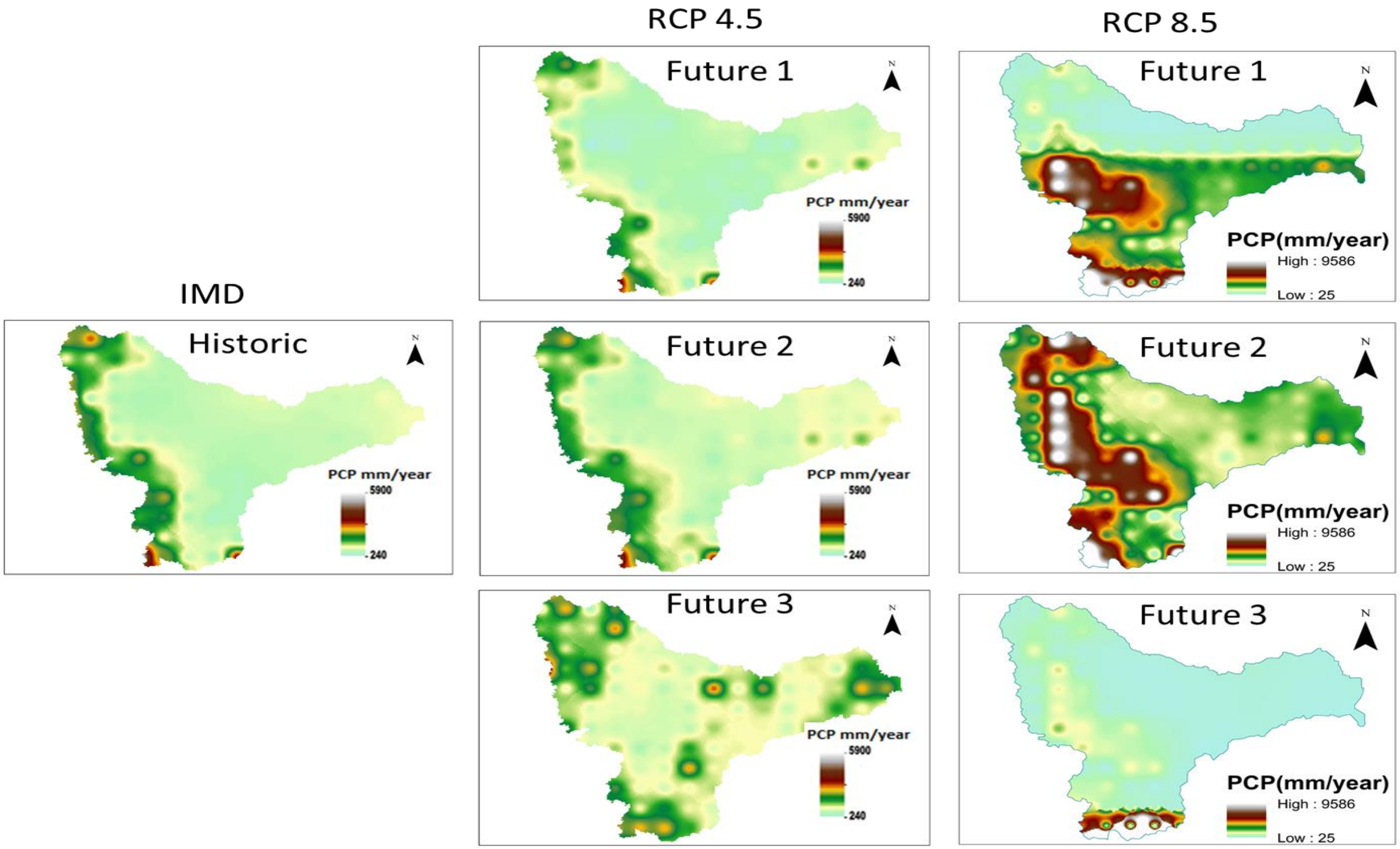


Figure 6.15 Annual average variation of precipitation (mm/year) spatially for Historic and Future periods of Krishna river basin under RCP4.5 and RCP 8.5 scenarios.

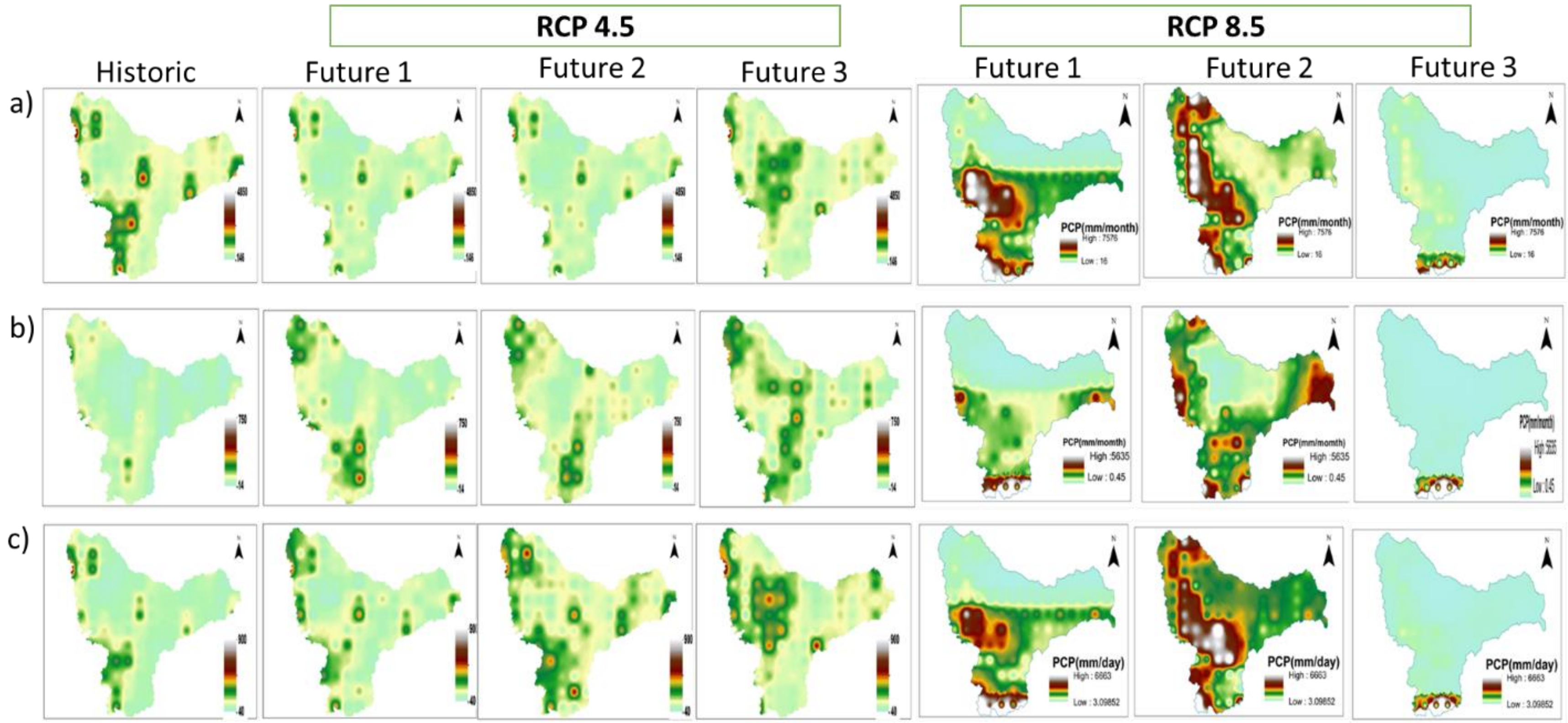


Figure 6.16 Spatial variations in precipitation (mm/month) of Krishna basin a) Monsoon (June-Sep) b) Winter (Oct-Jan) c) Summer (Feb-May) for Historic and Future periods under RCP 4.5 and RCP 8.5 scenarios.

The seasonal variations of precipitation i.e. Monsoon (June-Sep), Winter (Oct-Jan) and Summer (Feb-May) are shown in Figure 6.16. Almost 90% of the precipitation is received during the monsoon months from May to October under RCP 4.5. Extreme precipitation values are observed near the south portion of the basin for future 1 and 3 periods of RCP 8.5 scenario, whereas the remaining portion of the basin projects precipitation similar to the values of other scenario. The number of extreme precipitation values are reduced in future periods of the basin under RCP 8.5 compared to 4.5. Decreased precipitation is observed in Future periods compared to the historic period. There is an increase in precipitation values in the central portion of the basin in future 3 period. Increase in precipitation values are observed in winter and summer seasons of future periods compared to the historic period. It reflects the shift of the monsoon in future periods. Even extreme values are also observed in the central parts of the basin compared to the historic period in Winter and Summer seasons. Minimum temperature values show decreased values in monsoon and winter periods till future 2 and increase in the minimum temperature values in summer season of all future periods. Maximum temperature represents increase in all seasons of the future periods compared to the historic period. Overall increase in precipitation and temperatures is observed in future 3 period of Krishna basin.

The peak values are observed in June (560mm in Historic, 410mm in future1, 490mm in future 2, 520 mm in future 3), while the minimum value of 280mm in future 1 and a maximum value of 485mm in future 3 period are detected in July. Overall increase of precipitation values is noticed in all months of future 3 period. Increase in Minimum and maximum temperature values were observed in all months of the future periods. March to May months project high temperature values ranging from 20°C/day to 28°C/day of minimum temperature and 33°C/day to 44°C/day of maximum temperature. Peak values of Maximum temperatures observed in April are 34° C/day in Historic period, 36° C/day in Future period 1, 42° C/day in Future period 2 and 44° C/day in Future period 3 respectively under RCP 4.5 scenario. An overall increase of 2^0 to 3^0C/day is observed in the basin under RCP 8.5 scenario.

6.3.2 Future streamflow projections

The relationship between the magnitude and frequency of streamflow for future period is explained using Flow Duration Curves (FDCs) at three-gauge stations: Huvinhedgi, Mantralayam and

Pondhugala for both RCP scenarios shown in Figure 6.17 and Figure 6.18. These curves enumerate the flow of exceedance for a given level of probability developed under Annual, Monsoon and Non-monsoon basis, which helps water managers in obtaining water availability under climate change. Figure 6.17a presents the FDC of Huvinhedgi gauge station representing the total flows upstream of the basin, which shows an overall decrease in flows of future 1 period with similar flows in future 2, and future 3 periods as historic. Even though future periods 2 and 3 project an increase in precipitation of the basin, there is a decrease observed in the high flows (flows that exceed 10-30% of time) and low flows (flows that are exceeded 80% of time). This is mainly due to a likely increase in temperature. The median flows (flows that are exceeded 30-70% of time) are similar to the historic period flows.

Annual FDC of the Mantralayam and Pondhugala stations show a decrease in the high and low flows and increase in the median flows under RCP 4.5, 8.5 scenarios. Decreased flows are observed in the Future1 period. For FDC of Monsoon period, High flows are projected throughout the period with decreased values in the future periods compared to the historic period. It is even reported by many studies that Krishna river basin is more vulnerable to increase in human consumptive use of surface water resources, reduction in surface water base flows due to over abstraction of ground water and fewer releases to ocean (Amarasinghe *et al.* 2007). It also suggests that hydrological changes anywhere in the basin affect the basin adversely in terms of decrease in the total water availability and spatial redistribution of water during times of drought. Hence, it is important to consider the deficits of water availability for drafting water use policies in the Krishna River basin.

6.3.3 Climate change impact assessment

The impact of climate change on water resource of the basin was estimated by driving the calibrated SWAT model with REA weather data obtained from the ensemble of five RCMs for the historic and three future periods. The analysis of streamflow was performed on a monthly basis. The REA precipitation data used in the SWAT model for the sub basins of Krishna River basin (Figure 6.19) suggests a decrease in the Annual average values of 20% in Future 1, around 4 to 6% in Future 2 periods while the projection for Future 3 projects same as for the Historic period, under RCP 4.5 scenario. The monthly streamflow simulated from the SWAT model for the Historic and Future periods were analysed, and the results are projected as the normalized values of Mean monthly flow as a ratio of the Annual flow. The absolute values of the streamflow as the ratio of the mean monthly flow and annual flow (Figure 6.19.a) and the relative changes with respect to the historic period (Figure 6.19.b) show an increase in Future 2 and Future 3 periods. Relative change in the streamflow suggests a decrease in the streamflow throughout the year with an increase in June month at the 3-gauge stations. Figure 6.19 presents Mean Monthly flow as a ratio of the Mean annual flow for the Historic and Future periods at Huvinhedgi, Mantralayam, and Pondhugula (Top: Absolute Values, Bottom: Relative change).

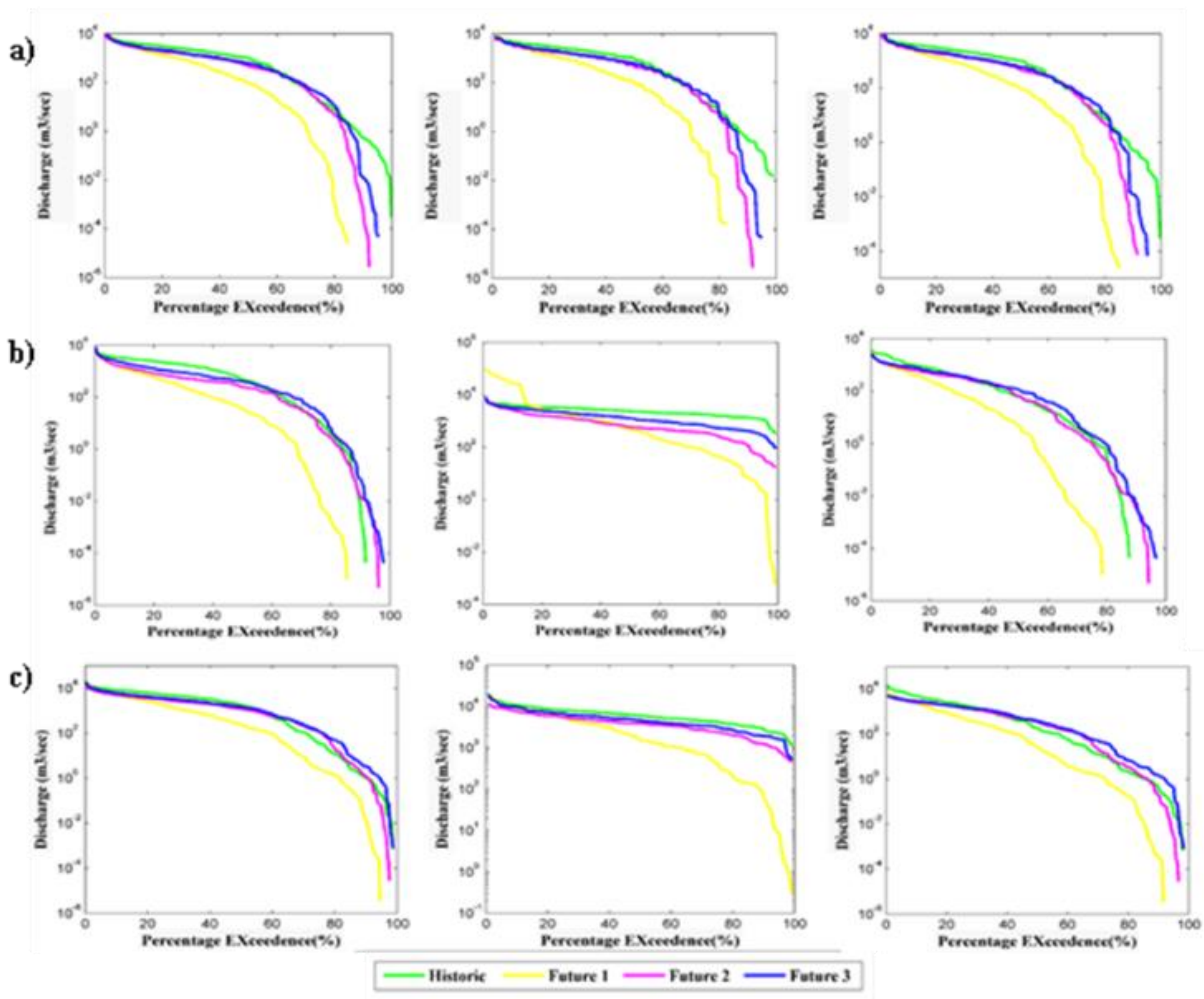


Figure 6.17 Flow Duration Curves of the gauge stations for the Annual, Monsoon and Non-monsoon periods under RCP 4.5 scenario at a) Huvinhedgi b) Mantralayam c) Pondhugala

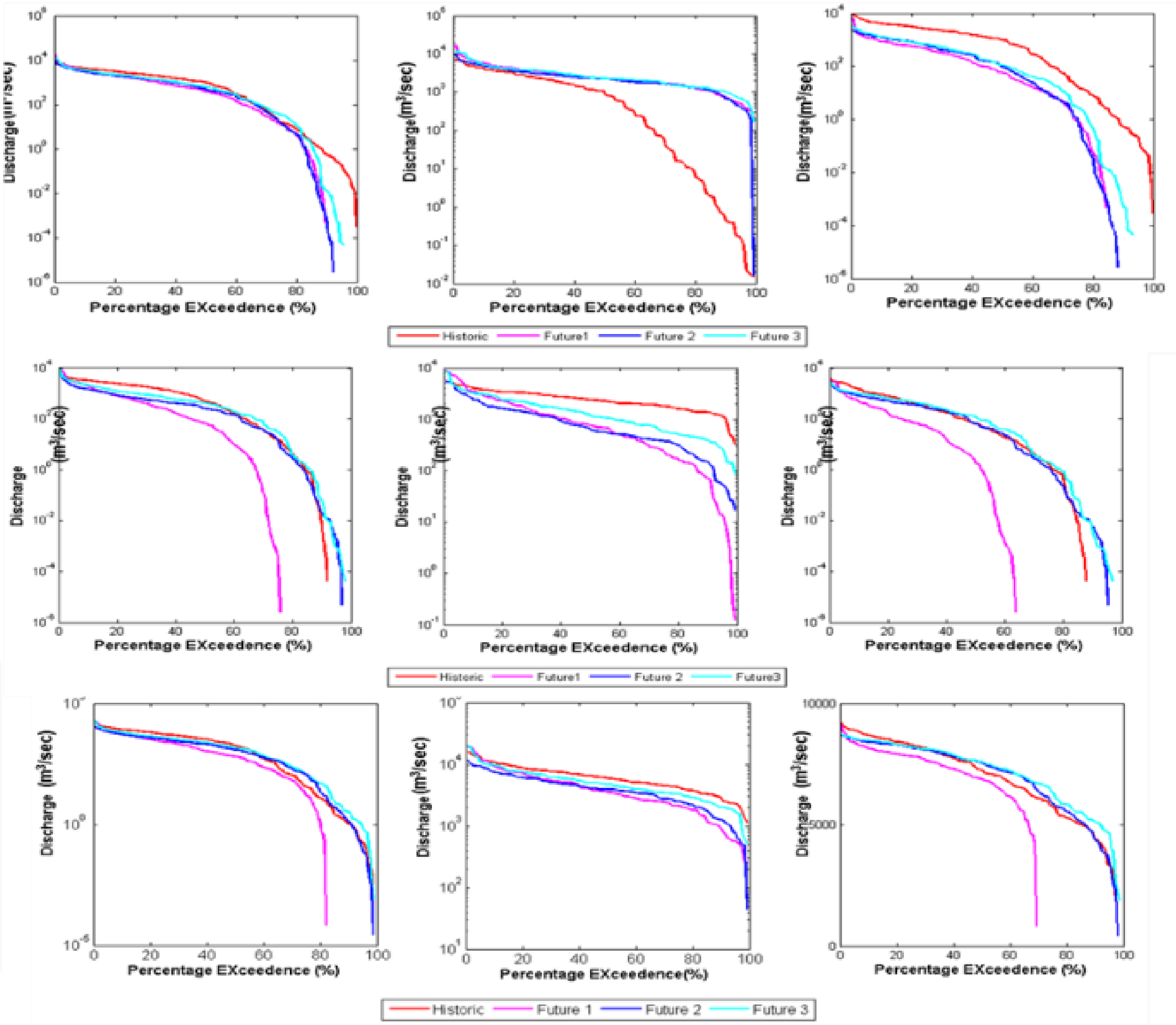


Figure 6.18 Flow Duration Curves of the gauge stations for the Annual, Monsoon and Non-monsoon periods under RCP 8.5 scenario at a) Huvinhedgi b) Mantralayam c) Pondhugala

The statistically significant trends in the annual streamflow of 50 sub basins obtained from the SWAT model set up was obtained using the Man-Kendall Trend test. The trend analysis suggests that almost all the sub basins project a decreasing trend in historic and future periods (Table 6.3). Figure 6.20 presents the positive (increase) and negative (decrease) in trends at the outlets of all sub basins spatially.

Table 6. 3 Number of Sub basins with increasing or decreasing trend

Climate Period	RCP 4.5		RCP 8.5	
	Increasing	Decreasing	Increasing	Decreasing
Historic	1	28		
Future I	-----	50	---	48
Future II	17	2	27	2
Future III	--	24	38	1

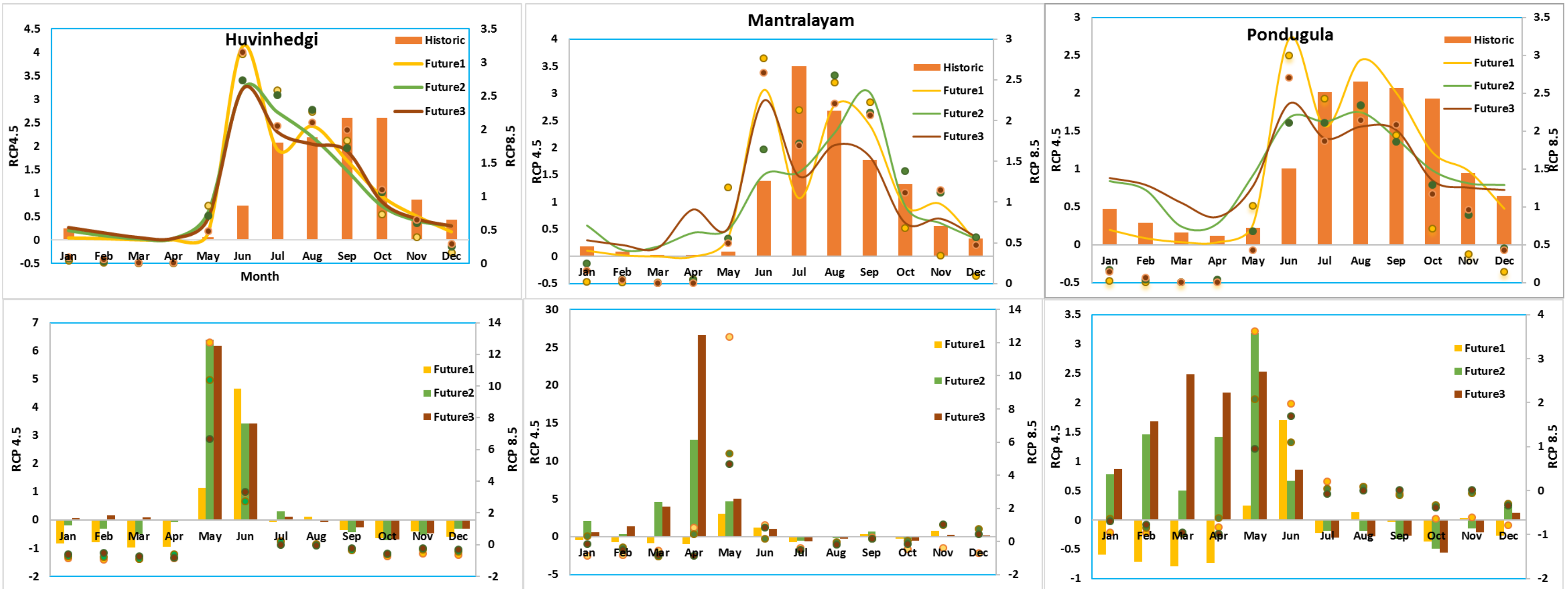


Figure 6.19 Mean monthly flow as a ratio of the mean annual flow for the historic and future periods of RCP 4.5 (Line graph) and RCP 8.5 (Scatter plot) at a) Huvinhedgi, b) Mantralayam, and c) Pondhugula (Top: Absolute Values, Bottom: Relative change).

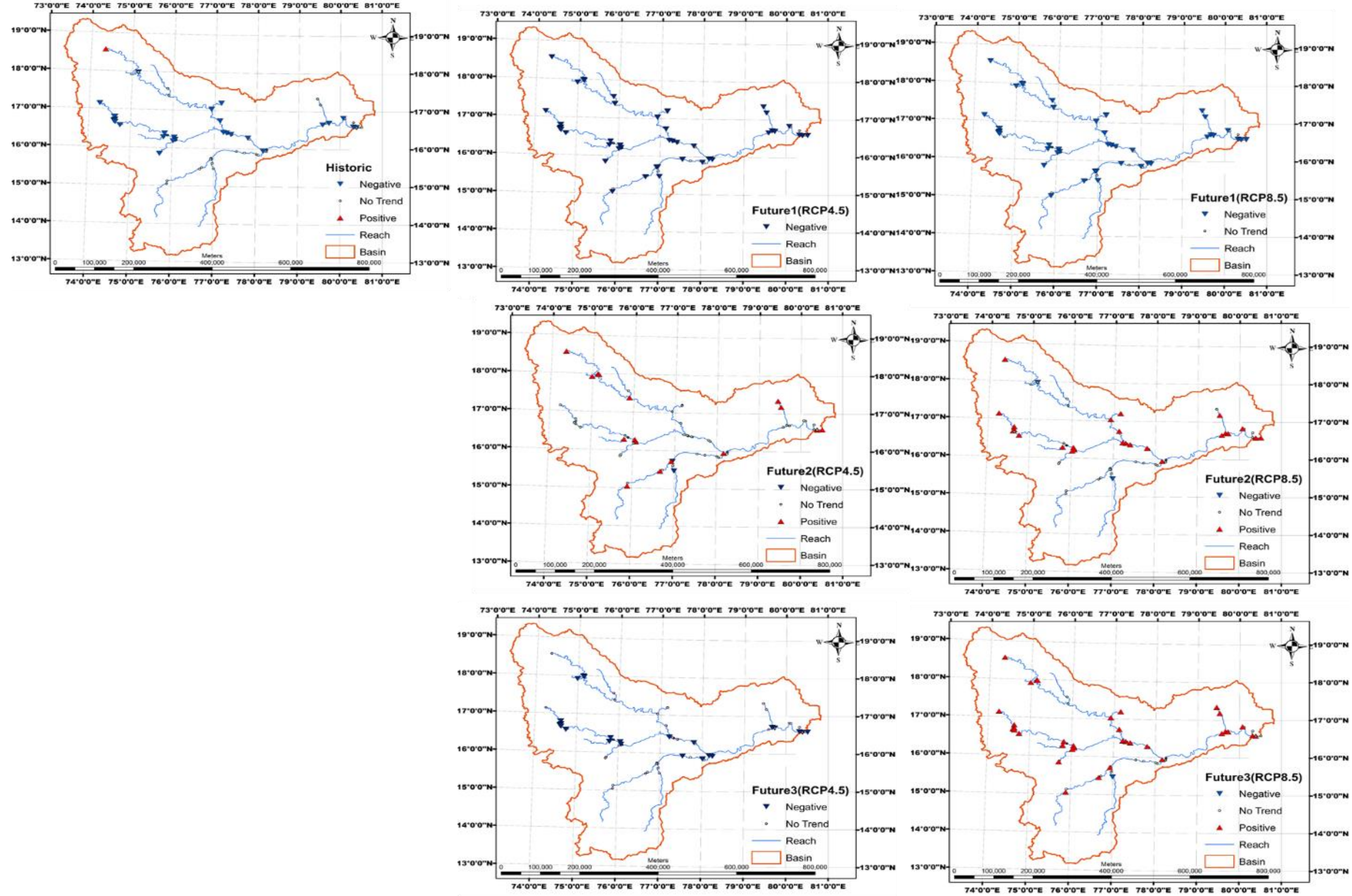


Figure 6.20 Spatially significant trends of annual streamflow under RCP 4.5 and 8.5 scenarios a) Historic b) Future 1 c) Future 2 and d) Future 3 periods

6.4 Drought Indices under climate change

In general, drought indices help in finding the commencement of drought events and facilitate the preparation for such severe conditions by measuring the severity through spatial and temporal characteristics of drought (Alley 1984). Most of the drought indices have a fixed time scale, but identification of drought at multiple scales is an efficient way of drought-based impact studies. However, SPI is selected for the present study as it calculates the indices at multiple time scales such as at 1, 2, 3,…48months over varied periods. For example, a 3-month SPI of any month represents the standard deviation in total precipitation of that month along with the preceding two months. It is a normalized index representing the probability of occurrence of an observed rainfall amount compared to rainfall at a certain geographical location over a reference period. Standardized Precipitation Index (SPI) is a most commonly used drought index calculated based on precipitation data (Vidal and Wade 2009) at all 132 grid points shown in Figure 6.21. In addition to SPI, hydrological drought interms of streamflow is quantified using Streamflow Drought Index (SDI) proposed by Tabari *et al.* (2013) at four different time scales for seven sub basins of the Krishna River basin (Figure 6.21). The uncertainty modelled REA climate model data is used for evaluating the drought indices of the basin. The REA weights obtained for all 132 grids using the concept explained in Section 3.2.2 of Chapter 3. For example, the assigned final weights for different RCMs of different hydro-climatic variables are presented in Table 6.4 for one grid point (13.5,77.5).

From Figure 6.16, Spatial variations of ensemble average precipitation for the future periods under RCP 4.5 scenario shows an increase in precipitation values throughout the basin. However, RCP 8.5 scenario projects a decrease in precipitation values compared to historic periods. Based on the projections i.e. low precipitation, the Trend analysis carried out in the basin enhances the importance of drought analysis. The percentage change in annual average Future precipitation compared to Historic period of Krishna basin at all grid points is shown in Figure 6.22. The positive value in percentage change represents the decrease in projected precipitation compared to the observed precipitation. An increase in annual rainfall is noticed across many parts of the basin like Tungabhadra and Lower Krishna basins in Future 1 period, whereas an increase of about 0 to 20% in Middle Krishna and Bhima basins and 30 to 50% in Lower and Tungabhadra regions are observed in Future 2 period. In Future 3 period, an increase of about 30 to 80 % in Bhīma and Middle Krishna basins in Future 3 period represents RCP 4.5 scenario.

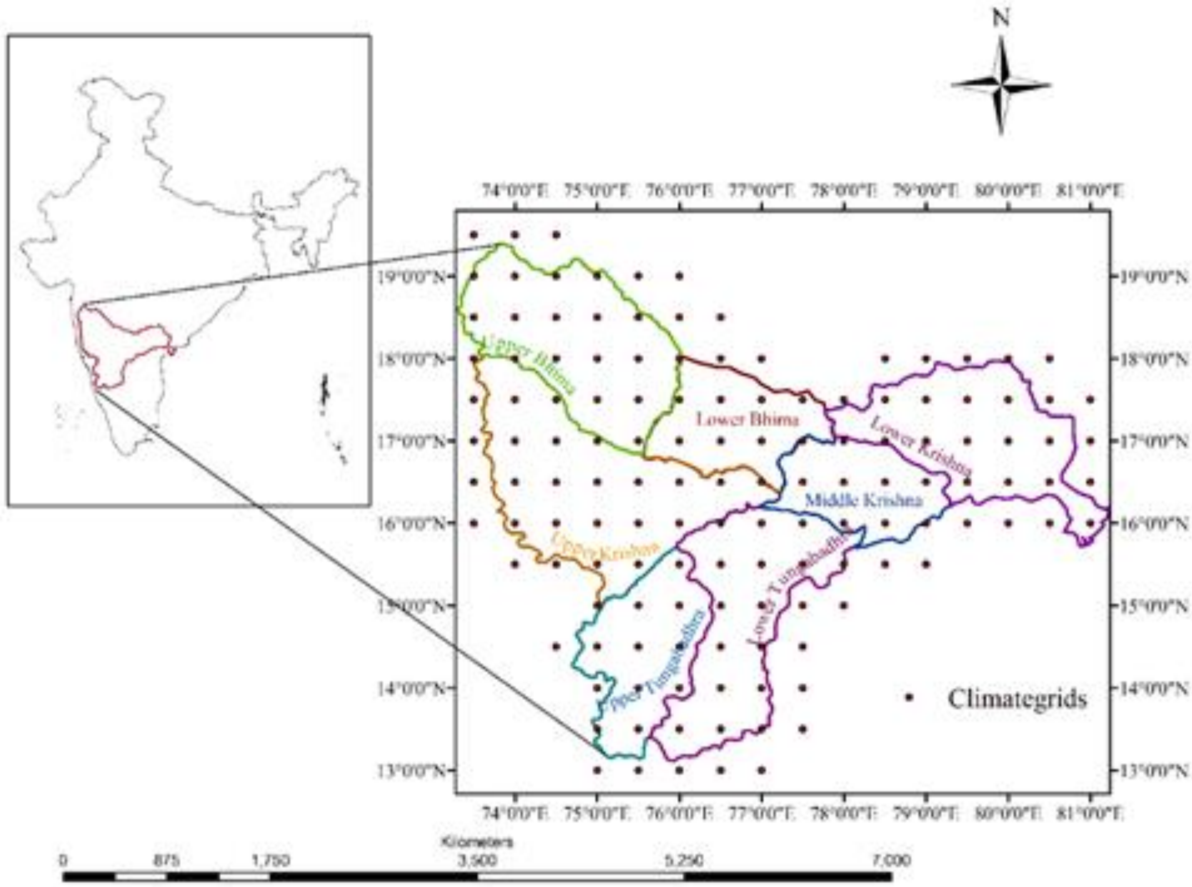


Figure 6.21 Sub basins of Krishna river with the climate grid points.

For RCP 8.5 scenario, a decrease of about 40 to 80% is observed in Future 1 and 3 periods whereas in Future 2 period an increased precipitation is projected throughout the basin. Further, changes in the monsoon and non-monsoon periods and percentage changes are investigated for the three future periods and shown in the Figures 6.23 and 6.24. Monsoon precipitation change is identical to the annual average precipitation change. However, for the non-monsoon period, the quantity of increase in precipitation is high in most parts of the basin.

Table 6.4 REA results of the hydro-climatic variables for (13.5, 77.5) grid point

Precipitation

Model	Historical	2020-2044		2045-2069		2070-2094	
	1980-2004	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
ACCESS	0.1486	0.0000	0.1460	0.0000	0.9944	0.0000	0.0940
CCSM	0.2295	0.0001	0.3568	1.0000	0.0048	0.0000	0.5364
CNRM	0.2750	0.0000	0.1408	0.0000	0.0006	0.9999	0.2442
MPIESM	0.1381	0.0000	0.3564	0.0000	0.0002	0.0000	0.1254
NORESM	0.2089	0.9999		0.0000		0.0000	

Maximum temperature

Model	Historical	2020-2044		2045-2069		2070-2094	
	1980-2004	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
ACCESS	0.22016	0.11402	0.121413	0.264346	0.070947	0.212079	0.264368
CCSM	0.193244	0.024267	0.637381	0.212358	0.547613	0.110369	0.231069
CNRM	0.206573	0.249615	0.078688	0.078084	0.251249	0.02894	0.190061
MPIESM	0.200514	0.359089	0.162519	0.140549	0.130191	0.368041	0.314502
NORESM	0.17951	0.253009		0.304663		0.280571	

Minimum temperature

Model	Historical	2020-2044		2045-2069		2070-2094	
	1980-2004	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
ACCESS	0.180468	0.134781	0.983188	0.02905	0.085062	0.066271	0.179577
CCSM	0.282463	0.011749	0.001862	0.819074	0.079589	0.157125	0.352152
CNRM	0.22222	0.253629	0.013301	0.046505	0.063946	0.352676	0.291931
MPIESM	0.159209	0.417908	0.001649	0.03315	0.771403	0.249035	0.176339
NORESM	0.15564	0.181934		0.072221		0.174892	

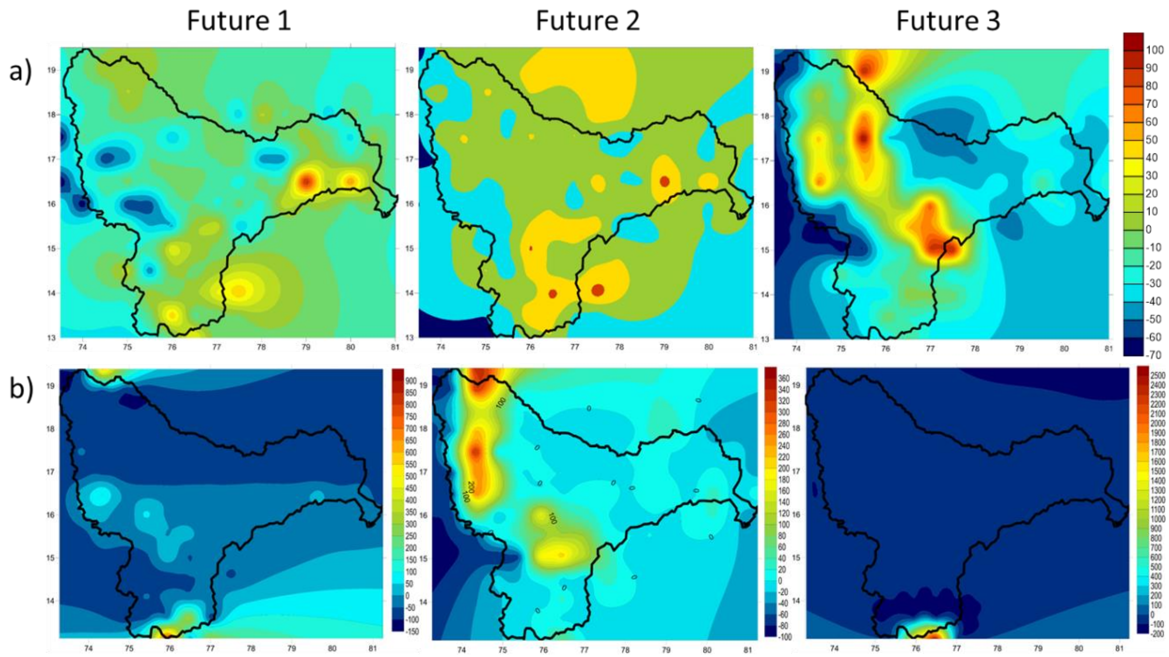


Figure 6.22 Percentage change in the Average annual rainfall across Krishna basin for Future1, Future2 and Future3 periods a) RCP4.5 b) RCP8.5.

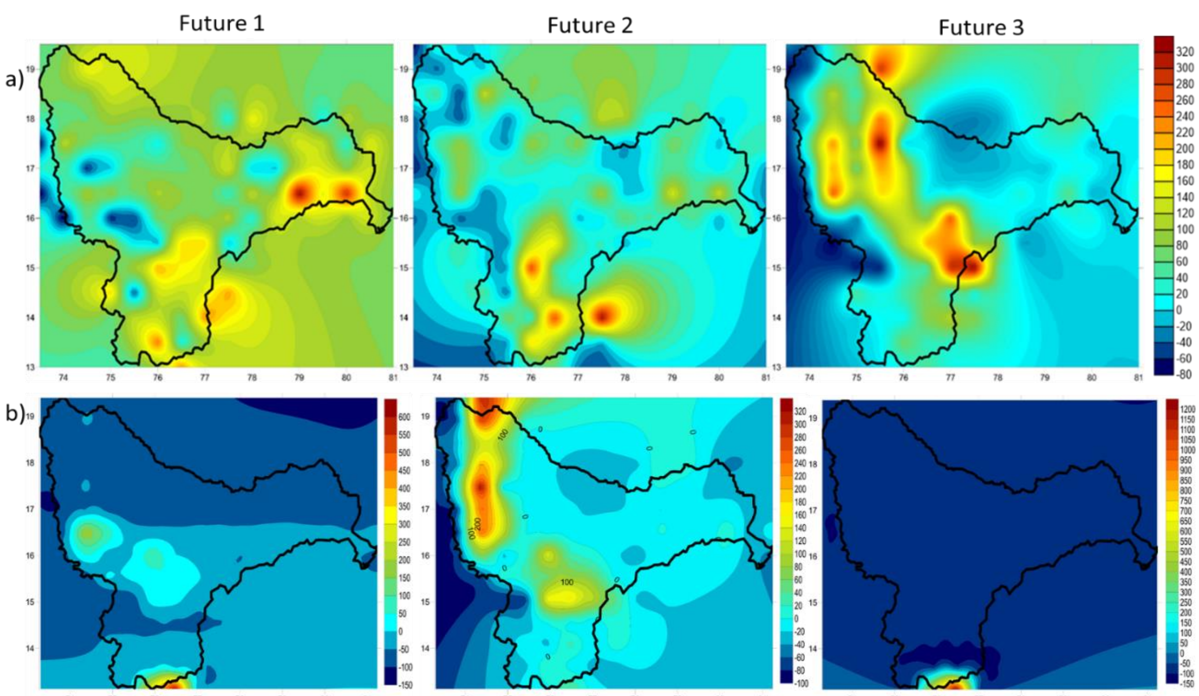


Figure 6.23 Percentage change in the Average Monsoon rainfall across Krishna basin for Future1, Future2 and Future3 periods a) RCP4.5 b) RCP8.5.

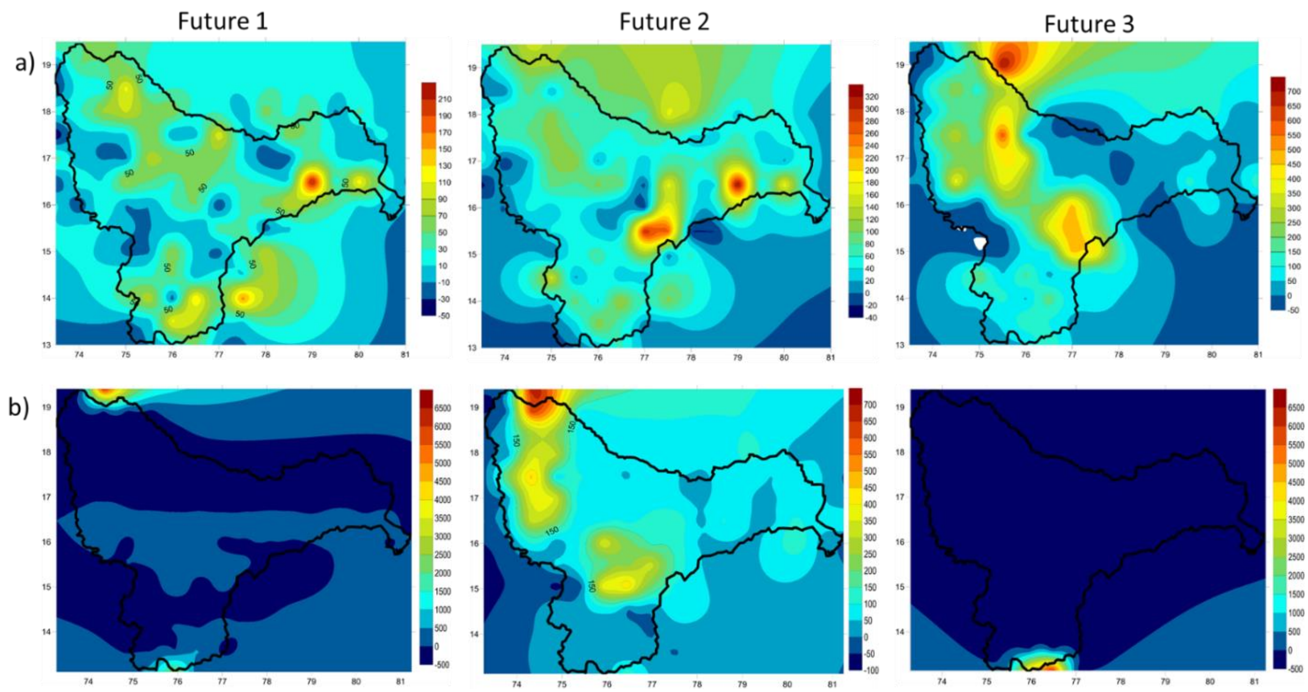


Figure 6.24 Percentage change in the average Non-Monsoon rainfall across Krishna basin for Future1, Future2 and Future3 periods a) RCP4.5 b) RCP8.5.

Frequency of drought was modelled for the ensemble historic and future periods across Krishna basin for both the scenarios. Figure 6.25 presents the frequency of severe wet condition in the basin under RCP 4.5 scenario, and later on using RCP8.5 model, in Figure 6.26. Frequency of wet events is very low in Historic period. Bhima and Tungabadra region were predicted to have high wet conditions in both the scenarios. Future 2 period in the basin was observed to have good number of wet conditions across the basin. Decrease in wet conditions was modelled for most parts of the basin under RCP 4.5 and RCP 8.5. The variations in drought frequency are shown in Figures 6.27 and 6.28. The spatial variations in frequency of drought events show an increase in lower Krishna and Tungabadra regions of the basin. Less drought events were noticed for future period 2, while a great increase in drought frequency was noticed, especially in Bhima and Middle Krishna regions of the basin. Middle and Lower Krishna regions are considered to be drought prone for most of the year as it receives a very small amount of monsoon precipitation. The frequency of the severe wet and drought events predicted in both RCP 4.5 and RCP 8.5 scenarios are similar, with RCP 8.5 events being high in the basin. The frequency of severe wet conditions predicted under RCP 4.5 scenario are greater than that predicted by RCP 8.5.

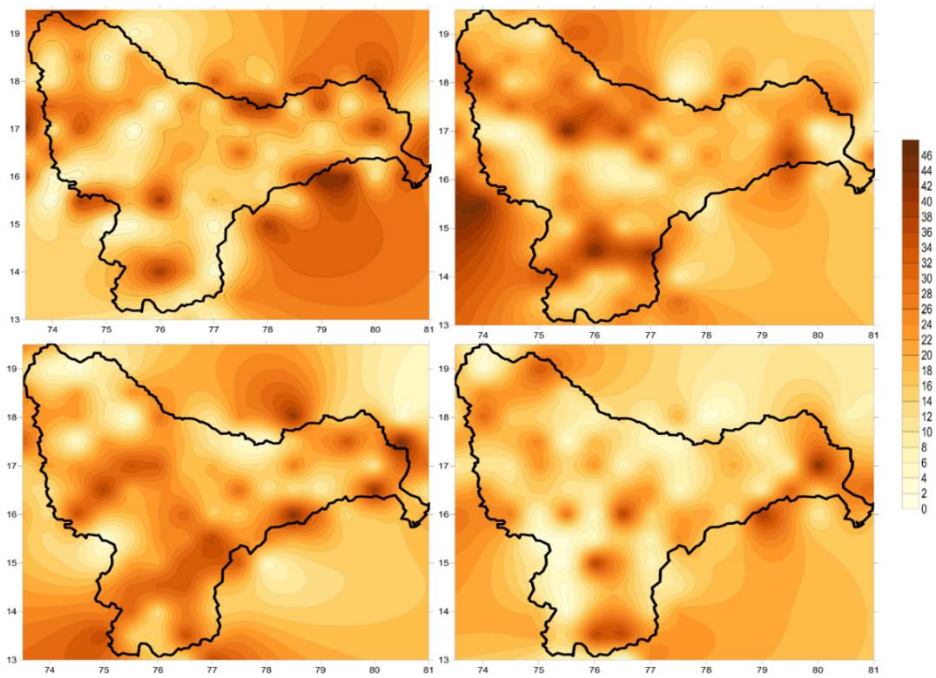


Figure 6.25 Frequency of the Severe Wet conditions based on SPI 12 for Historic and Future periods under RCP 4.5 scenario

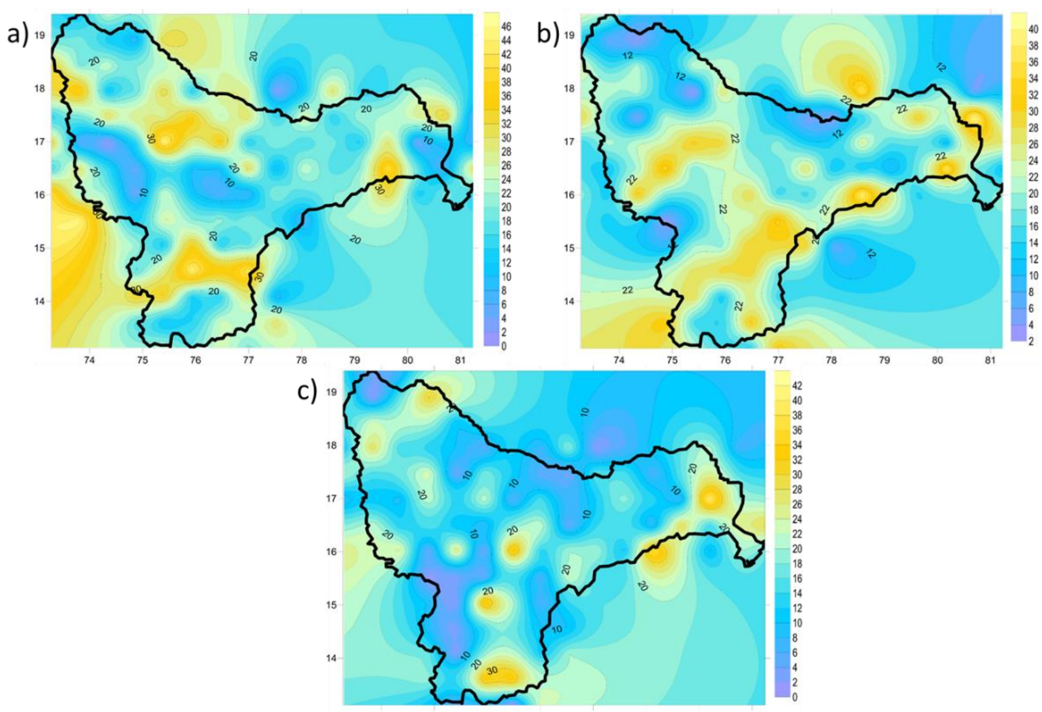


Figure 6.26 Frequency of the Severe Wet conditions based on SPI 12 for Future periods under RCP8.5 scenario.

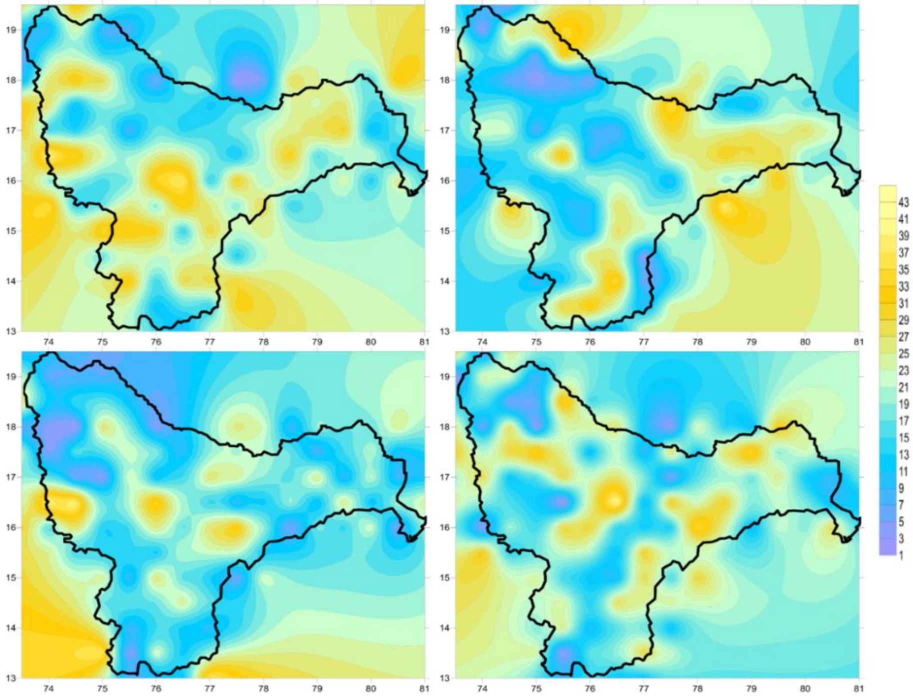


Figure 6.27 Frequency of the Severe Drought conditions based on SPI 12 for Historic and Future periods under RCP 4.5 scenario.

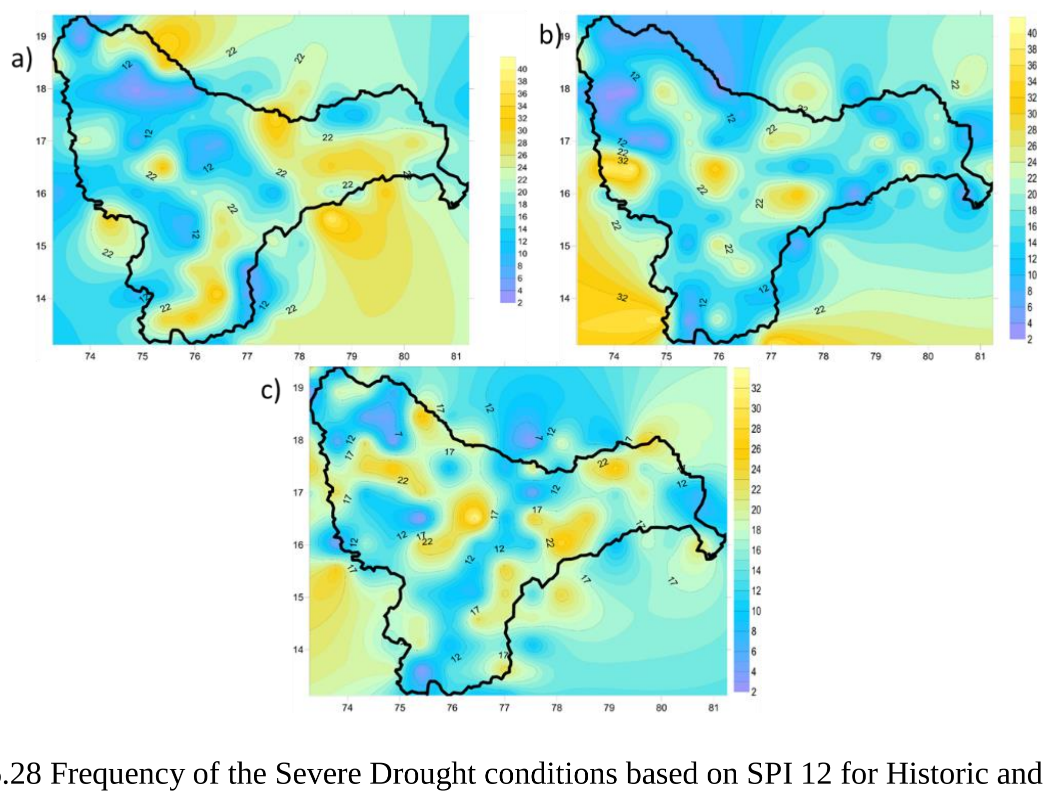


Figure 6.28 Frequency of the Severe Drought conditions based on SPI 12 for Historic and Future periods under RCP 8.5 scenario.

The 5th and 95th percentile SPI values obtained from the time series of Historic precipitation data were defined as the threshold values at each grid cell for severe drought and wet events (Burke and Brown 2008) for the three future periods. The low (5th), median (50th) and high (95th) percentile SPI values for 12 months' time scale for all the 132 grids are shown spatially in Figures 6.29 to 6.34. Low and high percentile SPI values have been identified as severe drought and wet events, respectively. However, median percentile values represent the mild drought and wet conditions in the basin. The variations in the magnitude of the events show seriousness of drought in that region. During Historic period, the magnitude of low value varies from -1.98 to -1.28. The low percentile value increases to -2.68 in Future 1 period and decreases to 1.88 in many parts of the basin during Future period 2. About 60% of the basin shows low values varying from -2.28 to -1.98 in Future 3 period. The magnitude of the 5th percentile values was slightly lower in the RCP 8.5 scenario compared RCP 4.5.

The median values in Figure 6.31 and 6.32 vary from -0.4 to 0.28 in the basin, in which -0.4 to 0 is considered as mild drought and 0 to 0.28 as mild wet conditions. The basin is subjected to mild wet conditions as shown in Figure 6.31 in historic period with an increase in mild drought conditions observed in Future 2 periods throughout the basin. The severity of the median percentile values is predicted to be more under RCP 4.5 scenario compared to RCP 8.5 across the basin. The high percentile values representing the wet conditions vary from 1.2 to 2.3 with a classification as moderately wet to severe wet conditions. In Figure 6.33, the high flow values across the basin show that 90% of the basin indicate to magnitude of moderate wet conditions. Increase in wet events is observed in Future periods compared to the historic period. Similar results with high values are projected in Future periods of the basin under RCP 8.5 scenario (Figure 6.34).

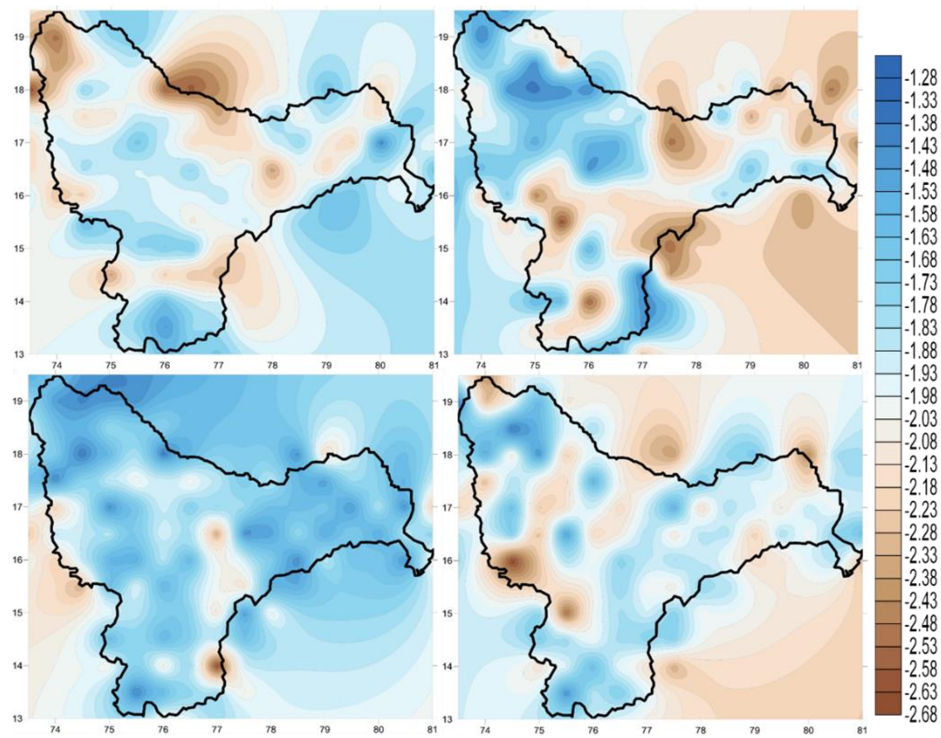


Figure 6.29 Low values (5th quantile) of the SPI 12 a) Historic b) Future1 c) Future2 d) Future3 for RCP 4.5 scenario.

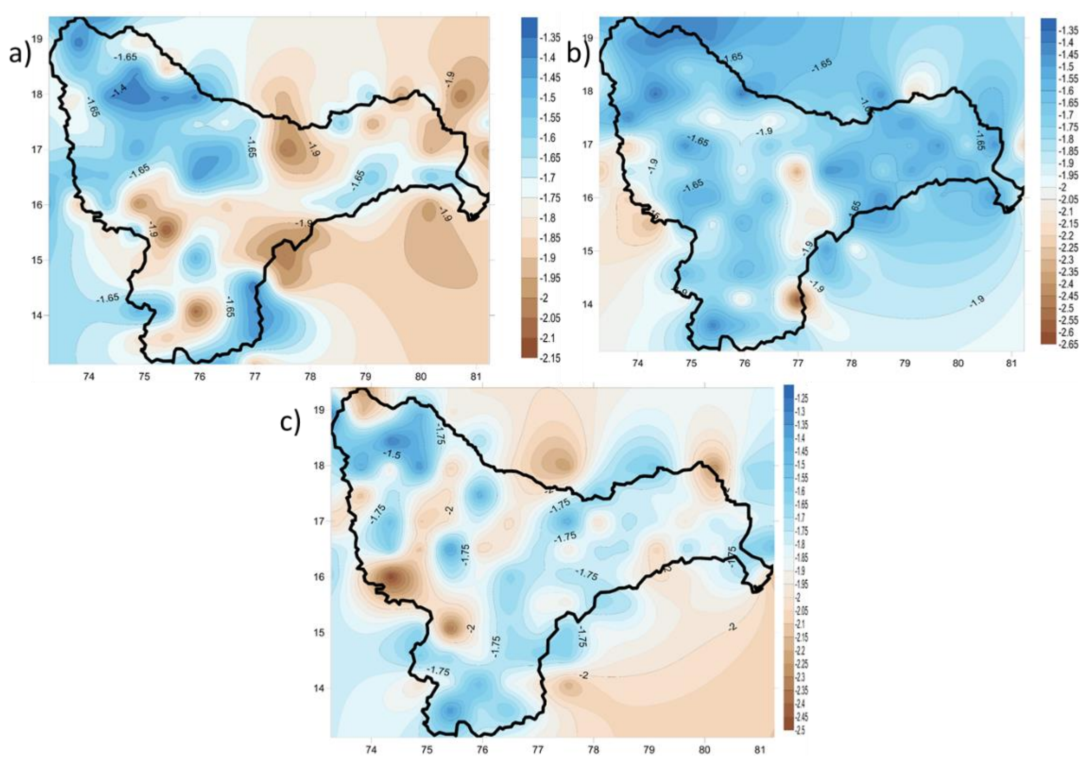


Figure 6.30 Low values (5th quantile) of the SPI 12 a) Future1 b) Future2 c) Future3 for RCP 8.5 scenario.

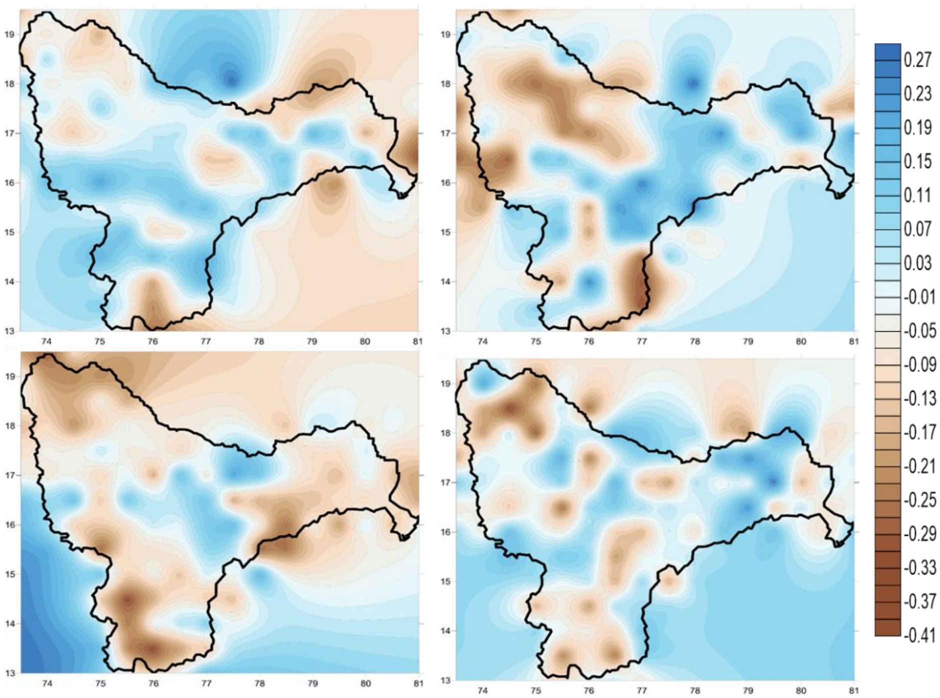


Figure 6.31 Median values (50th quantile) of the SPI 12 a) Historic b) Future1 c) Future2 d) Future3 for RCP 4.5 scenario.

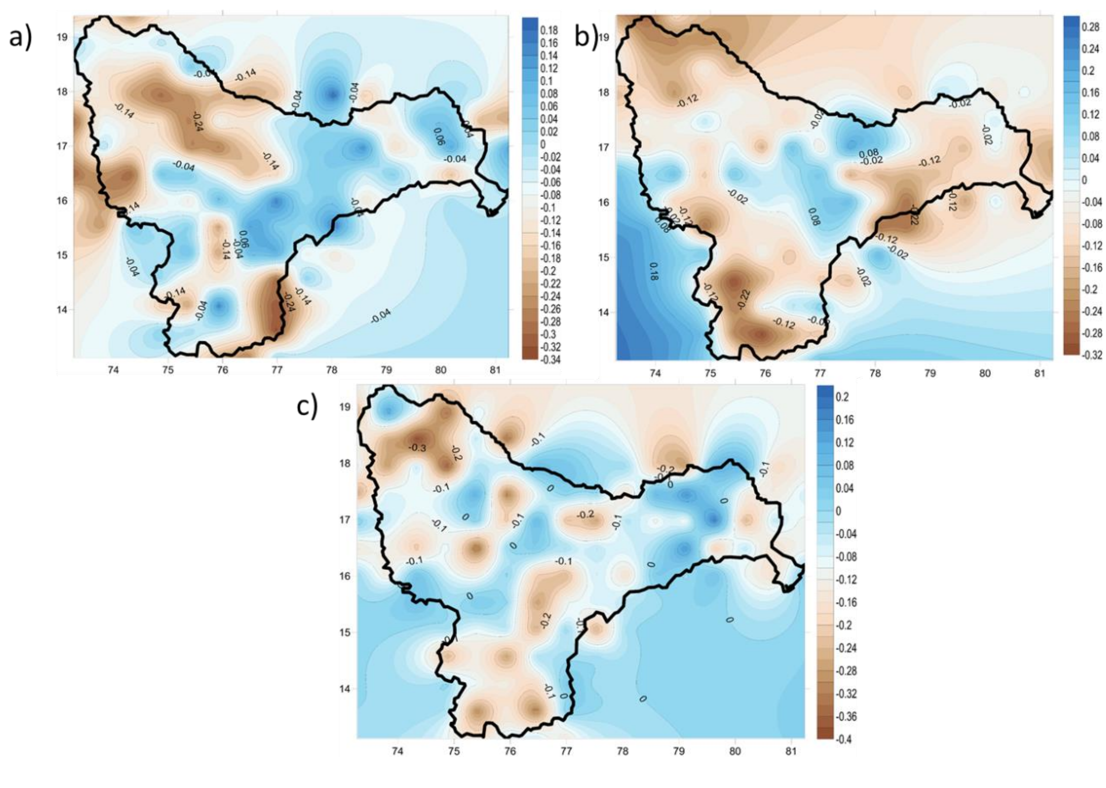


Figure 6.32 Median values (50th quantile) of the SPI 12 a) Future1 b) Future2 c) Future3 for RCP 8.5 scenario.

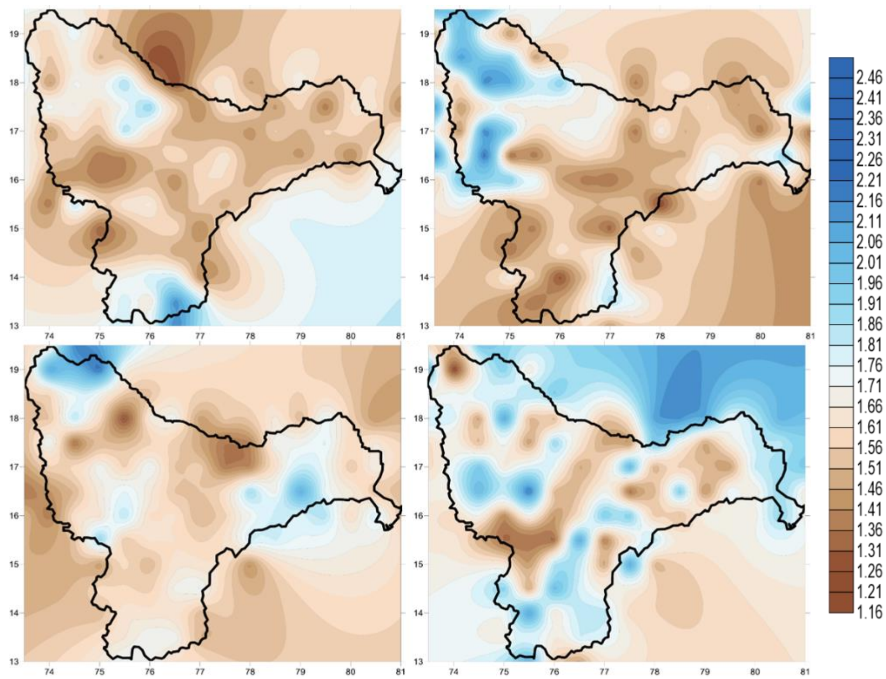


Figure 6.33 High values (95th quantile) of the SPI 12 a) Historic b) Future1 c) Future2 d) Future3 for RCP 4.5 scenario

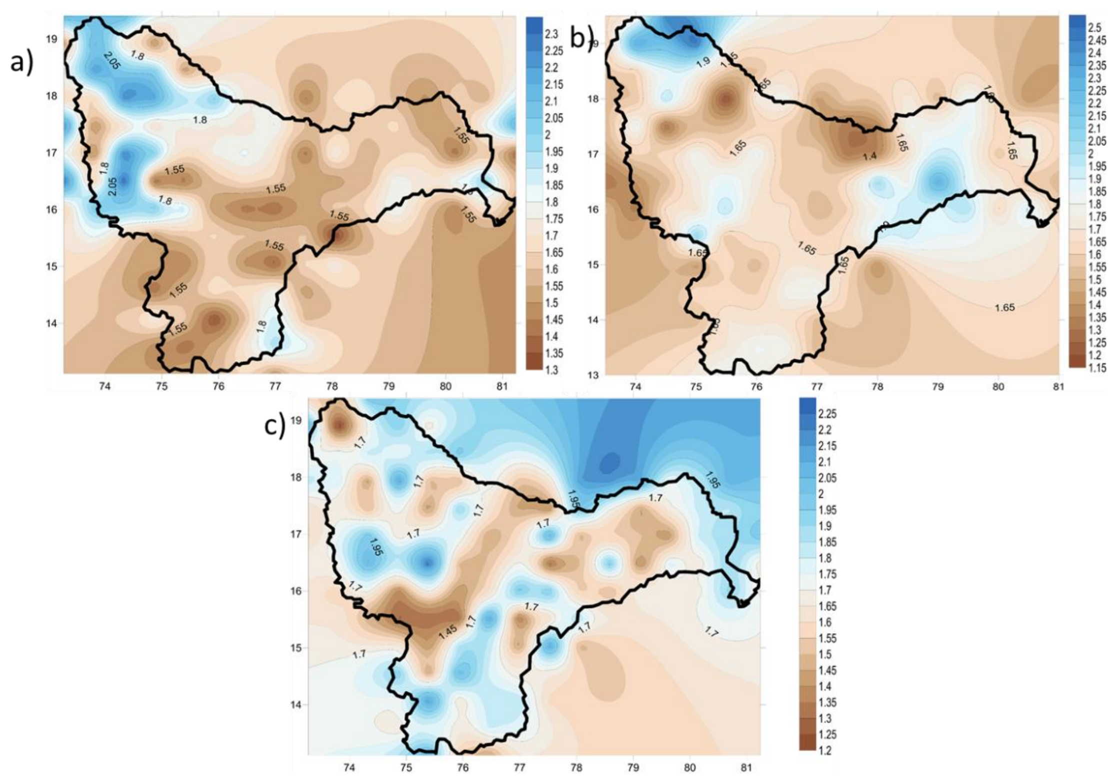


Figure 6.34 High values (95th quantile) of the SPI 12 a) Future1 b) Future2 c) Future3 for RCP 8.5 scenario

In addition to SPI, SDI is also evaluated to analyse the effect of climate change on streamflow. The streamflow obtained from the calibrated and validated hydrological model SWAT is employed for estimating the drought indices. The drought indices are calculated at seven sub basin outlets of the Krishna River namely Upper Bhima, Lower Bhima, Upper Krishna, Middle Krishna, Lower Krishna, Upper Tungabadra and Lower Tungabadra. SDIs are calculated for 3,6,9,12-month timescales for Historic and Future periods of the basin under RCP 4.5 and 8.5 scenarios. The temporal variations of the streamflow data simulated using REA climate data for both scenarios are compared to the historic periods are shown in Figure 6.35 to 6.37. Boxplots were used to project the temporal variations of the SDI estimated for different time scales. The box represents 50% range of values with the bar being the median value. The whiskers at the two ends represents extreme values with the values beyond the whisker being outliers. Upper ends of the whiskers show an increase in the values steadily in future periods.

Figure 6.35 presents SDI values of the Upper Bhima and Lower Bhima basins. The range of drought indices under RCP 4.5 varies similar to the historic period indices, whereas SDI evaluated for RCP 8.5 scenario projects that the upper Bhima basin will be under no drought conditions. The reason is that streamflow simulated is based on REA climate projections, which show normal precipitation throughout the basin without any variations. The SDI calculated is dependent on the streamflow simulated in the earlier months, where it is projected that the basin is under no drought condition. In lower basin, SDI value range is subjected to severe drought conditions in Future 2 period and severe wet condition in Future 1 period as shown in Figure 6.35.

The distribution of SDI values for the Upper, Middle and Lower Krishna basins are shown in Figure 6.36. More wet indices are observed in basins for all future periods. Though the basin is subjected to an overall increase in precipitation in Future 2 period compared to other periods, more drought indices were observed in Future 2 periods of the Middle Krishna basin. SDI-3 of the Middle and Lower Krishna basins suggest no drought conditions in the basin, as the streamflow simulated does not project intra annual variations. Figure 6.37 presents the boxplots of the SDI for the Upper and Lower Tungabhadra basins. It also represents high number of wet conditions for the future period, However severe drought conditions in future 3 period in both the basins in both RCP scenarios.

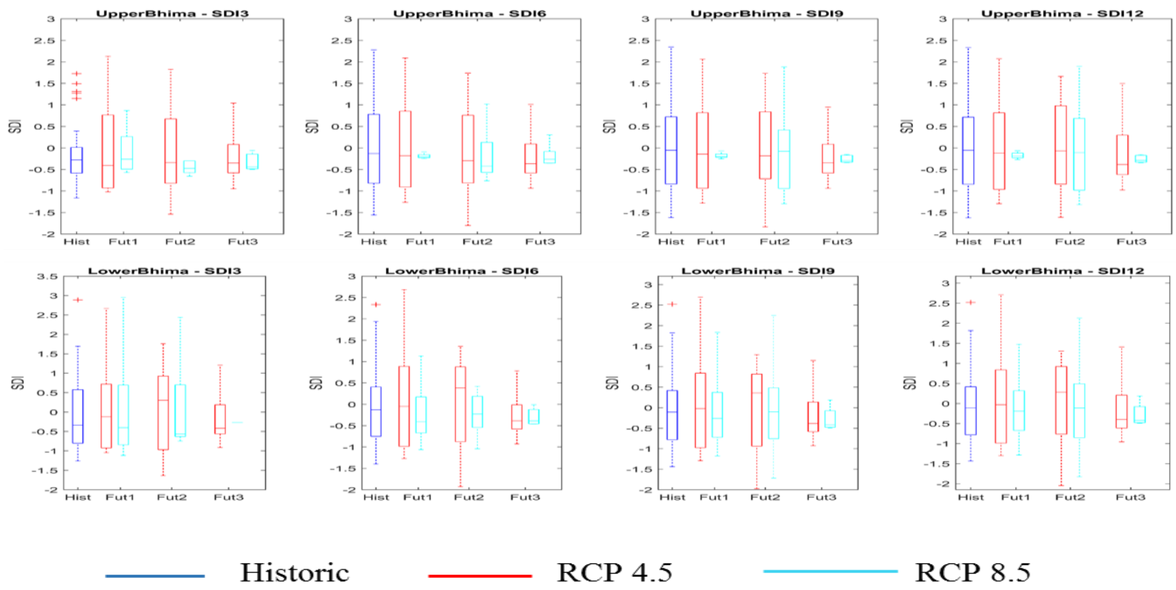


Figure 6.35 Temporal variations in the SDI values for the Upper and Lower Bhima basins under RCP 4.5 and RCP 8.5 scenarios.

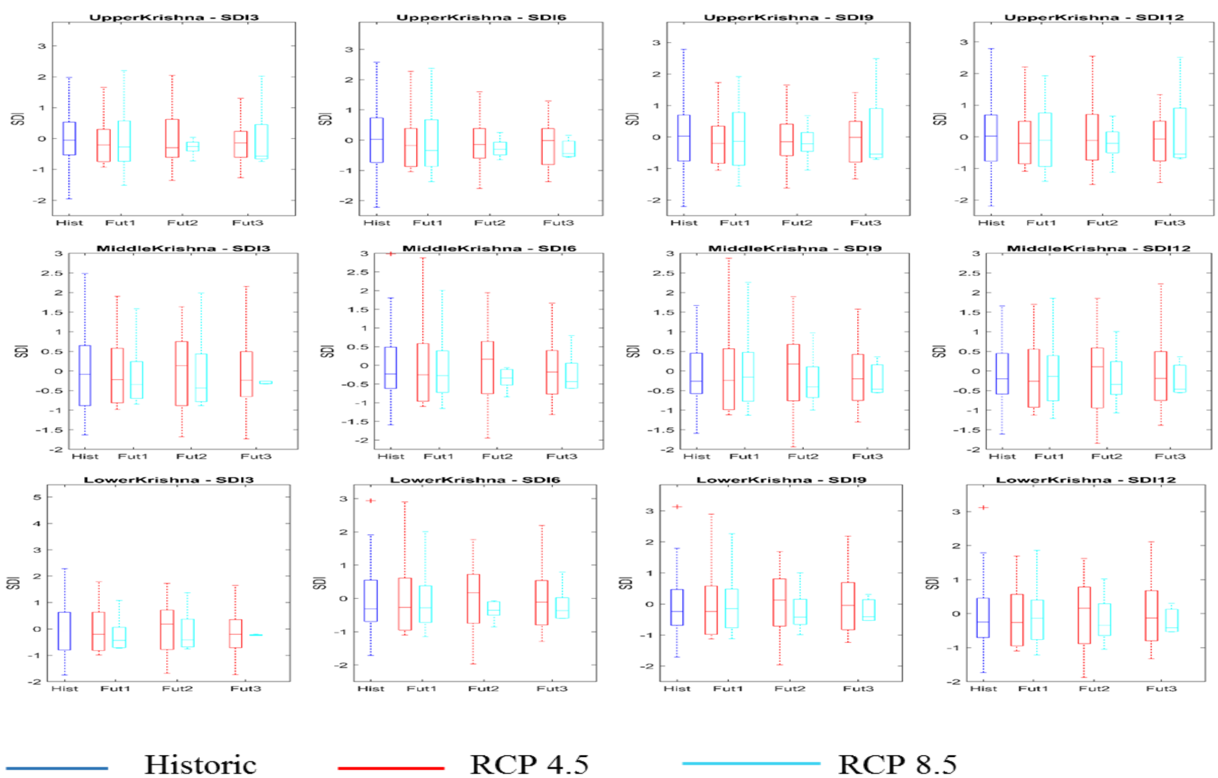


Figure 6.36 Temporal variations in the SDI values for the Upper, Middle and Lower Krishna basins under RCP 4.5 and RCP 8.5 scenarios.

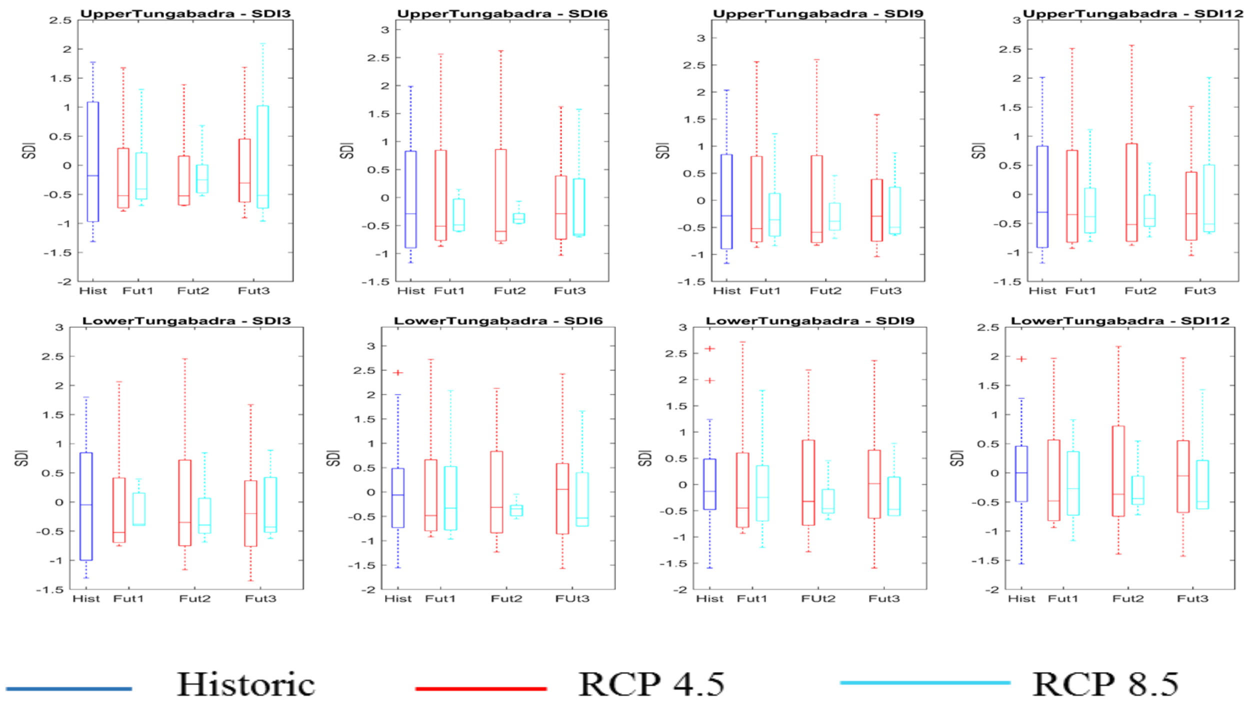


Figure 6.37 Temporal variations in the SDI values for the Upper and Lower Tungabadra basins under RCP 4.5 and RCP 8.5 scenarios.

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6.5 Combined effect of climate and LULC changes on water balance components

Economic growth, development of human and ecosystem of the country are mainly dependent on natural resources such as land and water. These resources are subjected to immense pressure caused by urbanization and industrialization due to increase in human population. In addition to these, water systems are affected by climate change in the form of variability of temperature and rainfall both spatially and temporally, water balance changes, sea level rise, etc. Hence, land use and climate variability are two important factors affecting the water resources and sustainability of the ecosystems. In the Hydrological processes, the parameters like evapotranspiration, infiltration and interception are mainly subjected to land use changes based on varied surface and subsurface flows (Wang *et al.* 2014, Niraula *et al.* 2015). Climate change leads to specific variations in hydrologic regimes and impact patterns of water resources spatially and temporally (Chien *et al.* 2013, Khoi and Suetsugi 2014). The effect of both LULC and climate changes on the parameters of the hydrologic cycle is significant to workout necessary decisions for the proper utilization and management of water resources in future periods. Variations in water balance components like Evapotranspiration, Base flow, Surface and Sub surface runoff spatially and temporally are important for management of water resources. Irrigation system design and management, hydrologic water balance, crop yield simulation, planning and management of water resources and water loss optimization by improving the usage of water in agriculture are various fields which have evolved based on these changes.

Effect of LULC and climate on the wate balance components of Munneru watershed was simulated using calbrated and validated SWAT model. The responses of the study area to the precipitation, maximum and minimum temperatures, Evapotranspiration, Baseflow and Surface Runoff were shown spatially. Maximum precipitation values were observed to decrease from decade to decade as shown in Table 6.5. Lowest prescipitation is observed in the year 2030 with minimum and maximum values as 40.96mm and 57.81mm respectively. The maximum and minimum temperatures are noticed to increase by 2°C by 2040. Hence, it is evident that changes in precipitation and temperature values affect the water balance components adversely.

Table 6.5 Observed minimum and maximum values of the Meteorological and Water balance Components.

Variables	1985		1995		2005		2020		2030		2040	
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Precipitation (mm)	60.63	105.53	49.09	81.36	40.17	72.14	53.75	75.86	40.96	57.81	43.57	61.5
Minimum Temperature(°C)	21.69	22.89	21.91	23.06	22.34	23.42	22.65	23.9	22.92	23.99	23.33	24.47
Maximum Temperature(°C)	31.63	32.09	31.89	32.39	32.42	32.95	32.77	33.41	32.96	33.56	33.7	34.4
Evapotranspitation (mm)	31.04	66.68	28.6	63.8	27.21	63.71	35.18	61	32.61	56.7439	33.17	59.08
SurfaceRunoff (mm)	27	47.94	19.43	32.37	13.06	28.35	11.35	17.87	5.43	8.84	6.83	13.3
Baseflow (mm)	3.58	10.99	0.139	5.57	0	0.48521	4.36	7.43	0.41	2	0	1.17

It is apparent from Figure 6.38 that decreasing rainfall scenarios tends to decrease in the average annual baseflow and surface runoff as presented in Figures 6.42 and 6.43. Evapotranspiration is directly related to the temperature. Hence, the response of evapotranspiration in Figure 6.41 projects varying values from decade to decade with maximum value in 2020. The decadal annual average values of Evapotranspiration, Surfacerunoff and Baseflow are compared with annual average values for the Historic period i.e. 1975-2005 is 45.72mm, 28.94mm and 3.27mm. The spatial variations in Figures 6.38 to 6.43 reveals that if an increase in temperature under a given precipitation decreases, there is a decrease in surface runoff and a baseflow with an increase in Evapotranspiration. All the results project maximum change from 1985 to 1995 as the LULC change is more in 1995 with fewer changes in 2005 compared to 1995. Simulations for the Future period (2006-2040) were carried out by considering similar changes to 2005. Hence, decadal changes in the water balance components project less variations in the between decade 1995-2005 when compared to 1985 to 1995. Evapotranspiration is more in 2020 (Figure 6.41) i.e. 10% more in comparison with the annual average value of the Historic with an increase of minimum and maximum temperatures of around 3% (Figure 6.39 & 6.40). Baseflow predicted for 2030-2040 period is almost zero as shown in Figure 6.42. Surface runoff is predicted to be 50% less in 2020, 2030, 2040 (Figure 6.43) i.e. 48%, 77% and 65% with a decrease of about 9%, 32% and 25% respectively in precipitation (Figure 6.38).

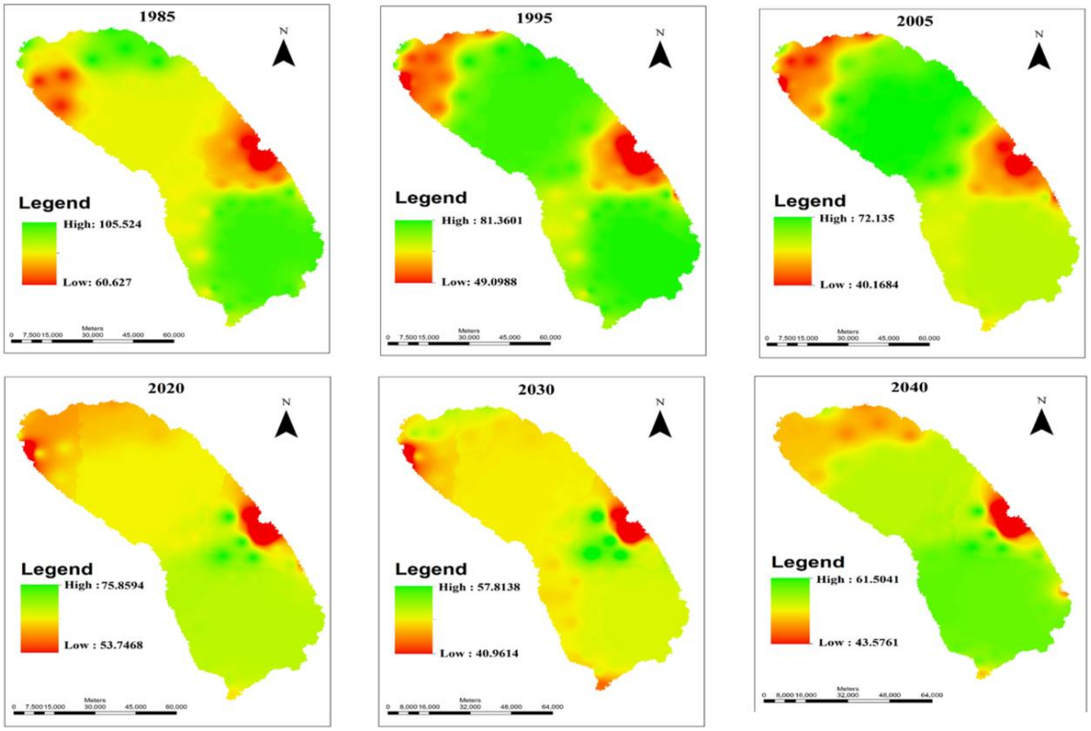

Figure 6 38 Variations of the Precipitation data spatially for the six decades.

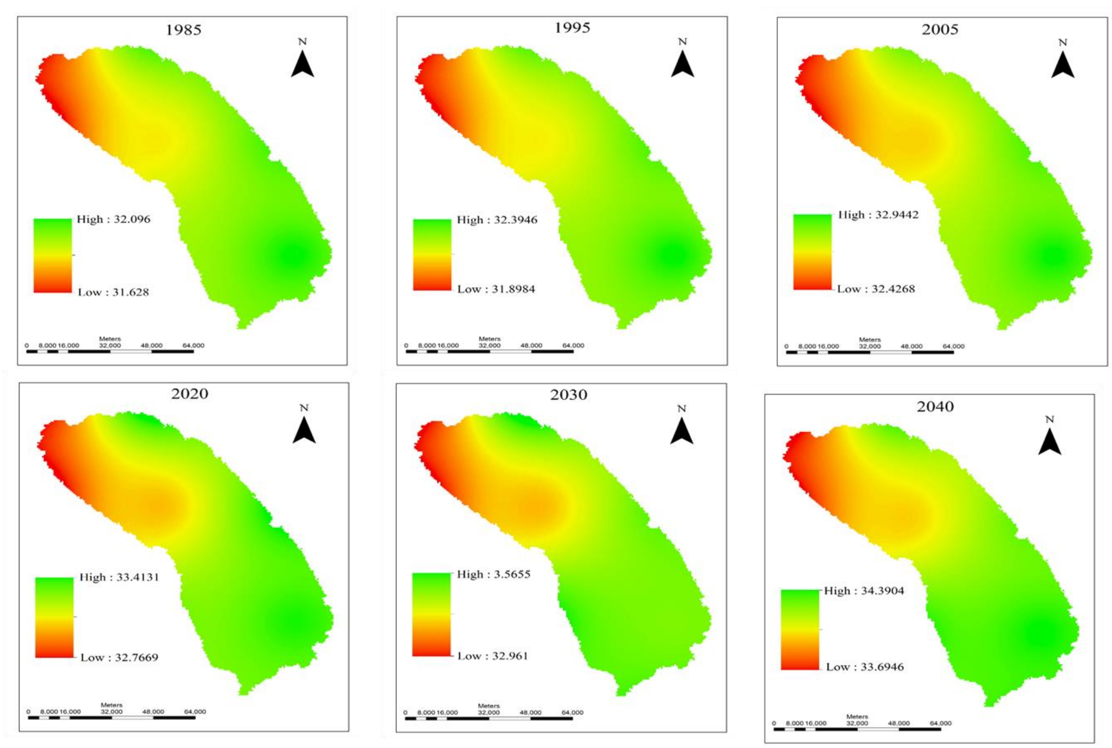

Figure 6.39 Variations of the Maximum Temperature data spatially for the six decades

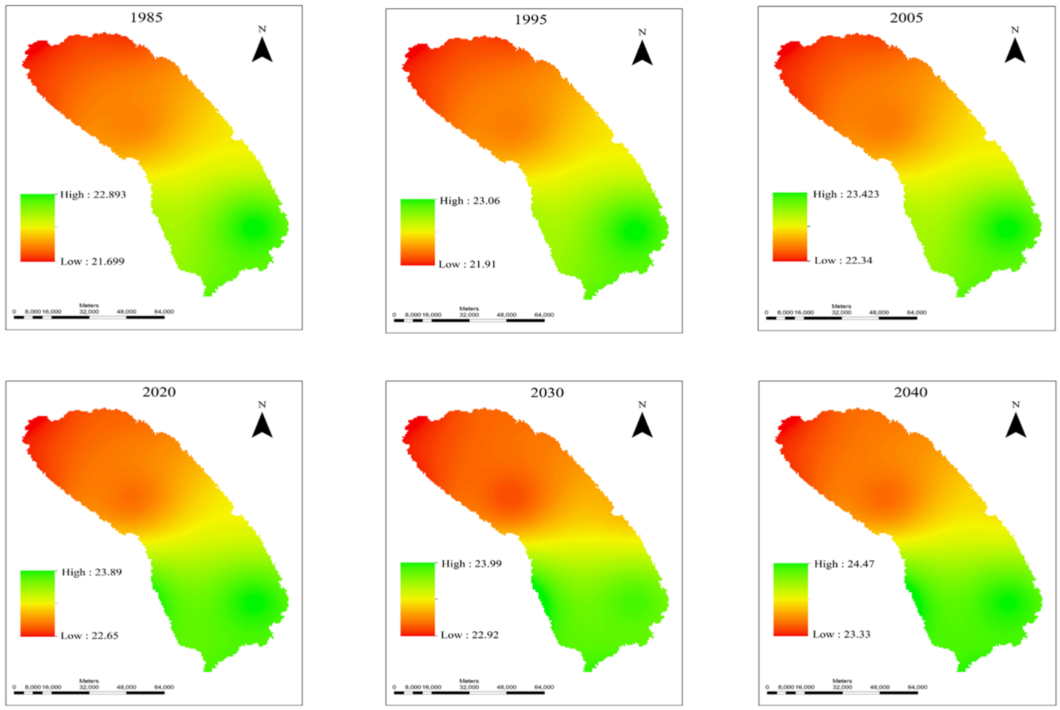

Figure 6.40 Variations of the Minimum Temperature data spatially for the six decades

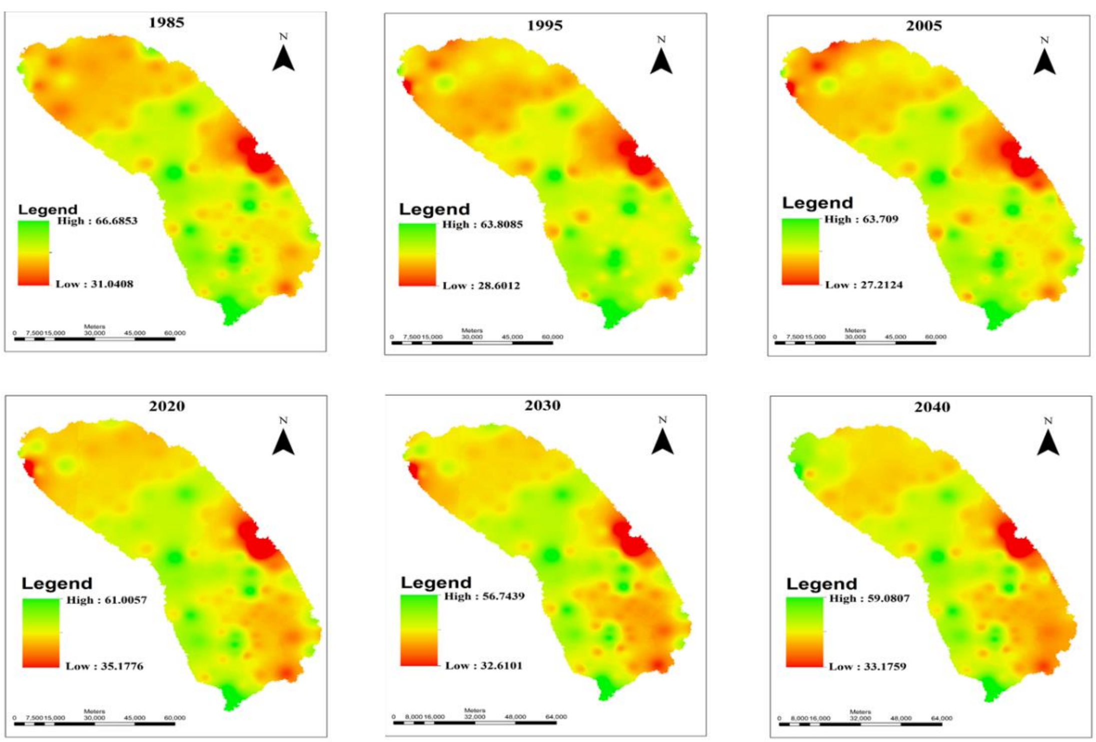

Figure 6 41Variations of the Evapotranspiration data spatially for the six decades.

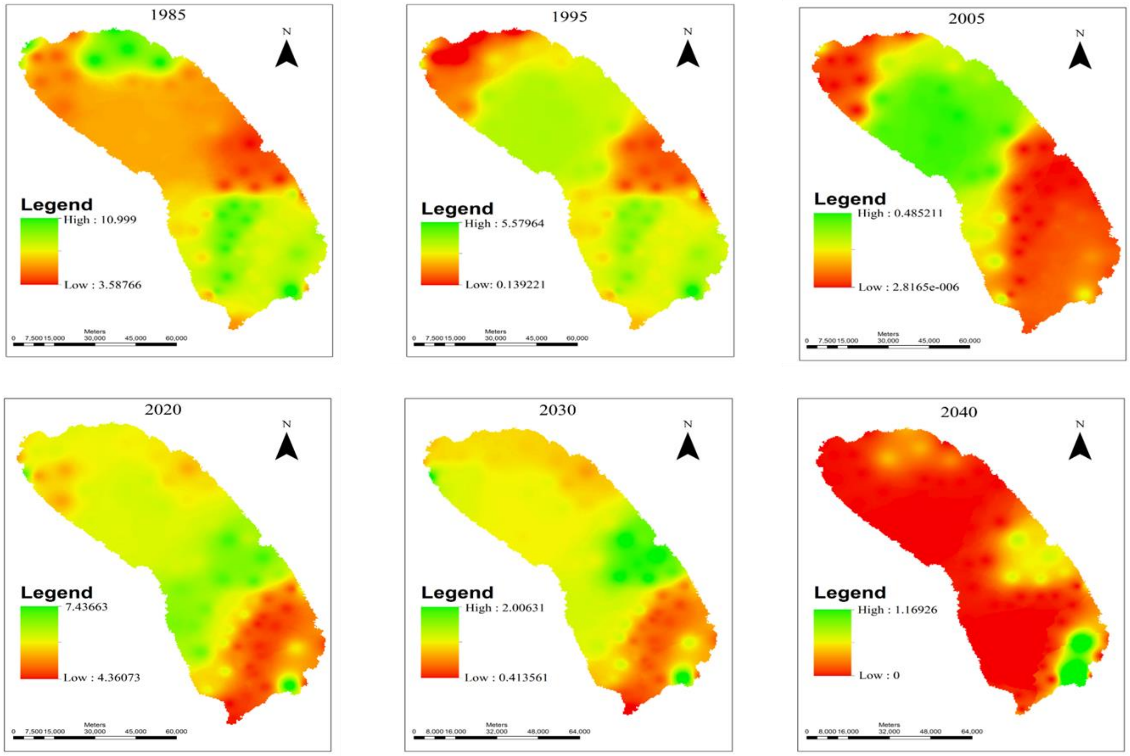

Figure 6.42 Variations of the Base flow spatially for the six decades.

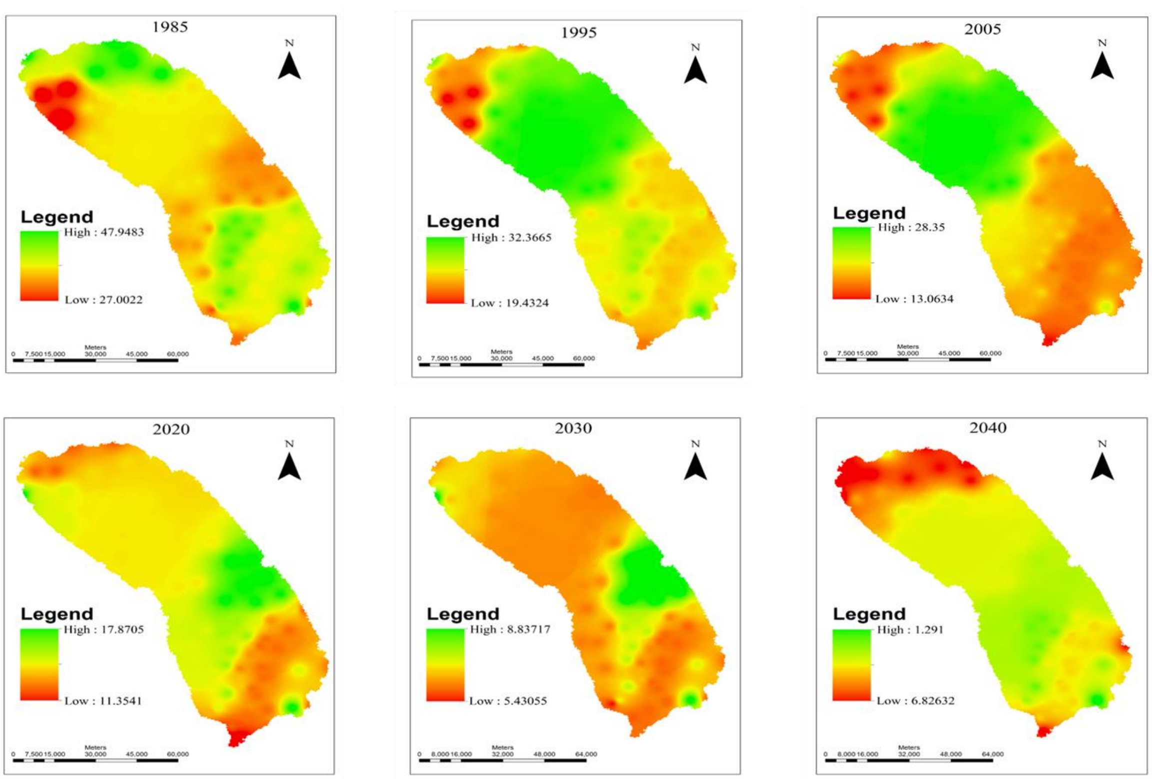

Figure 6.43 Spatial variations of the Surface runoff for the six decades.

The variations in water balance components with respect to precipitation, minimum and maximum temperatures temporally are shown in Figure 6.44. Observations made for surface runoff and base flow show a similar decreasing trend with precipitation from 1995 to 2005. Evapotranspiration and temperatures show an increasing trend, as they are directly in proportion with each other.

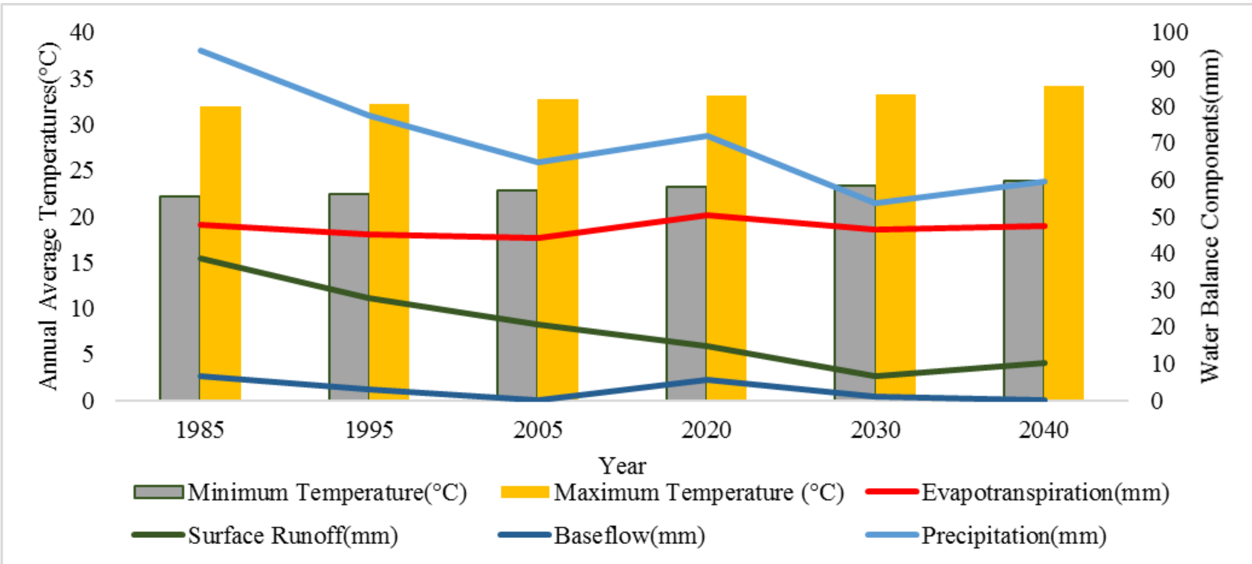

Figure 6.44 Temporal variations of climate variables and water balance components

6.6 Adaptation policies for Reservoir Operating Systems

From the previous chapters, it is observed that the Middle Krishna and Lower Krishna basins are subjected to severe drought conditions. Literature review in chapter 2 also emphasises the importance of adaptation to climate change in the management of water resources in the Krishna river basin. Based on the impact studies on Krishna river basin, Nagarjuna Sagar dam was selected for evaluating the effect of climate change and to develop the adaptation policies for mitigating the effect of climate change. The salient features and a view of the reservoir are presented in Table 4.1 and Figure 4.14 respectively. The ensemble climate model data of RCP 4.5 scenario is used to simulate the streamflow in the reservoir and is used for developing adaptation strategies. Adaptation strategies for future projections are developed considering the 'business as usual' scenario and with optimal operating policies. Hydrologic impact on the reservoir operation is mitigated considering the performance criteria evaluated for the adaptation policies. Climate change impact on multipurpose reservoir systems and four performance criteria (reliability with respect to time and volume, resilience and vulnerability) are evaluated using the r package known as "reservoir"[2].

The performance criteria obtained were studied initially with the standard operating policy (SOP) using current rule curves of the observed data. Increase in demands like Irrigation, water supply etc., and the projected ensemble climate model data-based streamflow obtained from SWAT model are used for projecting the future hydrologic scenarios. The performance indices projected with the SOP for future scenario show decrease in reliability, while the vulnerability and resilience are likely to increase because of climate change. Therefore, a stochastic Dynamic Programming (SDP) model was used to derive an adaptive optimal monthly operating policy by addressing the inflow uncertainty with the objective of maximizing reliabilities with respect to multipurpose reservoirs. Based on the adaptation policies generated using SDP, release policy decisions have been proposed for Future periods. The storage yield curves have been developed to minimize the storage volume with change in the targets for future periods. For generating adaptation policies, the water releases are obtained from data of the reservoir operation. The annual surface water requirements for the Nagarjuna Sagar dam are presented in Table 6.6.

[2] https://cran.r-project.org/web/packages/reservoir/reservoir.pdf

Based on the quantities listed in Table 6.6, the main purpose for NS dam is irrigation while generation of Hydropower was neglected in developing the reservoir operation policies. Monthly streamflow values obtained at the Nagarjuna sagar dam from calibrated and validated SWAT model were considered as inflows to the reservoir. Figure 6.45 presents mean monthly variations of the streamflow during calibration and validation of the models and these were in good agreement. FDCs developed for the Annual, Monsoon and Non-monsoon periods of three future periods are shown in Figure 6.46. FDCs project low flow values in streamflow for Future1 and Future3 periods.

Table 6. 6 Surface water requirements for Nagarjuna Sagar dam

Purpose	Quantity (Mm^3)
Irrigation	44230
Domestic	3348
Industrial Use	4813
Hydro power	1154
Total	53545

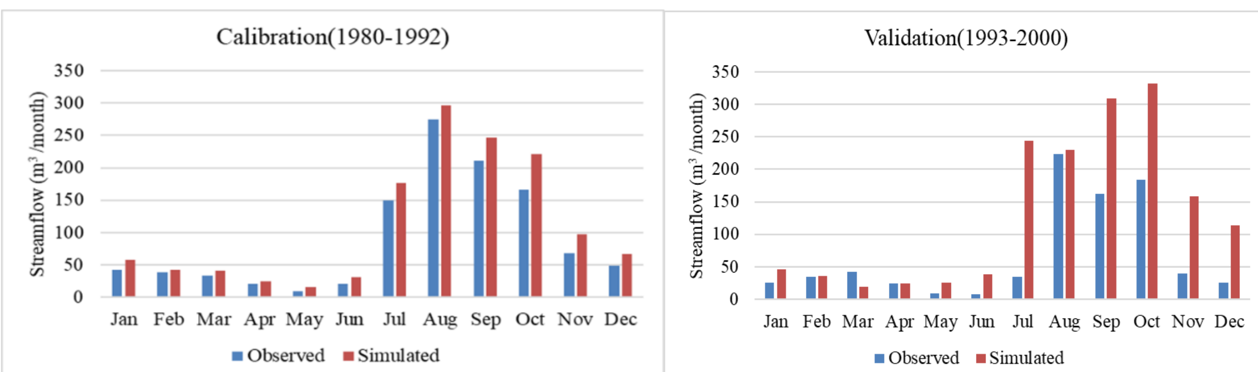

Figure 6.45 Mean monthly variations of the observed and simulated streamflow during Calibration and Validation periods

Standard operating policy aims to meet all demands in a period of given water availability. SOP has been generated considering the target as 0.6 times of the mean obtained based on the observed inflows. An optimal adaptive policy needs to be formulated to optimize the impacts of climate change on reservoir operations. The adaptation strategies are developed by considering increase in the demand and availability of water. From Fig 6.46, high inflows to the reservoir are observed in the future 2 and 3 periods supports to raise the releases for the future periods considering the increase in demand. SDP model addresses the uncertainty associated with inflow to derive an optimal monthly operating policy for future scenarios with the objective of maximizing reliabilities. Performance indices were evaluated for the adaptation strategies recommending the best strategy to be adapted in future scenarios. Better performance indices were obtained with 0.6xmean as target from SDP compared to the indices of SOP. Targets for the adaptation strategies were fixed by a number of SDP iterations for future periods based on the performance Indices, as shown in Table 6.7. Best fit strategy was fixed based on the High Reliability and Resilience with low Vulnerability values. The effect of the adapted targets for the SOP and SDP for Historic and Future periods are shown in Figures 6.47 to 6.49 investigated using the performance indices. The increase in resilience values are observed in the operating policy developed using SDP in Figure 6.48.

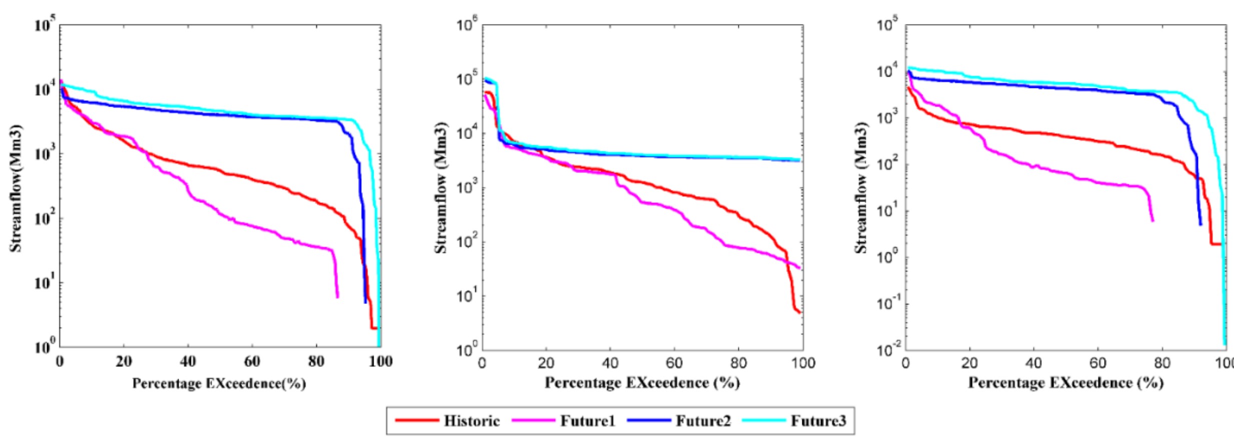

Figure 6.46 Flow Duration Curves of Annual, Monsoon and Non-Monsoon periods

Table 6. 7 Summary of Performance Indices

Inflow	Target	Time Reliability	Volumetric Reliability	Resilience	Vulnerability
Observed	0.6*3815	0.89	0.92	0.09	0.93
Historic		0.97	0.98	0.25	0.9
Future1		0.6	0.66	0.14	0.79
Future2		0.92	0.93	0.1	0.85
Future3		0.98	1	0.8	0.25
Historic	0.6*3815	0.96	0.97	0.75	0.4
Future1		0.62	0.69	0.87	0.13
Future2		0.92	0.93	0.77	0.14
Future3		0.99	1	0.3	0.33
Historic	Minimum	0.74	0.88	0.42	0.58
Future1		0.48	0.61	0.16	0.83
Future2		0.82	0.9	0.26	0.48
Future3		0.86	0.95	0.4	0.53
Historic	Maximum	0.26	0.59	0.19	0.75
Future1		0.19	0.39	0.08	0.91
Future2		0.36	0.65	0.14	0.74
Future3		0.36	0.69	0.16	0.74
Historic	Mean	0.42	0.71	0.28	0.68
Future1		0.3	0.48	0.16	0.76
Future2		0.5	0.74	0.26	0.63
Future3		0.52	0.79	0.32	0.56
Future1(SDP)	0.3*3815	0.93	0.97	0.56	0.61
Future2(SDP)	0.8*3815	0.91	0.93	0.54	0.7
Future3(SDP)	0.85*3815	0.94	0.98	0.6	0.46

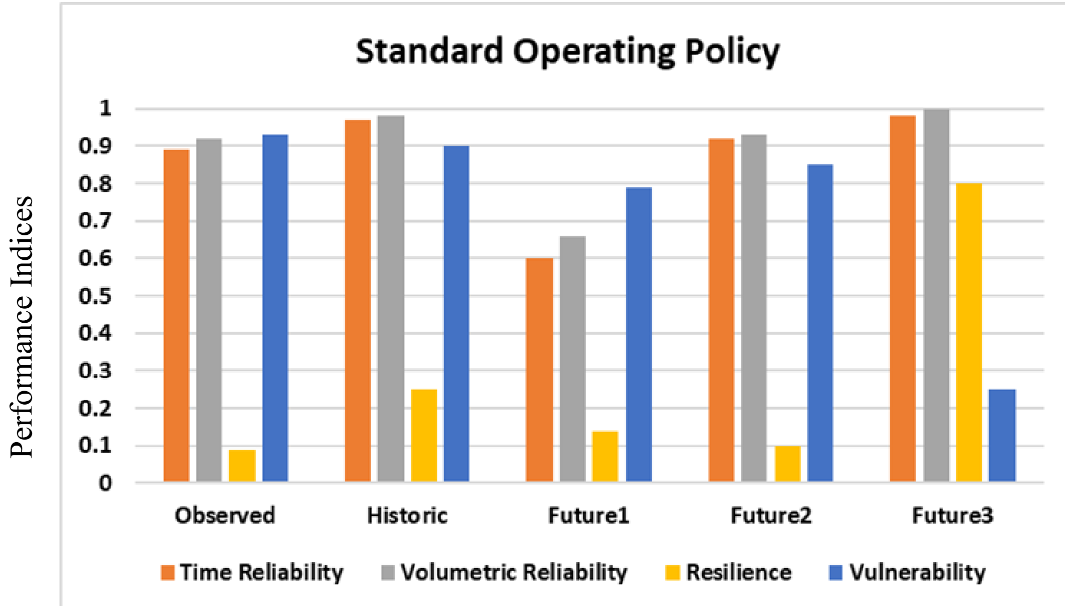

Figure 6.47 Effect of applying SOP on performance measures for Historic and Future periods

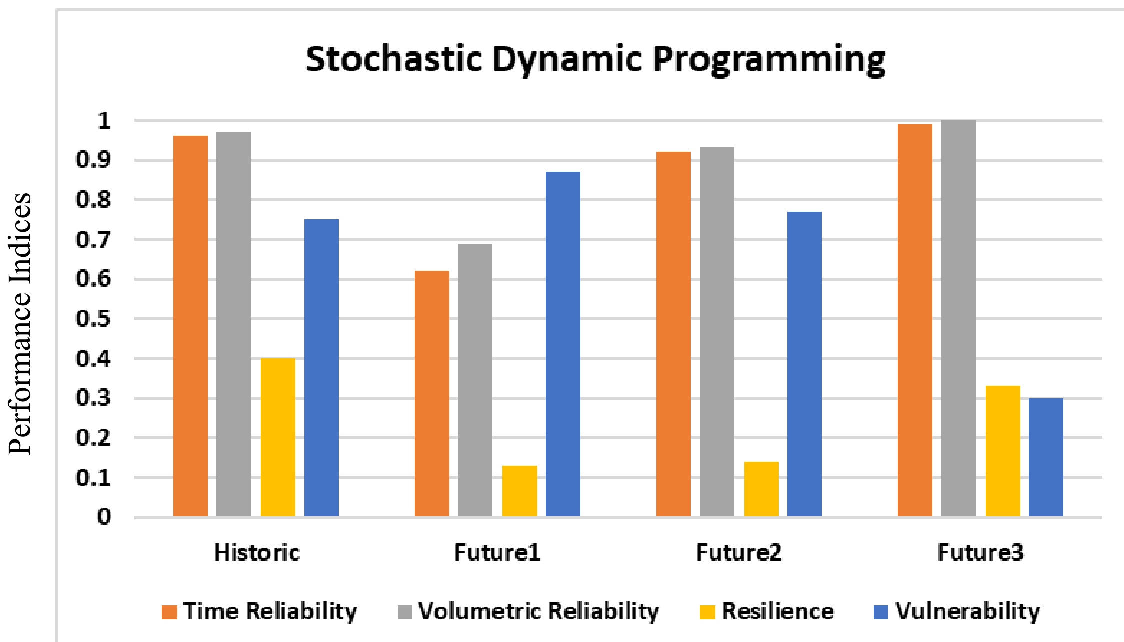

Figure 6.48 Effect of applying SDP on performance measures for Historic and Future periods

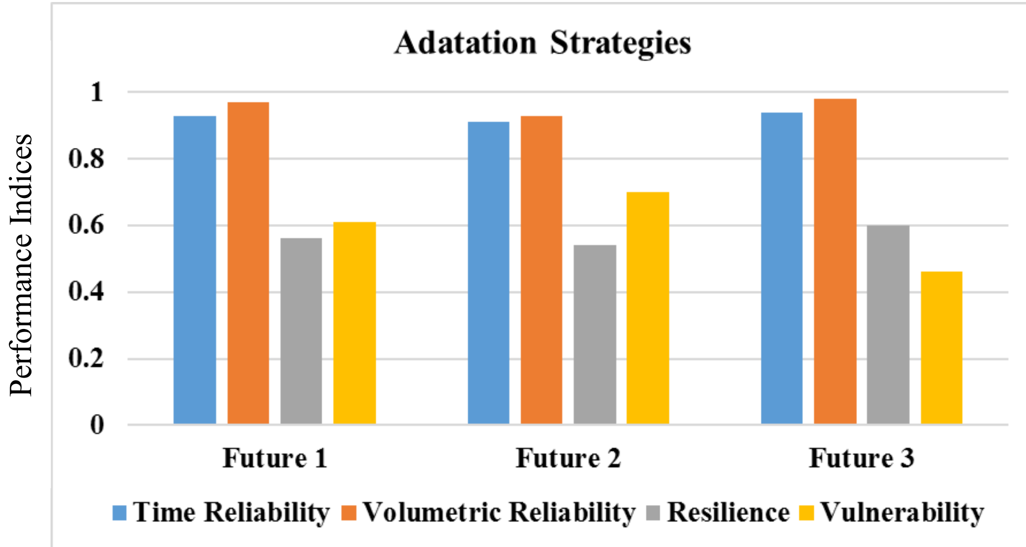

Figure 6.49 Performance measures of Adaptation strategies using SDP for Future periods

Figure 6.49 presents the adaptation strategies for three Future periods with different targets as shown in Table 6.7. Increase in vulnerability is observed in Figure 6.49, but there is an increase in resilience supporting the significance of the adaptation policies. Based on the performance indices, the storage – yield curves are developed for the future scenarios to mitigate the risk of climate change and are shown in Figure 6.50. Storage yield curves in Planning a system allow one to determine the storage required for given yield and reliability, whereas for existing system it helps in determining the sustainable yield. The behavioural analysis obtained with fixed yield and reliability is used to estimate the storage capacities for the operation of reservoirs under changing climate. In order to obtain the storage yield relation, a demand profile (Table 6.8) is generated based on the observed releases. The targets for future periods based on reliability (Table: 6.7) is considered for developing the curves. Generally, multipurpose reservoirs operation policies are designed to obtain a reliability of 70 to 80%. The storage-yield curves are developed to minimize the storage volume with the change in the targets for the future periods. Figure 6.51 presents the rule curves, which act as a source in managing resources without affecting performance and help to mitigate the risk of climate change.

Table 6.8 Factors of demand based on observed releases

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Demand	0.54	0.5	0.53	0.32	0.12	0.2	1.1	3.0	2.32	2.04	0.77	0.57

From the observed data, it is observed that annual current water demand is 22066.45Mm^3. from using the same demand profile (Table 6.8), with the reliabilities obtained from adaptation policies, the annual water demand is minimized to 7852.047 in Future 1 period considering the impact of climate change on operating the reservoir. As the climate change predicts increase in precipitation and stream flow, the annual water demand is maximised to a value of 26,693.21Mm^3 in Future period 2 followed by 27313.55 Mm^3 in Future period 3. It is observed that adaptive policies project more releases recommending higher reservoir elevations in August as permitted by the rule curve. Progressively increasing weightages for irrigation and water supply in policies for Future 2 and Future 3 leads to higher releases, especially in August, for these policies. Therefore, a risk assessment strategy considering the risk of flooding needs to be formulated. This strategy can be used to derive changes in reservoir operation rules for successful mitigation of climate change impacts.

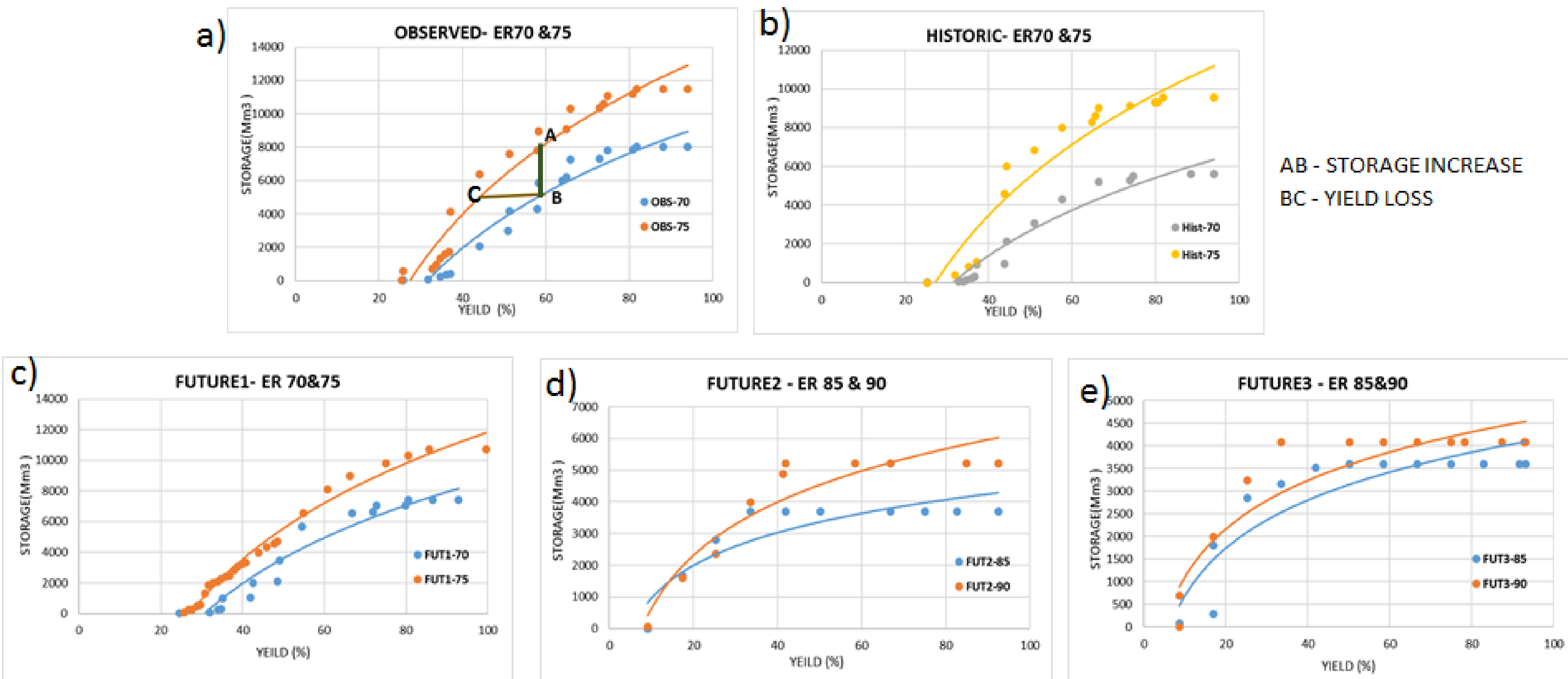

Figure 6.50 Impact of climate change on reservoir Storage –Yield for different Empirical Reliability (ER) values a) Observed b) Historic c) Future 1 d) Future 2 e) Future 3

Figure 6.51 Proposed rule curves based on Empirical Reliability values for Future periods

6.7 Closure

In this chapter, climate change impact on the streamflow of Wardha, a subbasin of Godavari river is analysed using multi climate model data base of two scenarios using SWAT. Effect of the uncertainty modelled ensemble climate model on Krishna River with respect to Drought analysis is investigated. The results of LULC and climate change on Agricultural watershed and the Adaptation policies to mitigate the impact of climate change on reservoir operating policy are discussed in this chapter.

Chapter – 7

Summary and Conclusions

7.1 Summary

In the present research work, climate change impacts have been simulated for Krishna and Wardha river basins for present and future periods. Future projections of climate obtained from dynamically downscaled data from 9 GCMs with two climate forcing's of RCP 4.5 and RCP 8.5 are bias corrected using nonparametric quantile mapping method. Multi-site calibration and validation of SWAT model has been carried out for Wardha and Krishna river basins. Bias corrected RCM data is incorporated in the calibrated and validated SWAT model of Wardha basin to evaluate the monthly and annual variations of the streamflow and water balance components due to climate change. Uncertainty of the climate model data is reduced by developing the REA for two climate scenarios. Spatial and temporal variations of drought have been examined over Krishna basin and hotspots with extreme high and low values are identified. Future projections of streamflow induced by ensemble climate model data with RCP 4.5 and RCP 8.5 scenarios are simulated from calibrated SWAT model. FDCs at three-gauge points have been generated with different levels for different time periods. Trend analysis for all the sub basins generated from SWAT are examined using Mann Kendall trend test. Hydrological drought at all the sub basin outlets are evaluated using SDI focusing on the intensity and severity of the reduced rainfall and runoff. An agricultural watershed prone to LULC change along with the climate change is further analysed for spatial variations of water balance components. Reservoir operation under changing climate is monitored and adaptation strategies have been developed to manage the resources optimally without effecting the reliability of reservoir using SDP. The storage yield curves for future scenarios are generated from the adaptive policies on monthly basis.

The methodology developed is to investigate the hydrologic changes of Wardha basin under climate change of 5 different models and different scenarios. Initially, dynamically downscaled climate data of the parent global models under Coordinated Regional Downscaling Experiment (CORDEX) is retrieved for 27 grids of 0.5° x 0.5° resolution for RCP 4.5 and RCP 8.5 emission scenarios. The observed high resolution of 0.5° x 0.5° gridded rainfall and minimum and maximum temperature data over Wardha basin are collected from Indian Meteorological Department (IMD), Pune. Bias in multiple climate model data in comparison with observed data is corrected using the non-parametric quantile mapping method. The SWAT model was developed for the basin with all necessary data and is calibrated with data for 1984 to 1996 and validated for a period of 1997 to 2003 using observed streamflow data at three-gauge stations. Goodness of fit of calibrated model is verified with R^2 and NSE values as presented in Table 5.2.

From the initial study, it is observed that the projections from the different climate models are different from each other. Therefore, it is wise to consider an ensemble of climate models for future projections. In this study, Krishna river is considered for the climate change analysis for future periods with ensemble mean of two scenarios. Initially, model uncertainty related to ensemble models and the parameter uncertainty associated with different return levels are considered. The intermodal uncertainty resulting from the ensemble of projections is addressed using the Reliability Ensemble Average (REA) method considering the performance and convergence criteria. Subsequently, SWAT model is used to simulate the future streamflow values under RCP 4.5 and 8.5 scenarios. The high-resolution meteorological data such as precipitation, maximum and minimum temperatures are extracted from different climate models under CORDEX experiment. The ensemble average of different meteorological data from RCMs after REA analysis shows better agreement of the minimum and maximum temperature with respect to observed series. On the other hand, the extreme precipitation events are not captured by the ensemble mean. Hence, to correct the bias, a non-parametric quantile mapping is performed only for the precipitation data. Then the bias corrected ensembled precipitation data with ensemble temperature data are incorporated in the multi-site calibrated and validated SWAT model with monthly streamflow values using SUFI-2 of SWAT-CUP. The future projected stream flows under RCP 4.5 and RCP 8.5 are factored to analyse the probability of non-exceedance using FDCs and Trend analysis using Mann-Kendall trend test.

Based on the results of the former study on Krishna river basin, the basin is noticed to be subjected to low precipitation and decrease in streamflow. Hence, drought based on the climate and streamflow is analysed for future projections. Severity, frequency and intensity of meteorological drought is monitored using Standardized Precipitation Index (SPI) over the basin using the ensemble mean of 5 models under RCP 4.5 and 4 models under RCP 8.5 scenarios. Similarly, Streamflow Drought Index (SDI) is quantified at the outlets of seven sub basins of the Krishna river. Spatial variations of the meteorological drought and temporal variations of the hydrological drought are assessed over the basin.

Based on the impact study of climate change on various sub basins of Krishna river, Middle and Lower Krishna basins are identified as the most affected regions. In addition to climate change, the impact caused due to LULC change is also monitored for an agricultural watershed of the lower Krishna basin. Decadal LULC images of 100m resolution are used for inducing the change in SWAT model which is calibrated and validated. The variations of water balance components due to climate change and LULC changes are examined spatially.

Further, Nagarjuna Sagar reservoir located in the middle Krishna basin is selected to assess the hydrologic impacts of climate change under uncertainty and adaptation policies developed for future without affecting the reliability of reservoir operations. The streamflow obtained from Bhima and Upper Krishna is considered as inflows to the reservoir. The performance of the reservoir operations is evaluated using Standard Operating Policy. Adaptation policies for the Future scenarios are developed considering the increment in demands with increase in population. Based on the adaptation policies, rule curves for storage yield with reliability of not less than 70% are developed for future scenarios.

7.2 Conclusions

The following are the conclusions of the study presented in the thesis.

- Among the five models, NORESM model projects similar results with observed data while other models ACCESS, CCSM, CNRM and MPIESM show lower values of 41%, 53%, 58% and 16% respectively. Annual average precipitation from climate models of the basin projects high values with an increase of about 40% to 50% during historic period.

- The analyses of the annual and monthly streamflow variations suggest that RCP 4.5 scenario produces lower values of streamflow under decreased precipitation and increased temperature.
- Streamflow projected using RCP 8.5 scenario simulates maximum values compared to RCP 4.5 with a percentage change of 100-200%
- The inter and intra annual variations of projected streamflow show much variations compared to observed values projecting the uncertainty in climate model and hydrologic model simulations.
- Water balance components of basin simulated for future projections and two different scenarios are quantified. Prominent streamflow is observed under RCP 8.5 scenario, as a result of extreme rainfall events.
- The REA precipitation data of Krishna basin projects a decrease in the annual average values of 20% in future 1, around 4 to 6% in future 2 periods, whereas future 3 projects the same values as in the historic period under RCP 4.5 scenario.
- Decrease of 36% in annual average precipitation is observed in Future1, 10% increase in Future2 and 60% decrease in Future3 periods under RCP8.5 scenario with an increase of 6°C observed in the basin by the end of 2100.
- The spatial annual average values of REA precipitation suggest a decrease of about 40% in Tungabhadra and Lower Krishna basin during Future 1 period.
- Spatial variations of annual average precipitation values of Krishna basin for Future 3 period estimate percentage decreases of 30 to 100 in Bhīma and Middle Krishna basins.
- Non-monsoon increases in precipitation of about 10-50% are observed in many parts of Krishna basin during future 3 period.
- The performance of the hydrological model is considered to be good and satisfactory with R^2, NSE and relative bias values ranging from 0.52 to 0.86, 0.32 to 0.58 & -41.9 to 79.8 during calibration and validation of the model for Krishna river basin.
- FDCs generated in the basin projects decreased flow in Future1 period at 3-gauge stations. FDC generated at gauge stations provides information about the flow at a given level of probability, which empower the development of management practices.

- Trend analysis predicts that the basin is about to face decrease in streamflow at most of the sub basins in RCP 4.5 scenario and increase of stream flow in sub basins in RCP 8.5 scenario.
- Increase in average monsoon precipitation of about 120% to 300 % is observed in Tungabhadra and Bhima basin for Future 1 and 2 periods respectively.
- The annual, monsoon and non-monsoon changes in the precipitation are among the two projected scenarios where RCP 8.5 projects low precipitation values throughout the basin.
- The severity of the drought events is more in Tungabhadra and Lower Krishna regions during future1 and more in Bhīma, Upper and Middle Krishna regions during future 3 periods, with high frequency.
- Though there is an increase in monsoon precipitation, SPI calculated for 12-month basis shows less frequent wet conditions and drought events of more frequency, for future periods and two scenarios.
- Extreme drought events are observed in Upper Krishna and some parts of the Tungabhadra in Future 1 period and Upper and Lower Krishna regions in Future 3 periods of RCP 4.5.
- SDI calculated with the reference period of 12 months in all the sub basins shows that more than 50% of the data prevails drought conditions in Upper Krishna, Middle Krishna, Lower Krishna, Upper Tungabhadra and Lower Tungabhadra basins during future 1 period.
- SDI generated for the sub basins shows that Tungabhadra basin is less affected by drought while Bhima, Middle and Lower Krishna region are more prone to drought conditions in future periods.
- Change in the first two decades (1985-1995) shows 100% rise of forests, 50% rise in urban land area, around 100% decrease in cropland/woodland, 60% fall in water bodies with not much changes in the next two decades (1995-2005).
- Increase in temperature and decrease in precipitation results in decreased values of surface runoff and base flow with an increase in evapotranspiration.
- Increase is expected in Evapotranspiration of about 10%, 1.7%, 3.84% in 2020, 2030, 2040 decades respectively with a decrease of about 50%. Zero-base flows are predicted in most of the basin by 2040.

- Storage – Yield curves developed for varied targets report decrease in the yield at full and dead storage volumes with increased reliabilities.
- The rule curves obtained propose 58% decrease in release during future period 1 and increase in release of about 38% in future 2 and 3 periods.

7.3 Research Contributions

The following are the important research contributions of the present study:

- For the reduction of multi model uncertainty, REA is developed. The REA data show more correlation with the observed climate data.
- SWAT model is applied for Wardha, Krishna, Munneru and Middle Krishna basin which helps to simulate all hydrological process of the basins.
- Adaptation policies are developed for the optimal reservoir operations with a reliability of not less than 75% for Nagarjuna sagar dam.
- Rule curves for the monthly operating of the reservoir are developed for future scenarios under climate change.

7.4 Scope for Further Study

The scope for further study related to this work is as follows:

- Multiple ensemble scenarios, other than REA can be used for impact studies.
- Land Use Land Cover change modelling of the Krishna river basin can be incorporated in climate change impact analysis.
- Development of adaptation strategies considering multi-purpose reservoir system can be another area of research.
- Development of community-based adaptation strategies for various cropping patterns in the various sub basins can also be investigated.

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Appendix A

The maximum and minimum REA temperatures of the Future periods are presented as the box plots(A.1and A.2) on monthly basis.

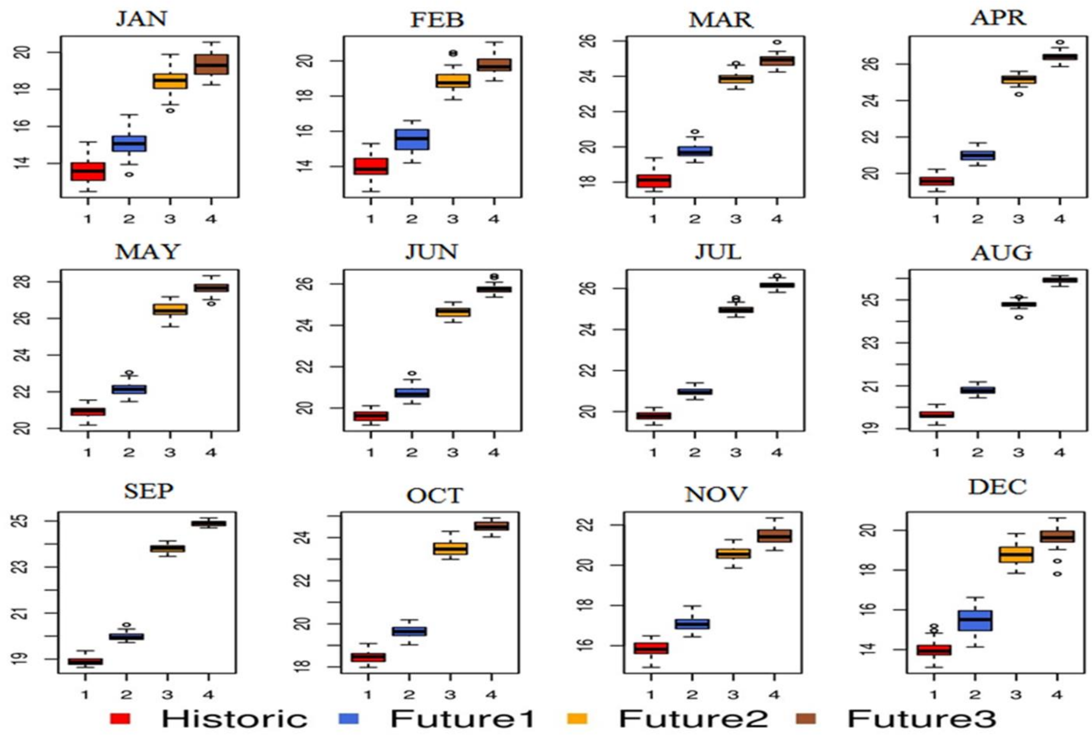

Figure A.1 : Temporal variations of Minimum Temperature (^{0}C/day) for the Historic, Future1, Future2 and Future3 periods.

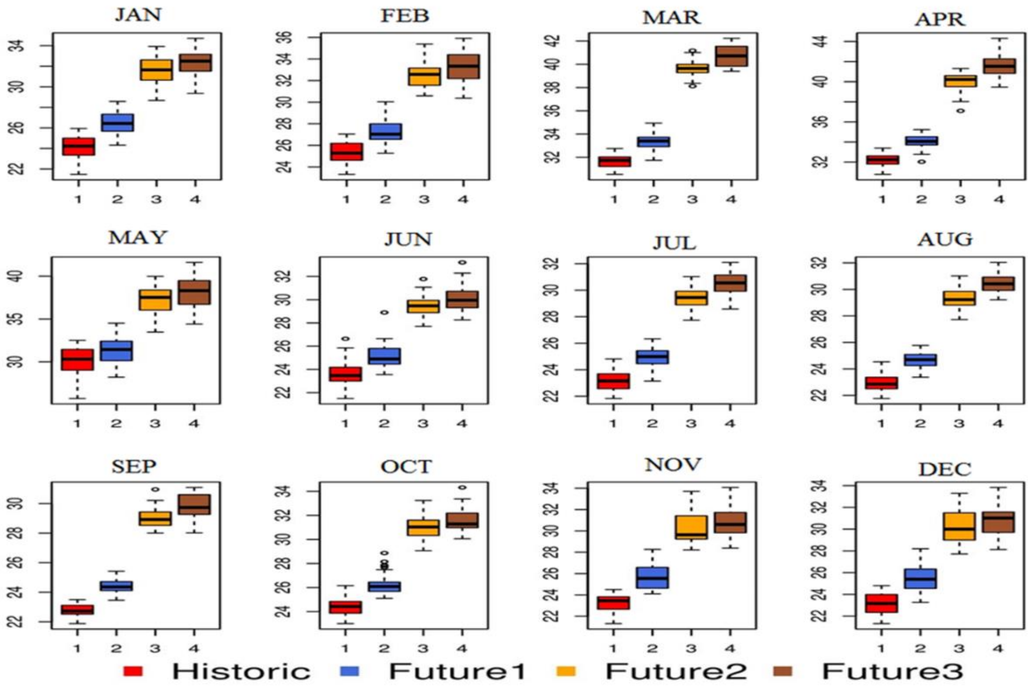

Figure A.2: Temporal variations of Maximum Temperature (^{0}C/day) for the Historic, Future1, Future2 and Future3 periods

LIST OF PUBLICATIONS

Journals:

- **Naga Sowjanya, P.,** Venkata Reddy, K and Shashi, M., "Intra and Inter Annual Streamflow variations of a Watershed under changing climate", *ISH Journal of Hydraulic Engineering*, pp.1-12
- **Naga Sowjanya, P.,** Venkata Reddy, K and Shashi, M.," Spatial and Temporal variations of climate variables over a River Basin", *Journal of Rural Development Volume:37 Issue 2, April-June 2018.*
- **Naga Sowjanya, P.,** Venkata Reddy, K and Shashi, M.,"Climate change effect on Water resources using Climate Model Data an River basin", ***International Journal of Research in Engineering and Technology*** Volume: 04 Special Issue: 11, 150-154.
- **Naga Sowjanya, P.,** Venkata Reddy, K, Shashi, M., and Das J "Future Streamflow Projections Under Changing Climate Using CORDEX Simulated Data over Krishna River Basin, India ", Journal of River Basin Management (Under Review).

Conferences:

- **Naga Sowjanya, P.,** Venkata Reddy, K and Shashi, M., " Impact of Landuse Landcover and Climate change on a Watershed using SWAT", ***Hydro 2017, 22nd International Conference on Hydraulics, Water resources & Coastal Engineering,*** *21-23 December2017, Ahmedabad, India.*
- Venkata Reddy ,K., Sri Lakshmi Sesha Vani Jayanthi., Tharani Kotrike., **Naga Sowjanya ,P.,** " Geospatial Modelling tool for climate data retrieval", ***International Conference on Climate Change Innovation and Resilience for Sustainable Livelihood*****,** 12 – 14 January 2015, Kathmandu, Nepal.
- **Naga Sowjanya, P.,** Venkata Reddy, K and Shashi, M., "Effect of Estimated Runoff under changing climate on Regional Watershed", ***International Conference on Modeling Tools for Sustainable Water Resources Management,*** Department of Civil Engineering, Indian Institute of Technology Hyderabad: 28-29 December 2014.

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If I have missed out on saying something, I hope you understand.

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