Development of Adaptation Strategies for Water Demand Management of a Tank Based Irrigation System under Climate Change

Submitted in partial fulfilment of the requirement for the award of the degree of

Doctor of Philosophy

by

Sri Lakshmi Sesha Vani Jayanthi

Roll No. 716101

Supervisor

Prof. K.Venkata Reddy

DEPARTMENT OF CIVIL ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY

WARANGAL-506004, INDIA

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Dedication

This thesis is dedicated to all the people who have supported me throughout my education. Thanks for making me enjoy the amazing journey.

THESIS APPROVAL FOR PH.D.

This Thesis entitled "**Development of Adaptation Strategies for Water Demand Management of a Tank Based Irrigation System under Climate Change**" prepared by **Ms. Sri Lakshmi Sesha Vani Jayanthi** (Roll No. 716101) is approved for the degree of Doctor of Philosophy.

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DECLARATION

This is to certify that the work presented in the thesis entitled "**Development of Adaptation Strategies for Water Demand Management of a Tank Based Irrigation System under Climate Change**" is a bonafide work done by me under the supervision of **Prof. K. Venkata Reddy** and was not submitted elsewhere for the award of any degree.

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Roll No. 716101

Date:

NATIONAL INSTITUTE OF TECHNOLOGY

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This is certify that the thesis entitled "**Development of Adaptation Strategies for Water Demand Management of a Tank Based Irrigation System under Climate Change**" being submitted by **Ms. Sri Lakshmi Sesha Vani Jayanthi** for award of the degree of Doctor of Philosophy to the Faculty of Engineering and Technology of **National Institute of Technology Warangal** is a record of bonafide research work carried out by her under my supervision and it has not been submitted elsewhere for award for any degree.

(Dr. K. Venkata Reddy)
Thesis supervisor
Professor
Department of Civil Engineering
National Institute of Technology Warangal

ABSTRACT

Climate changes are inevitable, and the accelerating rate of climate change impacts on the water sector requires climate vulnerability reduction and climate change adaptation measures. Global and regional studies of the implications of climate change on water resources are viewed as critical steps toward anticipating and preparing for the future climate change. In the context of climate change, the assessment of detrimental effects on water resources for optimal allocation and risk management has become a challenge for the research community. The changing nature of the climate as a result of human-induced disturbances draws a considerable amount of attention to water resources and hydrology. Regional Climate Models (RCMs) are the most credible resources for assessing the induced impact in the future for efficient risk and resource management at the regional level.

The present research work initially deals with climate variability and trend analysis during historic and future time periods. Later, the climate change impact on an irrigation tank is assessed with the help of hydrological modeling and high-resolution RCM data. The impact of climate change on the irrigation tank lake water level fluctuations and irrigation water demand in the command area are examined. Finally, adaptation strategies for water demand management are developed.

In the initial part of the thesis, the historic and future projected changes in the three major climate variables (precipitation, maximum and minimum temperature) are investigated for the Telangana region, India. For this purpose, climate variability and trend patterns are estimated using observed climate data obtained from Indian Meteorological Department (IMD) and RCM data from the Coordinated Regional Downscaling Experiment (CORDEX) database. The data from 1951 to 2013, is used for analysing the historic climate variability and trends and for future analysis data from 2020 to 2050 under both RCP 4.5 and RCP 8.5 are used. Coefficient of variation (CV) is used for evaluating climate variability at daily, monthly and annual time scales, and the identification of trends in climate variables, both parametric (Linear Regression) and nonparametric methods (Mann-Kendall and Sen's slope) are used.

For observed IMD data, the results of both parametric and non-parametric tests revealed a substantial increasing trend in daily maximum and minimum temperatures. Whereas daily precipitation shows no discernible trend, indicating precipitation uncertainty. Maximum and minimum temperatures have risen significantly, influencing precipitation patterns. The RCP

4.5 ensemble data showed an increasing trend for precipitation and maximum temperature, but no significant trend in minimum temperature in North Telangana Zone (NTZ) and sections of Central Telangana Zone (CTZ), and a decreasing trend for South Telangana Zone (STZ). RCP8.5 ensemble results for future scenarios predicted less rain and higher daily maximum and minimum temperatures. CTZ is most vulnerable to climate change.

In the second part of the thesis, the impact of climate change on Pakhal Lake, which is an important irrigation tank supplying water for more than 30,000 acres of agricultural land in Telangana state. Soil and Water Assessment Tool (SWAT), a physically distributed hydrological model is used for modeling of the catchment hydrological response, in order to study tank inflows variations. Since the selected study area is an ungauged catchment, the SWAT model was set up using IMD data for the time period from 1985 to 2005 for the Konduru catchment – a gauged watershed that is downstream of the study area. SWAT model calibration and validation were performed for the Konduru catchment area using the Sequential Uncertainty Fitting (SUFI-2) algorithm in SWAT-Calibration Uncertainty Program (CUP). Regionalization approach is used to transfer the fitted model parameters to the Pakhal watershed.

For the analysis of future climate projections, two sets of climate data are used i.e. CORDEX and NEXGDDP under both RCP 4.5 and RCP 8.5 scenarios. The climate models are bias-corrected using a nonparametric quantile mapping method. The bias-corrected RCM data is used as SWAT model input to evaluate the monthly and annual variations of the future streamflow and water balance components. Uncertainty in the climate models is reduced by developing the Reliability Ensemble Averaging (REA) method. The calibrated and validated SWAT model is used for the simulation of the hydrologic components of Phakal Watershed for Baseline (1986–2018), Future-1 (2020–2050), Future-2(2051–2080), and Future-3 (2081–2099) periods. For simulating the future hydrologic conditions, four CORDEX-RCM outputs under RCP4.5 and RCP8.5 scenarios were used.

The hydrologic components for Phakal Watershed were simulated using the SWAT model that has been validated and calibrated, during Baseline (1986–2018), Future-1 (2020–2050), using REA ensemble of 21 NEX-GDDP models. For the analysis of climate change, the simulated hydrologic conditions are compared with the observed data. The NEX-GDDP models are at a higher spatial resolution than the CORDEX models with a resolution of 0.25^{o}. The CORDEX model results exhibited a significant change in hydroclimatic variables in Future-1 when compared to other future time periods. Hence, future-1 is considered for simulation using NEX-GDDP data for comparison between the two data sets.

The results from the climate change analysis reveal that surface runoff amounts are going to be impacted significantly by climate change. The future tank inflow simulation results also exhibit a significant decrease. Future-1(2020-2051) is the most vulnerable as it experiences the highest decrease in tank inflow. The results project a streamflow decrease of as high as 59 % in tank inflows from historic to future time periods. A significant decreasing trend is observed in the rainfall and lake inflows in the Phakal catchment. The outcomes of both future climate scenarios for NEXGDDP data are different. A decrease in streamflow is observed in RCP 4.5 which can be attributed to decreased precipitation and enhanced potential evapotranspiration (PET). Increased streamflow is predicted in RCP 8.5. Even though NEX-GDDP model data is at high resolution when compared to CORDEX, its correlation with observation data is less. The CORDEX model is found more reliable dataset for the climate change analysis of the study area.

The effect of climate change on water availability in Pakhal Lake is assessed by predicting future water level changes. Support Vector Regression (SVR) coupled with SWAT outputs is employed for predicting lake water levels under present and future climate change scenarios. The radial basis kernel (RBF) function was used to implement the v-SVR approach. Precipitation data, SWAT output data of potential evapotranspiration (PET), inflows, and outflow volume, are used as independent variables in the ν-SVR model, while tank level is the dependent variable. The results of future tank water levels indicate a significant decrease in lake water levels from October-March. (Rabi Season).

The irrigation water demand during historic and future periods is estimated using CROPWAT 8.0. The results show a significant increase in irrigation demand under CRODEX RCP 4.5 scenario. The irrigation tank performance indices are determined under the Standard Operating Policy (SOP) for future scenarios. The results indicate a decrease in reliability, while vulnerability and resilience are likely to increase because of climate change. Irrigation tank optimization is performed using Stochastic Dynamic Programming (SDP). Three adaptation strategies are considered for optimizing irrigation releases. The best fit strategy is chosen based on high reliability and resilience with low vulnerability values. The combination of 2

adaptation strategies i.e. mixed cropping and delayed plantation gives better performance for the Pakhal.

The climate change impact results from the study can be used for devising suitable adaptation plans for managing water resources in the Pakhal Lake region. Adaptive policies proposed for water demand management are useful for the effective utilization of water resources in the Pakhal command area while ensuring crop yield. The methodology proposed in this research work can be used for other irrigation reservoirs for climate change studies.

Keywords: Adaptation strategies, Climate Change Impacts, CROPWAT, Regionalization, SWAT Model, Support Vector Regression, Tank Irrigation.

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Nomenclature

The following list gives the notations used in chapters of 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
w_{int}	Initial weight in REA
F_{wm}	Weighted Mean CDF
F_{RCM_i}	corresponding CDF of the future simulated ith RCM
R^2	Coefficient of correlation
D	Demand or Target Release
τ	penalty cost exponent
R_t	Time based Reliability
R_v	Volumetric reliability
D_i	Target demand during ith period
$D_i^{'}$	Actual volume supplied during the ith 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 jth continuous failure sequence

ET_0	Reference evapotranspiration
ET_C	Crop evapotranspiration
σ	Standard Deviation
μ	Mean Precipitation.
α	Significance Level
w_{int}	Initial Weight
SW_{ti}	Soil water content at the end of the day
SW_o	Amount of initial soil water content on day i
t	Time in days
R_{dayi}	Amount of precipitation on day *i*
$Q_{surf\ i}$	Amount of surface runoff on day *i*
E_{ai}	Amount of evapotranspiration on day *i*
W_{seepi}	Amount of water entering the vadose zone from the soil profile on day *i*
Q_{gwi}	Amount of return flow on day *i*
Oi	Observed discharges at i^{th} observation
Pi	Simulated discharges at i^{th} observation
ξ	Epsilon
C	Capacity constant
K_c	Crop coefficient
P_{eff}	Effective rainfall
A_i	Irrigated area

R_t	Release of water at time t
B_t	Benefit at time t
S_t	Storage at time t
Qt	Inflow values at time t
C_t	Penalty cost
τ	Penalty cost exponent
D	Demand or target release
R	Reliability
$\boldsymbol{\varphi}$	Resilience
ή	Vulnerability
$\boldsymbol{fs}$	Number of individual continuous sequences of failure periods\
$\boldsymbol{f_d}$	Total duration of all the failures
sj	Volumetric shortfall during j^{th} continuous failure sequence
b_{Sen}	Sen's slope

Abbreviations

AI	Artificial Intelligence
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Networks
AR4	Fourth Assessment Report
AR5	Fifth Assessment Report
CDF	Cumulative Distribution Function
CFSv2	Climate Forecast System Version 2
CIR	Crop Irrigation Requirement
CORDEX-SA	Coordinated Regional Climate Downscaling Experiment - South Asia
CROPWAT	Crop Water and Irrigation Requirements
CTZ	Central Zone
CV	Coefficient of Variation
CWBM	-
CWC	Central Water Commission
CWR	Crop Water Requirement
DEM	Digital Elevation Model
DHSVM	Distributed Hydrology Soil Vegetation Model
DP	Delaying the Planting date
DSS	Decision-Support System
DSSAT	Decision-Support System for Agro-technology Transfer
DT	Decreasing Trend
EDR	Effective Degree of Regulation
ET	Evapo Transpiration
FA	Firefly Algorithm

FAO	Food and Agricultural Organization
GCM	Global Climate Models
GHG	Green House Gas
GIS	Geographic Information System
GLUE	Generalised Likelihood Uncertainty Estimation
GoI	Government of India
GP	Genetic Programming
GR4J	Génie Rural à 4 paramètres Journalier
HadRM2	Hadley Centre Regional Model 2
HBV	Hydrologiska Byråns Vattenbalansavdelning Model
HRU	Hydrological Response Units
HYLUC-CASCADE	HYdrological Land Use Change CASCADE Model
I&CAD	Irrigation and Command Area Development
IDW	Inverse Distance Weighting
IHACRES	Identification of unit Hydrographs And Component flows from Rainfall, Evaporation data
IIE	Increasing the Irrigation Efficiency
IITM	Indian Institute of Tropical Meteorology
IMD	Indian Meteorological Department
IPCC	Intergovernmental Panel on Climate Change
IRSHAM	Integrated Regional Scale Hydrological Atmospheric Model
IT	Increasing Trend
IWR	Irrigation Water Requirement
LBC	Lateral Boundary Conditions
LULC	Land Use and Land Cover
LWW	Lake Winnipeg Watershed

MAE	Mean Absolute Error
MC	Mixed Cropping
MCM	Million Cubic Meters
MK	Mann Kendall
MLP	Multi Layer Perceptron
MODFLOW	MODular finite difference FLOW model
MSE	Mean Square Error
MSE	Mean Square Error
NASA	National Aeronautics and Space Administration
NBC	Nested Bias Correction
NEX-GDDP	NASA Earth Exchange Global Daily Downscaled Projections
NSE	Nash Sutcliff Efficiency
NT	No Significant Trend
NTZ	Northern Zone
PCI	Precipitation Concentration Index
PCP	Precipitation
PET	Potential Evapo Transpiration
PRECIS	Providing REgional Climates for Impacts Studies
PSO	Particle Swarm Optimization
PWD	Public Works Department
QUMP	Quantifying Uncertainty in Model Predictions
QUMP	Quantifying Uncertainty in Model Predictions
RBNN	Radial Basis Neural Networks
RCM	Regional Climate Models
RCP	Representative Concentration Pathways
REA	Reliable Ensemble Averaging

RMSE	Root Mean Square Error
RVM	Relevance Vector Machine
SAR	Seasonal Auto Regressive model
SDP	Stochastic Dynamic Programming
SDP	Stochastic Dynamic Programming
SDSM	Statistical Downscaling Model
SEA	Simple Ensemble Averaging
SIMETAW_R	SIMulation of Evapo Transpiration of Applied Water
SIMEX	Simulation–Extrapolation
SNH	Standard Normal Homogeneity
SOP	Standard Operating Policy
SRES	Special Report on Emissions Scenarios
SREV	Square Root Error Variance
SRTM	Shuttle Radar Topography Mission
STZ	Southern Zone
SUFI	Sequential Uncertainty Fitting
SVR	Support Vector Regression
SWAT	Soil and Water Assessment Tool
SWAT-CIP	SWAT Calibration Uncertainty Procedures
TMAX	Maximum Temperature
TMIN	Minimum Temperature
TMPA	TRMM Multisatellite Precipitation Analysis
TOPMODEL	TOPography based hydrological MODEL
TRAC	Telangana State Remote Sensing Center
TRMM	Tropical Rainfall Measuring Mission
UID	Unique Identification

USGS	United States Geological Survey
VIC	Variable Infiltration Capacity
WASMOD	Water and Snow Balance Modeling System
WCRP	World Climate Research Program
WEAP	Water Evaluation And Planning
95PPU	95 percentage prediction uncertainty

Chapter 1

Introduction

1.1 General

Father of the Indian Nation Mahatma Gandhi, has tried to explain the importance of natural resources and their sustainability through his famous quote *"The earth, the air, the land, and the water are not an inheritance from our forefathers but on loan from our children. So we have to handover to them at least as it was handed over to us"*. Among the available natural resources, **water resources** are crucial and should be used in an integrated manner so as to achieve the socio-economic balance of a country. The availability of freshwater on Earth is limited and is varied spatially and temporally. Global water scarcity assessments suggest that the scarcity increases considerably in the future, in comparison with the present day (Hanasaki *et al.* 2008, 2013). Population growth, extensive urbanization, changing patterns of agriculture, and climate-driven changes are estimated to cause an acute impact on the water resources of developing countries (Meter *et al.* 2016, Neelakantan *et al.* 2017). Furthermore, as a result of climate change, water availability is projected to become restricted in most of the regions of the world.

Water scarcity is a serious issue in India, which affects a huge percentage of rural and urban population. It also extensively affects the ecosystem and agriculture. Water being a critical input to the agriculture sector, it is most affected among the other sectors due to the prevailing water crisis. India has only 4% of the fresh water resources of the world despite consisting almost 18% of global population (CWC Annual Report 2018). The availability of these water resources is distributed unevenly in many regions of India (both spatial and temporal), creating mismatch between water availability and water demand (Goyal and Surampalli 2018). Out of the available Indian water resources, 80% is used in agriculture. The ever-increasing population of India is posing a serious stress on food security, ultimately increasing the agricultural water demand. This is further worsened by the direct as well as indirect impacts of climate change.

Climate change is a major challenge to water resources management, food security and socio-economic welfare of the people in the 21st century. According to IPCC fifth assessment report (AR5), the period from 1983-2012 was probably the hottest period in the Northern Hemisphere in the past 1400 years. The global average surface temperature variation for the period 2006–2100 relative to 1986–2005 is projected to be in the values between 0.3°C and 4.8°C under the four Representative Concentration Pathway (RCP) 2.6, 4.5, 6.0, and 8.5 scenarios (Fig 1.1). All changes are with respect to 1986–2005. Time series of projections and uncertainty band (shading) are shown for scenarios RCP2.6 (blue) and RCP8.5 (red). For each RCP scenario, the mean and corresponding uncertainty are represented as colored vertical bars on the right-hand side of each panel, averaged over the years 2081-2100.

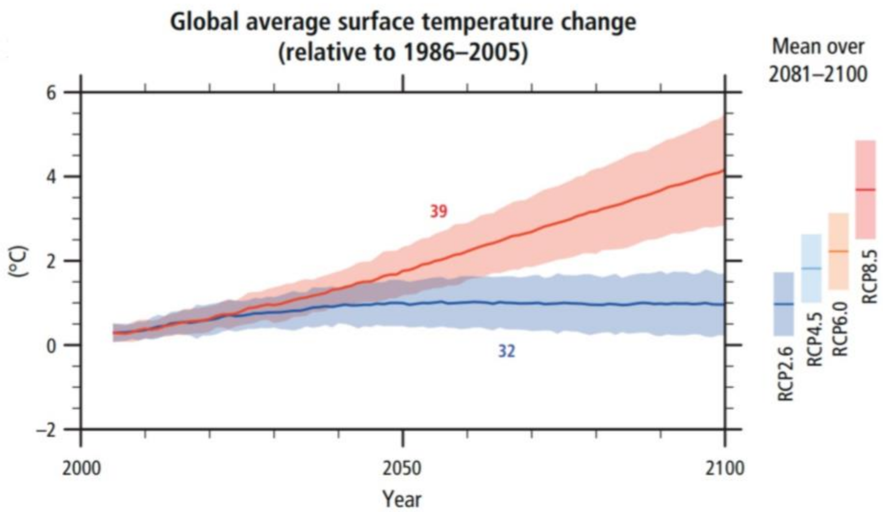


Figure 1.1 Global average surface temperature change from 2006 to 2100 as projected by multi-model simulations. ***(Source: IPCC 2014)***

The changes in climate has a significant impact on the natural systems, more specifically on the water resource systems. The precipitation pattern variability or melting of snow is modifying the hydrological systems consequently impacting the availability of water resources. Due to changes in water availability as well as temperature rise, climate change may have a detrimental impact on agriculture productivity across all agro-ecological zones. Rainfall variability and a decline in the number of wet days will have the most effects on rainfed agriculture. The changes in extreme weather and climate events are some of the adverse consequences of climate change which in turn pose a serious impact on water resources. Therefore, for efficient water resource planning and management, it is crucial for decision- and policy-makers to understand the implications of climate change on water resources.

1.2 Climate Change Impact Studies

Climate change and its variability can change the hydrological cycle and hydrological regime of the region and these changes can cause considerable impacts on the water resources of the region (Dibike and Coulibaly 2005). The increasing rate of global climate change pose a significant impact on local hydrological regimes and water resource availability. To predict the adverse impacts of climate change, there is a necessity for observed climate change analysis and assessment of climate variability under various climate scenarios (both historic and future). The use of climate models can help us better understand and anticipate how the climate will behave on a seasonal, yearly, decadal, and centennial time scale. They assist to understand past climate and projecting climatic conditions into the future. Models, which provide future projections on both a global and regional scale, are numerical representations of the climate system based on the physical, chemical, and biological aspects of its components.

General Circulation Models (GCMs), which are based on closed systems incorporating the entire Earth system, are used to model the large-scale aspects of the global circulation and other physical parameters. The sub-regions models, are created over a smaller region utilizing the boundary conditions produced by the GCMs, taking into consideration the local characteristics, in order to project the climate of a smaller sub-region. These sub-region models are Regional Climate Models (RCMs). GCMs are coarser in resolution which cannot be used for accurate analysis of study regional climate changes. This issue can be overcome by RCMs, which are at a finer resolution. To project climate into the future, the climate forcing is set to change according to a possible future scenario. IPCC has released different scenarios under the name of Representative Concentration Pathways (RCP), that provide several future scenarios and are useful tools for analysing how driving factors may affect future emission results and assessing the associated uncertainty.

The effects of climate change on local water resources can be better understood by analyzing climate variability using downscaled GCMs or RCMs under various climate scenarios. Due to the close association between the water resources and the climate, regional hydrology may be impacted by the global climate change. As discussed earlier (in Section 1.1), an increase in the surface air temperature is the consequence of rise in the concentration of greenhouse gases. Increase in the temperature results in the modification of key components of the hydrological cycle like precipitation and evaporation (Simonovic 2017). Planning and management of water resources will be impacted by changes in precipitation in a number of ways, including the design of hydrological structures, managing floods and droughts, and urban planning and development. Due to its reliance on the monsoon and water availability for production, India's agriculture economy is particularly susceptible to the projected climate changes. Therefore, it is crucial to evaluate the effects of climate change on the local hydrology. This will make it easier to plan adaption strategies for local agriculture and water resource management.

1.3 Climate Change Impacts on Semi-Arid Regions

Semi-arid regions cover 14.2% of the Earth's land surface and support 10% global population (Huang *et al.* 2016). Population growth, extensive urbanization, and climate-driven changes cause an acute impact on the water resources and agricultural productivity of semi-arid regions (Meter *et al.* 2016, Dong *et al.* 2018). These regions experience extreme seasonal and inter-annual precipitation variability resulting in frequent drought and flood conditions (Goff *et al.* 2000, Mail *et al.* 2016). Semi-arid regions are most sensitive to climate variability as the economy of these regions predominantly relies on rain-fed agriculture. This implies even a minute variation in precipitation and temperature patterns would have a significant impact on the agricultural productivity of the semi-arid regions (Huang *et al.* 2016).

The water resources are under considerable stress due to the uncertainty of precipitation and rising temperatures in semi-arid regions. The precipitation and temperature-related extremes result in an increased frequency of hydrological extremes such as droughts and floods. It is anticipated that extreme precipitation will significantly increase, especially in areas that are already experiencing wet spells, whereas dry weather conditions are predicted to increase in regions with dry spells in present climate conditions. These will put more strain on water resources, altering the hydrological cycle's elements like precipitation, evaporation, and runoff (Sharmila *et al.* 2015 These hazardous climate extremes are anticipated to have a damaging effect on semi-arid regions of developing countries, which are already struggling to manage their water resources (Ashok and Sasikala 2012).

In India, the semi-arid regions cover an estimated area of 53% of the total geographical area, most of which are concentrated in Southern India (Anbumozhi *et al.* 2001). In these areas almost the entire rainfall is confined to the 30 to 60 days of the monsoon months (IMD 1987). The low irregular rainfalls along with the extreme temperatures make these regions vulnerable to water shortage. Furthermore, the rainfall in India is highly dependent on the North-East and South-West monsoon, which results in seasonal variability of rainfall causing high runoff in monsoon period leading to floods and severe water scarcity in non-monsoon periods. This monsoon driven climate of India results in spatio-temporal mismatches between water availability and demand (Meter et al., 2016). Hence, there is an urgent need for effective water resource management projects in these rain-scarce semi-arid regions.

1.4 Hydrological Modeling for Climate Change Impact Studies

Hydrological modeling is utilized to understand the hydrological processes in order to provide accurate information for managing water resources in a sustained manner. Hydrological models are extensively used to assess the impact of a changing climate on the water cycle as well as to project future hydrological regimes (Teutschbein 2013, Kour *et al.* 2016). The models, when chosen appropriately, after performing calibration and validation, aid in the process of decision making. These models provide a scientific base to develop climate-risk management plans. Assessment of the climate change impacts on a hydrological system involves two steps: assessment of climate change and the response of hydrologic systems to climate change (Jiang *et al.* 2007). For this purpose, hydrological model simulations driven by GCMs and RCMs are frequently used, especially to make future projections of the major hydrological component i.e. streamflow.

For assessment of the effects of climate change, various types of hydrological models are utilized, including global, regional, and basin-scale, simplified conceptual, process-based, high resolution, semi-distributed, and lumped models (Kour *et al.* 2016, Krysanova *et al.* 2018). They can be applied to extend flow records in relation to longer records of rainfall, fill in gaps in broken records, and estimate river flows at ungauged sites. Some of the popular hydrological models are variable infiltration capacity model (VIC), TOPMODEL, hydrologiska bryans vattenbalansavdelning model (HBV), MIKESHE, and soil and water assessment tool (SWAT) model. The VIC model is a macro scale model, which is best suited for global scale studies that are applied for large river basins (Lundin *et al.* 2000, Treesa *et al.* 2017). MIKE SHE model limited to smaller catchments as it requires large data and physical parameters (Devia *et al.* 2015). HBV model gives satisfactory results especially for estimation of snowmelt, and is based on the degree day method (Bhattarai *et al.* 2018). TOPMODEL can be used for catchment scale predictions in ungauged basins (Krysanova *et al.* 2018). SWAT model was initially developed for dealing with agricultural water management issues, but its applications have expanded to river basin management, ground water, reservoir sediment yield, climate and land use change studies (Gassman *et al.* 2007). The key benefit of the model is that it only needs a minimal amount of direct calibration to produce accurate hydrologic predictions (Devia *et al.* 2015). Although any of the models listed above can be used to analyze the impacts of climate change, the SWAT model being a user-friendly open source model has gained a vast popularity in applying for climate change studies.

1.5 Climate Change Adaptation

The term "adaptation" refers to the modification of natural and human systems in response to the stressors and consequences of climate change. The effects of climate change on natural and human systems are alleviated by adaptation. Adaptation is important because it can reduce adverse impacts and enhance beneficial impacts, especially for human systems (McCarthy et al. 2001). Adaptation can be reactive or anticipatory (or proactive), depending on the timing, goal and motive (IPCC 1998). Reactive adaptation takes place after the impacts of climate change have occurred. Proactive adaptation is based on the expectation that climate will change rather than on its actual impacts. The negative impact of climate change can be managed by developing adaptation policies. Adaptation policies 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.

The IPCC Fourth Assessment Report (IPCC AR4, 2007) defines adaptation practices as *“actual adjustments, or changes in decision environments, which might ultimately enhance resilience or reduce vulnerability to observed or expected changes in climate”*. Water resource managers throughout history have been developing adaptation strategies to the impacts of weather and climate using a variety of practices which include irrigation, drainage, and flood control measures. However, the long-term climate changes pose a new challenge to water management as they are inherently uncertain (IPCC, 2007). To address the issues of both the present and future climate change, adaptation measures in water resource management policies and practices are required. Adaptation strategies which can bridge the gap between the water availability and demand are crucial to achieve water resilience at a particular region. For improved management of water resources, supply-side and demand-side adaptation techniques should be taken into account (Cheng and Hu 2012). Some of the adaptation strategies include change in water policy, strengthening non-traditional water resources, integrating river basin water resources management, strengthening water infrastructure. Development of alternative water resources through rainwater harvesting, change in water use efficiency and water allocation policies can also be considered as adaptation options. Further, heuristic or robust decision making frameworks can be developed which determine the adaptation solutions to climate change (Daron 2015).

1.6 Tank Systems in Semi-Arid Region

Rain water harvesting with local scale structures like "tanks" (relatively small reservoirs) is an essential component in managing water resources of semi-arid regions which have a limited precipitation. Over the centuries traditional tank systems have become a major source of irrigation which helped in the sustainable agricultural production in the semi-arid zones of Asian countries like India, Sri Lanka, Japan (Palanisami and Easter 1987, Unami *et al.* 2005, Arumugam *et al.* 2009) In India, these tanks are concentrated in the semi-arid region of Deccan plateau due to the terrain and soil conditions that are existent in the region (Narayanamoorthy 2007). About 60% of tank irrigation in the country is accounted for by Andhra Pradesh, Telangana, Karnataka and Tamil Nadu (Palanisami 2006, Ramakrishna, 2007Due to the fact that tanks still contribute for one-third of India's irrigation needs, they constitute a significant traditional source of water for the nation.

Tank irrigation method is one of the important water management strategies for coping up with the rainfall variability (Siderius *et al.* 2015). Most of the tanks are natural and with less cost for their construction facilitating individual farmers to maintain them on their own. These tanks are located in hydrologically favorable sites, some of them in chain links or cascades, capturing the rainfall and serving multiple users with irrigation having the major share (Shanmugham, 2007). These tanks allow for storage of excess water during floods which can be used during water shortage and aids in recharge of groundwater. Tank irrigation is important in semi-arid regions, as the small scale farmers rely almost entirely on the irrigation water. In the semi-arid and arid parts of South India, the tanks are essential not only for irrigation but also for maintaining the balance of the local eco-system. In addition to helping with irrigation, tanks supply water for a variety of uses, including livestock and human use, fish farming, ground-water recharge, flood control, and drinking water for rural and urban population (Siderius *et al.* 2015).

Tank irrigation systems are extremely fragile structures with simple operations. They need continuous surveillance, maintenance support, and conservancy. There are variety of problems associated with these irrigation systems like silting, reduction in design discharge, encroachment of tank beds, damage of tank bunds, etc. The development of large-scale gravity irrigation systems, the rapid spread of tube wells, and a decline in community management practices resulted in further depletion of the tank systems. In order to address the drought conditions, an evaluation and prioritizing of the restoration of the existing small storage systems in India's semi-arid and desert regions is required. The influence of climate change on tank systems must also be examined because most tanks are fed by rainfall, and climate extremes have a significant impact on the availability of water in tank systems. Conservation of tank systems in semi-arid regions with climate change perspective is necessary for resilient and sustainable water management. When maintained effectively, these tanks will support the development of the habitats surrounding to them.

Situated in Semi-Arid Region of Deccan Plateau, Telangana state of India has predominantly hot and dry climate. Since the precipitation being limited to 50-60 days in a year, the people in most of the region rely on the medium and minor irrigation tank system to meet their water needs. Approximately 85 percent of cultivated area is rain fed and tank irrigation is the main source of agriculture. The region had a long history of efficient and economical water usage as well as management, which was started by the Kakatiya dynasty. The economy of Kakathiya's was highly dependent on agriculture, so they vigorously implemented a policy of small tank irrigation which proved to be the only method of judicious water usage for the Telangana region. Most of the tanks were constructed just below the thickly vegetated land to ensure the yield from the tank catchment is more. The selection of site for tank construction was made in such a way that the sediment deposit from streams to tanks is less. The Kakathiya's constructed some of these reservoirs at huge capacity than required to mitigate any water shortage for one or two drought years.

The irrigation tanks developed by Kakatiyas were constructed making use of the existing natural terrain. The location of the site is selected between two hillocks on either side with a minimum length of the bund. Small tanks are constructed in the chain where surplus from one tank fills in another tank. The capacity of the tank is fixed at 2 to 3 times the available yield at the location of the tank. This chain tank system ensures that both the water scarcity (drought) and water excess (flood) conditions are taken care. The sluices are located at different levels so as to flush out the accumulated silt naturally under the head of water column that resulted in a negligible reduction in capacity of the tank due to siltation. The maintenance of these tanks was taken up by local village communities.

Their methodology in design and construction of tanks, which had evolved over the centuries, was recognized and used by subsequent rulers. However, by the end of the mid-19th century, most of the tanks were in a state of neglect especially with regards to the upkeep of the retaining strength of their embankments. These tanks have undergone major repair and renovation work during the end of the 19th century to avoid frequent breaching. The record shows that more than 5,000 tanks had been restored by 1900. Some of the tanks which were constructed 800 years back are still existent.

Due to a number of socioeconomic and institutional causes, including changes in the caste and class structures as well as changes in the pattern of land ownership, the use of tanks for irrigation significantly decreased following independence (Jayatilaka *et al.* 2003, Sakthivadivel *et al.* 2004). As a result of the prioritization of canal systems and the overuse of ground water, the minor irrigation was reduced (Sivasubramaniyan, 2006). The tremendous priority placed on the development of private wells and pumps is the main factor contributing to the downfall of tank irrigation (Balasubramaniayan, 2003). Farmers switched to well irrigation as a result of the development of wells and the introduction of green revolution technology because it offers high-quality irrigation that increases agricultural productivity. Thus, the changes in cropping and land use patterns, poor maintenance reduced the inflows and resulted in the disintegration of the tanks.

Poor administration, the absence of village institutions, and a lack of local involvement in tank operational procedures are the main contributors to the degradation of tank irrigation. Tank encroachment on the foreshore area, catchments area deforestation, poor operating conditions of the sluices, defective tank structures, weak farmers participation also lead to the detrioration of tank performance (Palanisami and Nanthakumaran 2000, Narayanamoorthy 2007, Prabakaran *et al.* 2018). The area that was irrigated under the tanks has decreased by almost 40% over the last few decades.

Telangana was formed by bifurcation of Andhra Pradesh, after continuous agitations of people in the region for about sixty years. The main reason for request of a separate state is an unbalanced share of natural resources between Andhra and Telangana regions. During the rule of the united Andhra Pradesh, much importance was not given to the traditional tank system of the region. Over the decades the negligence of repeated governments has led to the deterioration of the tank system in the Telangana region. Mission Kakatiya is a major program started by the State Government after the bifurcation of the united Andhra not only to revive the neglected water bodies but even to put them to optimum use. For the sake of improving tank irrigation in Telangana state, a project named Mission Kakatiya for distillation and restoration of tanks in a huge way (over all state) was started by the government of Telangana. The name mission Kakathiya adopted as a tribute to the Kakathiya rulers who constructed the tanks with utmost expertise and developed the tank irrigation system in this region during their rule.

The project aims at rejuvenating the 47,000 tanks and lakes spread over the state by the end of 2020 by focusing on 9000 tanks per year in order to bring them back to the original standards. The key points of this tank rehabilitation program are redistributed, localized management of tank systems and strengthening community-based institutions to take the responsibility for the sustainable development and management of the tank systems. A tank information system is developed by the Government of Telangana, by identifying the total number of tanks spread across the state and assigning a Unique Identification (UID) for each of the tank.

1.7 Research Motivation and Problem Formulation

In many regions of the world the demand for fresh water has been increasing continuously due to urbanization and population growth. Simultaneously, climate change is also contributing to the water stress, as it directly affects the hydrology of a region. Increase in water demand and climate change, have made it essential for decision-makers to come up with better water management strategies. In recent years, much of the research is focused on water resources management at river basin scale, developing climate change adaptation strategies for the river basin, which is not suitable for smaller regions with arid and semi-arid climate. Very few works have addressed sub-basin scale or region-specific adaptation and decision making under climate change scenarios. Furthermore, the impact of climate change on rainfed irrigation under tank systems has not been addressed properly.

Major parts of the Deccan Plateau in the Peninsular India come under semi-arid region. Even though big rivers like Godavari and Krishna pass through this region, it is very expensive to use these waters for irrigation because of the topography. Therefore, most of the dynasties ruled these regions build the irrigation tank systems. However, over a time period, these tank systems got neglected and led to deterioration, siltation and encroachment of tank systems. Due to poor maintenance of tank systems, most of agriculture in these regions converted to rainfed or depending on ground water resources which is creating a lot of stress on the farmers. The present Government of Telangana state initiated the Tank Rejuvenation Program on the availability of catchment, tank de-siltation capacity, rainfall pattern and climate change impact etc.

The erstwhile Warangal district, located in semi-arid region of Telangana, has predominantly hot and dry climate and is chosen for the study. The hydrology of semi-arid areas like erstwhile Warangal district is highly sensitive to climate variability. For example, relatively small rise in temperature and deficit in precipitation in the area could result in large decrease in runoff, increasing the severity of drought. Understanding the impact of climate change on the vulnerable resources would be useful to develop better strategies for management and conservation of water resources in the region, enabling water management planners to decide future demand and availability of water.

Since there is no perennial river flowing in the region and precipitation being limited to 50-60 days in a year, the people in the region rely on the tank system to meet their water needs. The tank systems of this particular region, which was designed and constructed by Kakathiya rulers, contributes significantly to the water resources of the district. Hence, it is necessary to estimate the water availability in the tank systems for judicious use of water resources. In this context, it is appropriate to develop a decision support system for a selected tanks system, which supports as adaptation strategy for the climate change by addressing the following interrelated scientific questions -

- How climate change really impacts the tank systems?
- What are future trends in rainfall to understand the tank filling strategies?
- What type of adaptation strategies need to be followed for sustainable tank irrigation under climate change conditions?
- What type of decision support system needs the tanks systems as an adaptation strategy for their sustainability?

Keeping the above questions in view, it was proposed to model the hydrological process of the selected study region to explore the changes in water availability with changing climate. The outcomes from this project are useful in developing the adaptation strategies for policy makers for the selected tank system. Further, the study assists to develop efficient water management and improved agricultural practices in semi-arid regions, in which tank systems are the primary source of irrigation.

1.8 Aim and Objectives of the Study

The main aim of this research study is to develop adaptation strategies for the management of water resources in an irrigation tank system of semi-arid region under changing climate. Based on the aim of the study, the following objectives are defined for research work:

- Evaluation of observed and model climate trends for a semi-arid region to identify the past and future climate change in the region.

- Hydrological modelling for assessment of the impact of changing climate on the Ungauged tank system of semi-arid region

- Evaluation of changes in the irrigation water demand with respect to future climate change scenarios for the selected tank system.

- Development of adaptation strategies for the selected tank system under climate change scenarios.

1.10 Outline of the Thesis

This thesis report consists of seven chapters. Current chapter consists of an introduction presenting the background and motivation of the study. The main aim and objectives of the research work are also presented in this chapter. Literature relevant to hydrological modelling, various climate models and their uncertainty, impact assessment, hydrological modelling, prediction of surface water levels and DSS for adaptation is presented in chapter 2. Chapter 3 consists of climate variability and trends in the selected semi-arid region using both observed and climate model data. Chapter 4 presents the hydrologic modeling SWAT of a selected semi-arid tank system under climate change scenarios. In Chapter 5, the application of the machine learning technique, Support Vector Regression Model (SVR) for the prediction of future tank water availability is described. The development of climate change adaptation policies for tank water management is presented in Chapter 6. In the last chapter of the thesis the summary and conclusions of the research work are presented.

Chapter 2

Literature Review

2.1 General

Based on the framed objectives in the last chapter, the literature review is carried out on the aspects related to tank systems in semi-arid regions, regional climate models data usage, hydrological modeling in tank systems, climate change impact assessment on water resources, and adaptation to climate change impacts on water resources in the tank systems. A detailed description of the reviewed literature is given in the subsequent sections.

2.2 Tank Systems of Semi-Arid Regions

Minor irrigation tanks are essential to meet drinking and domestic water needs. These tanks are mainly found in the semi-arid Deccan plateau region of India. They are strategically placed in hydrologically desirable areas, some of them in consecutive chains or cascades, effectively capturing rainwater, and they serve a variety of purposes, with irrigation accounting for the biggest share of their uses (Shanmugham, 2007). Traditional tank systems have aided in the sustainable production of agricultural goods in semi-arid regions of India, Sri Lanka, and South East Asia (Nagarajan, 2013). The development of large-scale gravity irrigation systems, the rapid spread of tube well technology, and the decline in traditions of community management resulted in the depletion of the much-needed tank systems. In recent years, a variety of efforts have been made in India to rehabilitate these traditional water management systems.

Ashok and Sasikala (2012) suggested that increasing temperature and variability in precipitation in semi-arid regions have reduced crop yields and increased vulnerability of the farmers. The study quantified the vulnerability of both farmers and irrigation tanks to rainfall variability in a rain-fed area. Tank performance was determined through adjusted tank performance measure, and vulnerability was estimated through livelihood vulnerability index. The results indicated that tank performance and livelihood vulnerability were higher in rainfall less than normal area. The authors suggested that there is a need for effective policies for the transfer of climate adaptation technologies in agriculture.

Nagarajan (2013) established a method for evaluating the degradation of tanks/ponds in a tank cascade system, and based on the hydrological and physical status of tanks, a tank rehabilitation index was derived. In order to address the drought conditions, it was determined that the small storage systems that are now present in semi-arid and dry regions require evaluation and prioritizing of restoration. Furthermore, the effectiveness of current irrigation techniques would be impacted by climate change. Higher irrigation needs would result from the expected increased variability in precipitation (longer drought periods).

Siderius *et al.* (2015) stated that the tank irrigation, serves more than 20% of cropped area in southern states, is one of the most important strategies for dealing with rainfall variability. Water is harvested during the monsoon and used during the dry season in tank irrigation systems. It is a versatile system in which the amount of water stored in the tank by the end of the monsoon determines what and how much land area farmers cultivate.

Several studies apart from the above mentioned ones have addressed the causes for the degradation of traditional tank irrigation systems like changes in management practices and the difficulties in reviving them are discussed (Pingle 2011, Arivoli and Ambujam 2016, Bebermeier *et al.* 2017, Reddy *et al.* 2018, Ramabrahmam *et al.* 2021). Future climate change will make conserving flood waters more important, making it more important to increase the storage capacity of irrigation tanks for boosting water availability for irrigation and water storage (Kumar 2017, Neelakantan *et al.* 2017, Reddy *et al.* 2018).

2.3 Climate Models and Uncertainty Analysis

Assessment of climate change impact on water resources requires an understanding of hydrologic and climate interactions. The climate change impact studies on hydrology are often done using hydrological models which require meteorological variables for current and future climate conditions at finer resolutions (Gosain et al., 2006; Mujumdar and Ghosh, 2008). The Global Climate Models (GCM's) run at a coarser scale and they cannot be used directly for impact studies at the regional or basin level as they might cause uncertainty in future predictions. As the GCMs lack finer spatial resolution, dynamical and statistical downscaling techniques are used for impact studies (Mujumdar and Ghosh, 2008; Tripathi et al., 2006). Among the statistical downscaling techniques, the Support Vector Machine (SVM) approach, Statistical Downscaling Model (SDSM), fuzzy clustering, and Relevance Vector Machine (RVM) approach have gained popularity in India (Tripati et al., 2006; Aanandi et al., 2008; Mujumdar and Ghosh, 2008; Mahmood and Babel, 2012, Meenu et al., 2012). Only a few studies have been carried out using dynamical downscaling techniques due to the high computational complexity (Devak and Dhanya, 2014).

Suitable Regional Climate Models (RCMs) are also used instead of downscaling techniques and the climate variables are projected into the future. RCMs were originally developed to provide fine-scale climate data for impact studies, but in the recent past, they are used as general modeling tools for regional climate change impact studies. However, these RCMs correspond to some extent of uncertainty, especially when used for climate change impact studies at the local or regional scale (Christensen *et al.* 2008, Gudmundsson *et al.* 2012, Singh *et al.* 2019). Hence, the following paragraphs review the literature related to climate models (GCMs and RCMs) and the techniques used to account for the uncertainty involved while using them for climate change impact studies.

Giorgi and Mearns (1991) contrasted the advantages, drawbacks, and applicability of the empirical and GCM nested limited area modelling techniques. They stated that while applying empirical techniques is simple, they are unable to capture mesoscale forcings, which are more susceptible to changes in climate. The GCM nested limited area models can simulate a variety of atmospheric and climatic phenomena, but they are computationally complex and expensive. They proposed rapid improvement in both the techniques for better representation of regional response in the context of climate change based on their strengths and weaknesses.

Giorgi and Mearns (2003) suggested using Reliability Ensemble Averaging (REA) to represent the multi model ensemble mean in probabilistic climate projections. With reliability based on simulation likelihood, the method takes into account the disadvantage of assuming that all simulations are probabilistically equal. The authors further claim that REA functions as an easy-to-use and adaptable tool for quantifying climate change and relating uncertainty, reliability, and change probability.

Fowler et al. (2005) examined the extreme precipitation over the UK using the HadRM3H regional climate model. The RCM was able to simulate the extreme rainfall at various return periods and durations despite the differences in spatial resolution between the observed and modelled data. Additionally, for shorter durations and in complex orographic regions, HadRM3H offers a better representation of the spatial variability of extreme precipitation. The authors hypothesized that RCM has the capacity to capture the variability in the extreme precipitation under enhanced greenhouse conditions, despite the model's tendency to overestimate the extreme in high altitude areas and underestimate it in rain shadow areas.

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. When compared to studies at the global level, regional studies have more uncertainties developed.

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.

In order to assess the change in water availability of the Indian River systems over time and space, Gosain *et al.* (2011) used the Regional Climate Model (RCM) - PRECIS with daily weather data from the Indian Institute of Tropical Meteorology (IITM) and the IPCC AR4 emission scenario.

Shrestha et al. (2011) studied the impact of climate change on the hydrologic regime of the Lake Winnipeg watershed (LWW), Canada using three RCMs for the prediction of climate variables and the SWAT model for hydrologic simulation. They stressed the need for numerous RCMs since hydrologic regimes simulated with various RCM forcings are prone to substantial errors, making it difficult to estimate a broad range of potential climate change effects.

Teutschbein and Seibert (2012) reviewed a variety of simple and complex bias correction techniques for RCMs and their selection in order to correct model deviations. When comparing the performance of bias-corrected data to uncorrected RCM data, bias-corrected data showed better streamflow performance.

Hagemann *et al.* (2013) evaluated the hydrological response to climate change and comprehensively estimate the future state of the global water resources, numerous global climate (three) and hydrological (eight) models were incorporated. This multi-model ensemble assists us to examine how hydrology models, in contrast to climate models, contribute to the uncertainty in projected hydrological responses. Due to the systematic biases, GCM outputs are unfit for the direct use in hydrological impact studies, so a statistical bias correction has been used. For some regions, the results exhibited a wide range of projected changes in water resources within the climate-hydrology modelling.

Woldemeskel *et al.* (2014) stated that the GCM projections are uncertain subject to standard errors in the model structure, scenarios and initial conditions and the overall reliability of impact assessments becomes questionable. A novel framework has been proposed for evaluating the uncertainties in GCM projections and impact studies. The GCM biases were corrected through nested bias correction (NBC) method and the uncertainty was quantified using an uncertainty metric i.e. the square root error variance (SREV). Finally, the uncertainty arising due to the parameter estimation in impact assessment models is treated using simulation–extrapolation (SIMEX).

Rajbhandari *et al.* (2015) examined the possible future changes in the climate over the Indus basin with the help of the outputs from the PRECIS model driven by data for three different lateral boundary conditions (LBC) from Quantifying Uncertainty in Model Predictions (QUMP) simulations using SRES A1B scenario.

Pinto *et al.* (2016) analysed the extreme precipitation events of the present and future climate over southern Africa. Parametric and non-parametric approaches were used to identify and analyse these extreme events using the Coordinated Regional Climate Downscaling Experiment (CORDEX) models. The performance of the CORDEX simulations suggested that the models were able to capture the observed spatial patterns of the extreme precipitation.

Das and Umamahesh (2017) assessed the spatio-temporal variation of water availability in Wainganga river basin under CORDEX simulated future projections. The uncertainties arising due to the use of multiple climate model projections were accounted for by using REA and the bias correction is done by quantile mapping method.

Sowjanya *et al.* (2018) analysed the inter and intra annual streamflow variation of Wardha watershed using CORDEX future climate projections. Before being employed in the hydrological model, the climate model simulated temperature and precipitation underwent bias correction because they are prone to severe biases from system model flaws brought on by inaccurate conceptualization, spatial disaggregation, and discretization within the grid cells.

Bokhari *et al.* (2018) projected the climatic changes in future for the Kabul River basin situated in mountain ranges of Pakistan and Afghanistan using the high resolution NEXGDDP data. An ensemble model derived from multiple climate models of NEX-GDDP data replicated observed spatial distribution and magnitudes of temperature and precipitation that is impossible to capture with coarse resolution GCMs.

The studies on RCMs confirm their efficiency in capturing the observed climate characteristics, however the significant biases remain and are found to be specific to individual models, regions and seasons (Dosio and Panitz 2016, Jain *et al.* 2019). The biases need to be addressed systematically using statistical bias correction methods (Christensen *et al.* 2008, Thrasher *et al.* 2012, Teutschbein and Seibert 2013, Fang *et al.* 2015, Ringard *et al.* 2017, Sahany *et al.* 2019, Enayati *et al.* 2021). The multi-model average or weighted multi-model averages outperforms any individual simulation and that the RCMs' uncertainty can be reduced significantly. CORDEX and NEXGDDP scenarios-based projections of future climate are suitable for impact and vulnerability assessment and developing adaptation measures(Abiodun *et al.* 2019, Jain *et al.* 2019, Musie *et al.* 2020, Rocha *et al.* 2020, Poonia *et al.* 2021).

2.4 Trends in Past and Future Climate Variables

Observational and historical hydro-climatic data are typically used for project planning and design related to water resources. In most of the water resources engineering, the stationarity, or time-invariant statistical properties of the time series under consideration, is assumed implicitly(Chen *et al.* 2007). A change in the global climate caused by an increase in greenhouse gases in the atmosphere would render such an assumption invalid. The spatio-temporal uncertainty of the rainfall distribution and temperature variation is one the fundamental impacts of climate change (Yadav *et al.* 2014). The analysis of these meteorological variables (rainfall and temperature) is an essential aspect in detecting the climate change (Gocic and Trajkovic 2013). To reduce the risks and vulnerability associated with climate change, it is essential to identify trends in precipitation and temperature based on historical data. The trend analysis helps assists in projecting the future scenarios and implementing the climate related policies(Feng *et al.* 2011, Gocic and Trajkovic 2013, Birara *et al.* 2015, Gajić-Čăpka *et al.* 2018, Praveenkumar and Jothiprakash 2018). In recent years, various studies have been carried out for identifying the future climate trends and changes across the world. The following paragraphs describe different studies that have been carried out on temperature (maximum, minimum or average) and precipitation trends.

Yunling and Yiping (2005) examined the climate change trends and characteristics during 1960–2000 using gauge stations located on the Lancang River (China) using monthly temperature and precipitation data. The results exhibited an raise in temperature and reduction in precipitation.

In the Hanjiang basin, Chen et al. (2007) looked at the temporal trends of temperature and precipitation as well as their regional distributions. Using a parametric t-test method called simple linear regression, the long-term linear trend was identified. The Mann-Kendall test, a non-parametric test for identifying trends and the distribution of the test statistic, was used to examine the non-linear trend as well as the turning point.

El Nesr et al. (2010) used information from 29 meteorological stations to analyze the temperature variations during a 29-year period in the Kingdom of Saudi Arabia. The maximum, minimum, and average temperatures throughout the year were found to be warming, with the exception of the winter season, when negligible cooling trends were identified.

Karaburun et al. (2011) used the Mann-Kendall test and Sen's approach to assess trends in Istanbul's annual, seasonal, and monthly mean, minimum, and maximum temperatures from 1975 to 2006.

Seven meteorological variables were examined by Gocic and Trajkovic from 1980 to 2010 for their seasonal and annual patterns in Serbia. Sen's and Mann-non-parametric Kendall's approaches were used to do the analysis. For the investigation, the meteorological data from twelve stations that had high-quality datasets with reliable data and sufficient record lengths were employed.

Yadav *et al.* (2014)processed the daily rainfall data, minimum and maximum temperature data to find out the monthly variability of rainfall and temperature in thirteen districts of Uttarakhand. Mann-Kendall (MK) Test has been used together with the Sen’s Slope Estimator for the determination of trend and slope magnitude.

Birara *et al.* (2015) evaluated the annual and seasonal variations in temperature and rainfall, and measured the trends across time and space for the ten stations in Ethiopia's Tana basin. Sen's slope estimator and the Mann-Kendall test were used to evaluate rainfall and temperature trends and variability. Inverse distance weighted analysis was used to determine the regional distribution of temperature and rainfall. According to the results, rainfall amounts declined at the majority of the stations.

Paul et al. (2017) used parametric (linear regression and robust linear regression) and non-parametric (Mann-Kendall and Sen's slope) methodologies to study the weekly, monthly, seasonal, and annual rainfall trend analyses for the Rajahmundry city, located in the Godavari basin area. For assessing the amount of fresh water available to satisfy the water demand for domestic and agricultural purposes, it has been suggested that the analysis of rainfall variability at a specific area is essential.

Praveenkumar and Jothiprakash (2018) used three precipation data sets, Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA), IMD gridded, and IMD gauge for analyzing the spatio-temporal variations of rainfall in the Indravathi river basin. The Mann-Kendall test is used to identify trends in rainfall series, while the Pettitt test and standard normal homogeneity (SNH) test are used to identify homogeneity. It is stated that TMPA and IMD gridded data provide an adequate representation of rainfall for studies of the climate and water resources at large catchment scales, particularly in areas with a dearth of data.

Worku *et al.* (2018) conducted a spatiotemporal analysis of temperature and rainfall patterns, both seasonally and annually, and its implications. Application of the MK test, Sen's slope, and precipitation concentration index (PCI). Crop production and climate variables were analysed using Pearson correlation analysis. It was concluded that adequate adaptation techniques must be devised based on the historical trends of erratic rainfall and persistent temperature increase in order to ensure crop productivity.

Gebrechorkos *et al.* (2019) analysed long-term patterns in East Africa, especially in Ethiopia, Kenya, and Tanzania, in terms of rainfall and maximum and lowest temperatures (T-max and T-min). The Climate Hazards Group's high resolution gridded rainfall (1981–2016) and temperature (1979–2010) data are taken from international sources. The MK test and slope in the time series are calculated using R's Trend package. The authors claim that this form of fine-scaled analysis aids in the identification of priority regions for the creation of adaption strategies.

Ademe *et al.* (2020) analysed the rainfall and temperature variability and trends in the Ethiopian highlands. The results of the meteorological analysis were compared to farmers' impressions, and it was concluded that they agreed with all of their assessments across all agroecosystems. According to the findings, farmers' decisions on management approaches are complicated by the unpredictable timing and distribution of rainfall. It was determined that in order to comprehend the climate issues faced by farmers in distinct agro ecological settings, a localized climate trend analysis is required.

The literature suggests that it is essential in climate change studies to initially analyse the existing trend in climatic variables by using the long-term data (Hladnik 2013, Yadav *et al.* 2014, Rahmat *et al.* 2015, Jana *et al.* 2017, Dubey and Sharma 2018, Gajić-Čapka *et al.* 2018).

2.5 Hydrologic Modeling and Climate Change Impact Studies

Hydrologic models offer a framework for conceptualizing and exploring the dynamics between climate and water resources(Li *et al.* 2015). A systematically calibrated and validated hydrological model can offer helpful information for the management and planning of water resources. 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. Through the simulation of hydrological processes, some models enable quantification of the effects of climate change on water resources (Montecelos-Zamora *et al.* 2018). For climate change impact studies, the selection of hydrological model plays a vital role as there are numerous models available. The relevant literature available on hydrological models and their applicability in water resources assessment under climate change is presented in the following paragraphs.

Gosain *et al.* (2006) assessed the impact of climate change on the water resources of Indian River basins using SWAT model coupled with HadRM2 daily weather data. According to the findings, under Green House Gas (GHG) scenarios, the amount of available runoff in the river basin continues to decrease.

Gassman *et al.* (2007) described several applications of the SWAT model and stated that it is a very adaptable and reliable tool that can be used to model hydrological process at different spatial scales. SWAT model is found efficient in replicating the hydrological response at annual and monthly basis.

SWAT was used by Ficklin et al. (2009) to simulate the hydrology and effects of climate change in California's predominantly agricultural San Joaquin watershed. According to the findings, rising temperatures changed plant growth patterns over time and changed how much water was needed for irrigation and evapotranspiration. Because of the reduced demand for irrigation during the summer, this led to an increase in stream flow. Overall, the findings show that the hydrology of the San Joaquin watershed is extremely vulnerable to anticipated future climatic changes.

Setegn et al. (2010) made use of hydrologic simulations from the SWAT model and outputs from 15 Global Circulation Models (GCMs) to study the vulnerability of water resources to climate change in the Lake Tana Basin. The authors advocate doing a comprehensive study of the effects of climate and land use or land cover change on the hydrological processes and variability of water resources in river basins.

George et al. (2011) developed a modelling framework using GCMs for climatic parameters, SWAT model for surface runoff simulation and MODFLOW for ground water simulation and water allocation-economic modelling to assess the water security and its economic value. The frame work has been applied to Musi Catchment, Andhra Pradesh, India to evaluate water security strategies under climate change.

Vano *et al.* (2010) evaluated the sensitivity of water supply systems in the Puget Sound basin cities of Everett, Seattle, and Tacoma to historical and projected future streamflow changes and water demands. The streamflow for three future time periods is simulated using the distributed hydrology–soil– vegetation model (DHSVM), couple with the downscaled ensembles of climate simulations obtained from the IPCC 4th Assessment Report. Further, reservoir performance under various climate change scenarios is assessed with and without implementing adaptations.

Yoshitani *et al.* (2011) developed an integrated regional-scale hydrological-atmospheric model (IRSHAM) for climate change study on Japan region. The study examined the efficiency of a fully coupled boundary layer model and aerially averaged land surface model when they are employed in an RCM.

Lauri et al. (2012) evaluated the individual and combined effects of reservoir operation and climate change on the hydrology of the Mekong River (using different GCMs). Five better performing downscaled GCMs are chosen for the study. Further, the reservoir operation optimization algorithm was developed to simulate the reservoir operations of both existing and planned hydropower dams.

Kizza *et al.* (2013) examined various regionalization techniques that could be used for modelling inflows to Lake Victoria. The transferability of model parameters between the basins is tested by WASMOD model by using three regionalization methods. Generalised Likelihood Uncertainty Estimation (GLUE) framework for uncertainty assessment is used for the model calibration. The model parameter transferability results were mixed. It was concluded that the regionalization uncertainty can be treated using ensemble regionalization approach.

Deshpande *et al.* (2014) used SWAT to investigate the effects of climate change on the various elements of the Krishna river basin's water balance The model is calibrated and validated using measured stream flow and meteorological data for the period 1970–1990 at a single gauge exit. Daily climatic simulations from the regional climate model PRECIS are used to create monthly water balance components like precipitation, surface runoff, water yield, evapotranspiration (ET), and potential evapotranspiration (PET). According to model predictions, the basin's annual discharge, surface runoff, and base flow will all increase by the middle of the next century.

Using ArcSWAT, Uniyal et al. (2015) assessed how the Upper Baitarani River basin in Eastern India would be affected by climate change on the blue and green waters (components of the water balance). Sequential uncertainty fitting (SUFI-2) optimization technique was used to calibrate the ArcSWAT model in the SWAT calibration and uncertainty program (SWAT-CUP). Based on the descriptions provided by IPCC, the SRES scenarios A1B, A2, and B2 used in this study. The research's conclusions demonstrated that the river basin is more sensitive to changes in rainfall than to changes in temperature.

Emam *et al.* (2016) assessed the water resources and risk of natural disasters in an ungauged basin of Aluoi district in Central Vietnam using SWAT model. The river discharge at the basin outlet was predicted using a regionalization approach. Three time scales were used to calibrate the model: daily, monthly, and yearly, using the river discharge, actual evapotranspiration (ETa), and crop yield data. The study used ratio method of regionalization and recommended that regionalization strategies to transfer parameters from contributor to ungauged basins in order to forecast river discharge data.

Luo *et al.* (2017) investigated the spatio-temporal patterns of the effects of climate change on water resources and extremes at ungauged locations. The SWAT and MIKE SHE models were both used in the study, and satellite-based rainfall data (TRMM) was used as the direct input and references of calibration or validation to set up the hydrological models. It was determined that combined results from the use of additional hydrological models were more effective for understanding the impacts of climate change on water resources. With regard to creating new water resource management policies and planning frameworks for locals, the use of remote sensing data combined with the climate change data provides a new technique to estimate the consequences of climate change in remote, unmeasured regions.

Sehgal *et al.* (2018) developed a near real-time hydrologic simulation framework by using the combination of SWAT model and National Center for Environmental Prediction coupled forecast system model version 2 (CFSv2) data to model the future projected daily hydrological balance components. The results indicated that the CFSv2 driven SWAT model provide a satisfactory performance at seasonal level as well as the near-real time predictions.

The major challenge faced during the hydrological modeling of tank systems is limited data availability as most of the tank catchments are ungauged. The water balancing in cascading tanks was performed using ROSES (Jayatilaka et al. 2003) CWBM (Jayakody et al. 2004) and HYLUC-CASCADE (Bishop et al. 2006) these models required a lot of fields observed data. The daily runoff of was estimated using the GR4J hydrological model then forecasted the volume of lakes by daily water balancing and verified by a combination of remote sensing and field observations (Ogilvie et al. 2018). The difficulty of modeling ungauged catchments can be overcome by applying suitable regionalization methods(Gitau and Chaubey 2010, Rahim and Hassan 2014, Emam *et al.* 2016, Rizzi 2017, Yang *et al.* 2018). SWAT model is a popular physically distributed model which 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(Abbaspour *et al.* 2004, Stratton *et al.* 2009, Mishra and Lilhare 2016, Pandey *et al.* 2017, Rani and Sreekesh 2019).

2.6 Prediction of Changes in Lake Water Levels

The lake surface water level fluctuations are effected by the external input processes, human interventions and most importantly climate change (Minale 2019). Many hydrological processes are extremely sensitive to climate change and the fluctuations in the lake water can be directly attributed to the variation in climatic variables like temperature, precipitation, and evaporation (Lin *et al.* 2015, Davraz *et al.* 2019). Seasonal lake level forecasts with a reasonable degree of accuracy, can help with water resource planning and management, including dam operations and water allocations (Lin *et al.* 2015).

Khan and Coulibaly (2006) implemented the support vector machine for the long-term prediction of lake water levels. The mean monthly water levels of Lake Erie from 1918 to 2001 are used to predict 12 months ahead water levels. The results from SVM are compared with multilayer perceptron (MLP) neural network and with multiplicative seasonal autoregressive model (SAR) and concluded that SVM outperforms the other methods. Additionally, the SVM displays inherent advantages as a result of its application of quadratic programming during model optimization and the structural risk minimization principle when formulating cost functions. Compared to conventional neural network models, these benefits produce a singular optimal and global solution.

Çimen and Kisi (2009) modeled the lake level fluctuations using SVM and artificial neural networks (ANN). The monthly level data of Lake Van, the largest lake in Turkey, and Lake Egirdir are subjected to the SVM method, a new regression technique for water resources. The estimated lake levels and the corresponding observed values are found to be in good agreement. Statistics for comparison include the mean square errors, mean absolute relative errors, and determination coefficient. The comparison reveals that the SVM-based model outperforms the ANN in terms of statistical performance.

Hipni *et al.* (2013) compared different types of Support Vector Regression (SVR) models with Adaptive Neuro Fuzzy Inference System (ANFIS) and found that the *n*-SVR model outperformed the other SVM techniques in forecasting daily water levels in Klang reservoir, Malaysia. The study concluded that the SVR model was the best regression type for lake water predictions.

Buyukyildiz *et al.* (2014) adopted five different artificial intelligence (AI) methods for predicting the water levels of Lake Beysehir. The estimation of the monthly change in water level was done using several neural network techniques and machine learning methods . To assess the effectiveness of the model, four metrics—root mean square error (RMSE), mean square error (MSE), mean absolute error (MAE), and coefficient of determination (R^2) are utilized. According to the results, ε-SVR model proved most reliable to estimate monthly water level when compared to other models.

Kisi *et al.* (2015) explored the applicability of novel method by coupling SVM with firefly algorithm (FA) for prediction of water levels of Urmia Lake. The FA was applied to estimate the optimal SVM parameters. The results form SVM-FA are compared with predictions results from genetic programming model (GP) and artificial neural networks model (ANN) and the results indicated a higher predictive capability for SVM-FA model.

Bucak *et al.* (2017) quantified the combined effect of climate and land use change on the Lake Beysehir. A novel approach of coupling SWAT model outputs with the SVR model to forecast future water availability in Lake Beysehir is adapted in the study. Apart from evaluating the future water availability in the lake, the study also proposed lake outflow management options by predicting maximum outflows allowed for maintaining the required lake water levels. The results indicated that climate change will cause the lake to dry up by the end of the century.

Changes in lake level are primarily caused by changes in precipitation and evaporation over the lakes and their catchment basins(Khan and Coulibaly 2006, Yang *et al.* 2017, Mohammadi *et al.* 2020). In this regard, these changes serve as a sensitive indicator of historical and current climate changes within the lake catchment basin(Buyukyildiz *et al.* 2014, Bucak *et al.* 2017, Davraz *et al.* 2019). The changes in the lake water level are governed by the balance of input and output components related to hydrological processes.

2.7 Crop Models for Estimation of Irrigation Requirement

Crop simulation models are effective tools for the assessment of potential effects of climatological, biological and other manageral factors on crop growth and development. They have been used in many studies across the world in the prediction of crop yields, irrigation planning for crops, optimization of irrigation water use, and understanding the climate change impacts on various crops (Kadiyala *et al.* 2015). In recent past several studies have incorporated crop simulation models for the assessment of the changes in irrigation requirement under climate change.

Lee and Huang (2014) studied the impact of climate change on the irrigation water requirement for rice in Northern Taiwan. Five downscaled GCM's are bias corrected and used for projecting the climate variables for the period 2046-2065. Hamon method for estimating evapotranspiration and water balancing model is used for determining the crop water requirement and irrigation demandIt is obvious from a comparison of the current (2004–2011) and the future (2046–2065) that climate change will result in increased temperatures and rainfall, which will raise agricultural water needs and increase effective precipitation during future cropping seasons.

Bouraima *et al.* (2015) quantified the crop reference and actual evapotranspiration (ETo and ETc) and the irrigation water requirements for rice crop in west Africa. CROPWAT model is used in the study for estimating the Crop Water Requirements (CWR) and suggested that the results aid in better irrigation practices, scheduling and efficient use of water in semi-arid regions, as the water supply through rainfall is limited.

Kadiyala *et al.* (2015) developed and validated a tool for investigating the impact of climate change on groundnut production in Anantapur district. Using a GIS and crop model-based interface, the CROPGRO-Peanut model from DSSAT was used to investigate the spatial effects of various genetic and agronomic management practices under both baseline and climate change scenarios.

Vibhute *et al.* (2016) developed a crop water demand based canal delivery system by combining CROPWAT and GIS tools. The geospatial database of different soil, water and crop parameters in the command area were developed and analyzed using the GIS tool. Further, the geospatial data were used to work out the irrigation schedule of different crops using CROPWAT model.

Tukimat et al. (2017) investigated how the demand for irrigation water would alter in a scenario of climate change in a heavily irrigated region of Malaysia. To model the changes in local precipitation and temperature, the statistical downscaling model (SDSM) is used to downscale the outputs from GCMs. After being calibrated and validated with historical data, the CROPWAT irrigation water demand assessment model is used to project possible changes in irrigation trend under SDSM projected climatic conditions.

Masia *et al.* (2018) studied the vulnerability of irrigated agriculture to climate change by estimating the changes in irrigation requirement, evaporation from reservoirs, and water availability in six irrigated districts of Mediterranean area across Italy. Simulation of evapotranspiration of applied water (SIMETAW_R) model is used in the study in combination with GIS platform. Each irrigation district is anticipated to experience a future water shortage because it was forecasted that climate change will result in reservoirs that are less resilient and more vulnerable.

Poonia *et al.* (2021) investigated the spatio-temporal impact of climate change on the crop water requirement (CWR) and crop irrigation requirement (CIR) for major crops in Sikkim. CORDEX climate data is used for future projections of climatic variables. Additionally, the possibility technique is used to analyse uncertainty in both GCM and scenarios. The findings showed that the most likely scenario for examining the impacts of changing climate on agricultural water demand is RCP 4.5.

Under climate change, the demand for irrigation water will be altered by variations in meteorological variables, and irrigation water will always account for the majority of water use in India(Madhusudhan *et al.* 2021, Busschaert *et al.* 2022). The estimation of irrigation water demand under climate change will provide an insight for effective management of agricultural waters(McNider *et al.* 2015, Vibhute *et al.* 2016, Tukimat *et al.* 2017, Salman *et al.* 2020, Madhusudhan *et al.* 2021, Poonia *et al.* 2021).

2.8 Climate Change Adaptation for Water Resource Management

Adaptation is the principle way for dealing with the effects of climate change. It involves taking practical actions to mitigate climate-related hazards, safeguard communities, and increase the economy's resilience. Studies have been conducted to evaluate India's vulnerability to drought due to climate change. The existing preparedness and mitigation mechanisms have been studied for drought risk reduction and identified no-regret adaptation options (Prabhakar et al., 2008). Community-based preparedness and mitigation planning is the key as it would greatly enhance the capacities of communities by broadening their coping range.

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 periods and then analysed the performance of annual hydropower generation by four reliability indices with respect to reservoir functions i.e., irrigation, hydropower, and flood control. Further, 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 existing 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.

Eum *et al.* (2010**)** calculated the optimal water releases for future periods under droughts using SDP 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.

Cheng et al., (2012) suggested that supply side and demand side adaptation strategies should be considered for water management. They concluded that demand management and water pollution control are key for climate change adaptation with respect to the water resources of China.

Bhave et al. (2014) assessed the potential effects of climate change in the Kangsabati reservoir catchment using the Water Evaluation And Planning (WEAP) model. Evaluation of the ability of stakeholder prioritized adaptation options is made. Check dams and expanding the extent of forest cover are two adaptation alternatives that are given priority utilizing pair-wise comparison and scenario analysis. According to WEAP simulations, both adaptation approaches decrease stream flow when compared to a base scenario without adaptation. Over the 30 year period, efficiancy of check dams in reducing stream flow decreases by 40 %, while that of forest cover increases by 47 %.

A framework for assessing vulnerability in arid and semi-arid regions that incorporates climate change as well as the concepts of hazard, exposure, sensitivity, and adaptability was proposed by Jun et al. (2016). For evaluating the risk and vulnerability to water resources, an indexing approach was used. As a means of lowering the risk of vulnerability to water resources, they suggested that the outcome would be beneficial to implement measures that increase adaptability and reduce exposure.

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 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 index 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.

Ashofteh *et al.* (2017) developed adaptation strategies for irrigation water demand management under climate change. Climate variables in the Aidoghmoush Basin (East Azerbaijan, Iran) are predicted using the HadCM3 climate model and greenhouse gas emission scenario A2. The FAO's (Food and Agricultural Organization) evapotranspiration method was used to forecast irrigation water demand, and the IHACRES model was utilized to simulate reservoir inflows.

Adeloye and Dau (2019) examined the ability of static and dynamic hedging operating policies to adapt to changing environmental conditions in order to increase the reliability and vulnerability of the irrigation water supply from Pong reservoir. By reducing the effects of water scarcity, the study illustrates the value of hedging as a climate change adaptation strategy. It also demonstrates how less complicated static hedging strategies can compete with more intricate dynamic strategies.

The review on past research shows adaptive operating rules are suitable for the reservoir management under the future changing climate. However, most of the studies focused on developing adaptive strategies for the reservoir involving flood control, hydropower, urban water supply, ecological conservation or comprehensive use.(Eum and Simonovic 2010, Raje and Mujumdar 2010, Ashofteh *et al.* 2013, 2017a, Turner and Galelli 2016, Zhang *et al.* 2017). Only few studies have addressed the development of adaptive strategies for irrigation tanks. This is of great concern as the tank water availability and irrigation water requirements are influenced by the changes in tank inflow as well as the changes of precipitation and temperature in the future climate(He *et al.* 2020, Gade *et al.* 2021, Busschaert *et al.* 2022, Incoom *et al.* 2022).

2.9 Critical Appraisal

An overview of tank systems in semi-arid regions, climate models data and uncertainty analysis, climate change impact on water resources, hydrological modelling in impact analysis of tank systems, and adaptation strategies for managing the water resources of tank systems are discussed in this chapter. Tank systems are of great importance in balancing the local hydrology of a region and the reviewed literature suggest that climate change impact analysis on these tank systems is crucial. This can be achieved by hydrological modelling of the tank catchment area and tank systems. Several studies have attempted to model the hydrological process of tank systems. Nevertheless, the hydrological modelling of these systems is a challenging task due to limited or non-availability of regional data.

It has been emphasized that analysing climate variability and trends under different climate scenarios is crucial for predicting the negative effects of climate change. Trends in the current and upcoming climate variables are frequently found and estimated in order to measure climate variability. Mann-Kendall and Sen’s slope tests are widely used non-parametric methods for detecting the trend and its magnitude respectively. Spatio-temporal changes in climatic variables at a fine scale can be achieved by analysing gridded data, and such analysis assists the policy makers to identify the priority areas for developing suitable water resources management. Various sources of uncertainties are associated with the climate change impact studies and it is essential to quantify the uncertainty for proper management and risk assessment. Keeping this in view, uncertainty arising due to RCMs need to be accounted by developing a multi-model ensemble approach. REA is the widely used and accepted method for multi-modeling ensemble approach.

Hydrological modelling has become an integral part of the climate change impact assessment which incorporates the physical parameters of a region. Therefore, physically based hydrological models with high resolution meteorological variables can be used to simulate the streamflow. There are several hydrological models currently used by researchers out of which SWAT has become recognized on a global scale as a reliable multidisciplinary watershed modelling tool. Numerous studies have supported SWAT's capability to replicate hydrologic response on an annual or monthly basis at various spatial scales. Further, SWAT model is popularly used for streamflow analysis in ungauged basins/watersheds. Accurate estimation of stream flow for ungauged watersheds can be achieved by regionalization. Regionalization is the process of transferring the information from gauged to ungauged catchments that have similar geological and morphometric properties. Model parameter regionalization is performed by developing regionalized model parameters values for ungauged watersheds by extending or extrapolating the calibrated values from gauged watersheds located within the same region. Since, the calibration and validation process for SWAT model is quite simple, it can be effectively used for streamflow prediction in ungauged watersheds.

Understanding the fluctuations in lake surface water levels is significant in climate impact analysis. SVR method is an efficient machine learning technique which can be combined with hydrological parameters for predicting lake water levels. Tank water levels for various climate change scenarios using SVR model can be predicted with SWAT model outputs. Climate change will have an impact on crop water demand because irrigation consumes the majority of available water. Estimating irrigation water demand based on climate change is critical for efficient use of tank water resources. To meet changing water demand, decisions on tank operational policy and water management strategies must be made. CROPWAT is a widely accepted crop simulation model, which estimates the crop water demand and irrigation demand by taking climate variables as input. Many studies proved that application of Stochastic Dynamic Programming (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.

As the tanks systems forms the lifeline for the people living in semi-arid regions, the main aim is to study the impact of climate change on an irrigation tank system located in a semi-arid region and suggest suitable adaptation strategies for effective water management. Initially, the observed and climate model simulated climate variability and trend is analysed for the entire Telangana state to identify the regions vulnerable to climate change. In the present study the uncertainty arising due to RCMs is accounted by developing a multi-model ensemble using REA approach. SWAT model is used to simulate the hydrological processes in selected tank system. Model parameter regionalization concept is used to transfer the calibrated model parameters to SWAT model setup for tank system. Tank water levels for various climate change scenarios are predicted with SWAT model outputs using SVR method. SDP is used to develop adaptive policies based on the future irrigation demand obtained from CROPWAT model for the selected command area of tank system.

Chapter 3

Climate Variability and Trends in Selected Semi-Arid Region

3.1 General

Semi-arid regions cover 14.2 % of the Earth's land surface and support 10% global population (Huang *et al.* 2016). Population growth, extensive urbanization, and climate-driven changes cause an acute impact on the water resources and agricultural productivity of semi-arid regions (Meter *et al.* 2016, Dong *et al.* 2018). These regions experience extreme seasonal and inter-annual precipitation variability resulting in frequent drought and flood conditions (Goff *et al.* 2000, Mail *et al.* 2016). Semi-arid regions are most sensitive to climate variability as the economy of these regions predominantly relies on rain-fed agriculture. This implies even a minute variation in precipitation and temperature patterns would have a significant impact on the agricultural productivity of the semi-arid regions (Huang *et al.* 2016). The regions that are already wet under present climate conditions are going to experience an increase in extreme precipitation events in the future, whereas dry spells are going to increase particularly in regions having dry conditions in present-day climate and increase the stresses on water resources which are likely to modify the components of the hydrological cycle like rainfall, evaporation, run-off (Sharmila *et al.* 2015).

In India, the semi-arid regions cover an estimated area of 53% of the total geographical area, most of which are concentrated in Southern India (Anbumozhi *et al.* 2001). In these areas, almost the entire rainfall is confined to the 30 to 60 days of the monsoon months. The low irregular rainfalls along with the extreme temperatures make these regions vulnerable to water shortage. The rainfall in the semi-arid areas of India is highly dependent on the North-East and

South-West monsoon, which results in seasonal variability of rainfall causing high runoff in monsoon periods leading to floods and severe water scarcity in non-monsoon periods. This monsoon-drivenn climate results in spatio-temporal mismatches between water availability and demand (Meter *et al.* 2016). Because of these climate variabilities and erratic rainfall conditions, the problem with water resources management is highly prevalent in semi-arid regions (Montenegro and Ragab 2012). The local governments of semi-arid regions are trying to implement water management policies that ensure enough supply of water for humans and animals and make irrigation viable. Hence, there is a prerequisite to analyzing the climate variability and trends of semi-arid regions for undertaking better water management policies.

Predicting the adverse effects of climate change requires an understanding of climate variability under various climate scenarios. The measurement of climatic variability typically involves the identification and assessment of trends in the observed and projected climate variables. The climate variability is statistically evaluated using the coefficient of variation (CV %) at both temporal and spatial levels, while trend analysis can be carried out using both parametric and nonparametric tests (Akinbile *et al.* 2015). Parametric tests assume that the climate data follows a statistical distribution whereas non-parametric tests do not rely on distributions (Praveenkumar and Jothiprakash 2018). Several studies have used both the parametric and non-parametric approaches to analyse the long-term variability and trends in climate variables (Chen *et al.* 2007, Mahmood and Jia 2017, Paul *et al.* 2017). Mann–Kendall trend test (Mann 1945, Sen 1968) is a highly accepted non-parametric test to detect significant trends in metrological time series data (Yadav *et al.* 2014, Birara *et al.* 2015, Jain *et al.* 2017). The method of Sen's slope estimator has been used widely in identifying the slope of the trend line in a time series which represents the magnitude of the trend (Jhajharia *et al.* 2014, Jain *et al.* 2017, Yacoub and Tayfur 2018).

In the present chapter, annual and monthly climate variability and trends are analysed. The goal of this study is to ascertain the variability and trends in the lowest and maximum temperatures (TMAX and TMIN), precipitation (PCP), and precipitation in Telangana, India, a semi-arid region. Grid-based rainfall and temperature data for the years 1951 to 2013 are acquired from the Indian Meteorological Department (IMD) in order to evaluate the observed climatic trends. Regional climate model (RCM) data from Coordinated Regional Climate Downscaling Experiment -South Asia (CORDEX-SA) under RCP 4.5 and 8.5 scenarios are utilized in the assessment of future (2020-2050) climate variability and trends for the region. The results of the investigation will improve our understanding of the risks under the changing climate.

3.2 Study Area

Telangana, the 29th state of India was formed on June 2, 2014, by bifurcation from the northern part of Andhra Pradesh. Telangana is situated on the Deccan Plateau covering 1,12,077 square kilometres. Even though two major rivers – Godavari and Krishna drain the entire state, with about 79% of the Godavari River Basin and about 69% of the Krishna River Basin, most of the land is arid. Apart from the major rivers, other minor rivers flowing in Telangana are Bhima, Dindi, Kinnerasani, Manjeera, Manair, Penganga, Pranahita, and Peddavagu and Taliperu.

Telangana is a semi-arid area with a typically hot and dry climate. This region receives predominant rainfall from the South-West monsoon and some part from North- East monsoons, but precipitation varies across the State. The annual rainfall is between 900 and 1500 mm in northern Telangana and 700 to 900 mm in southern Telangana, 80% of which is received from the southwest monsoons. Summer season starts in March, and peak temperatures are observed in May with average high temperatures in the 42 °C range. The winter season begins in mid-November and lasts until February with slight humidity and average temperatures in the 22–23 °C range. The state is susceptible to frequent drought and flood events. In recent years there has been an increase in climate variability and extreme weather events like thunderstorms, heat waves, unseasonal rains leading to frequent flooding. These events repeatedly affect water management and agricultural practices in the region, making the study and analysis of climatic change essential. For analysis purposes, the study area is divided into three zones – Northern Zone (NTZ), Southern Zone (STZ) and Central Zone (CTZ) which is shown in figure 3.1.

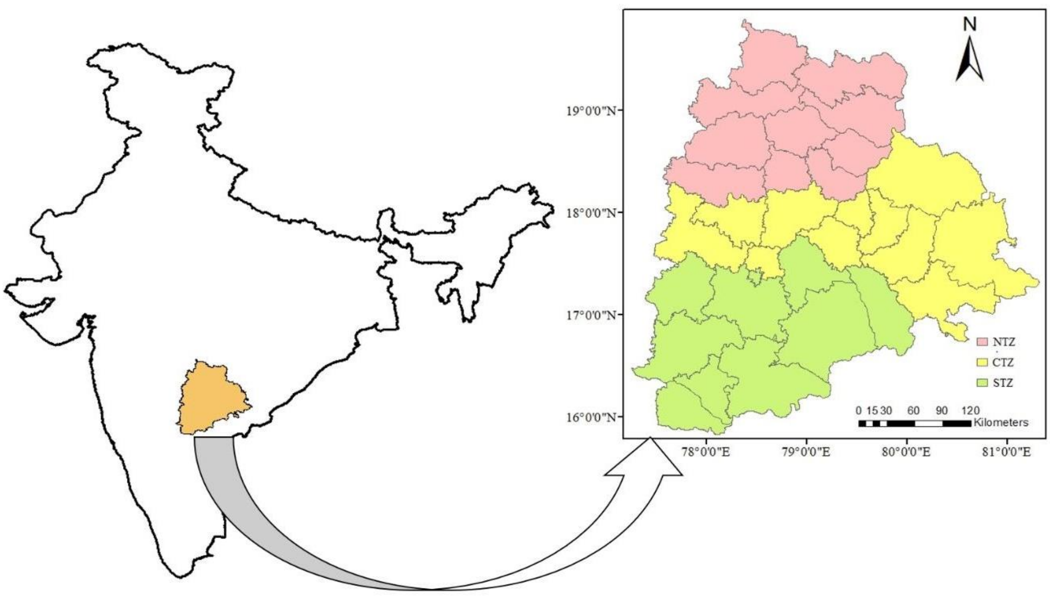


Figure 3.1 Location map of study area with three zones.

3.3 Dataset

Gridded climate data sets with 0.5°×0.5° resolution are obtained from the Indian Meteorological Department (IMD), Pune. Daily PCP, TMAX and TMIN data for 63 years i.e. 1951-2013 is considered for the grid points in the study area (Fig 3.2). The assessment of the future climate scenarios in Telangana, Coordinated Regional Climate Downscaling Experiment -South Asia (CORDEX-SA) data under RCP 4.5 and RCP 8.5 are considered. CORDEX is a World Climate Research Program (WCRP) to produce an improved set of regional climate change projections across the world. CORDEX considers an ensemble of different dynamical and statistical downscaling models that consider multiple forcing GCMs. Four RCMs are chosen from the CORDEX- SA Regional Climate Model (RCM) Experiments for the study with 0.44°×0.44° resolution, the details of which are given in table 1. The ensemble of all the four experiments in each scenario (i.e. RCP4.5 and RCP 8.5) is used in analysing the climate variability and trends for the future period. It is well known that using a single RCM simulation for climate change studies is not advisable, rather using multi-model ensemble data with a bias- correction method is effective in minimising the uncertainties in the assessment studies (Teutschbein and Seibert 2012, Dubey and Sharma 2018). In the present study, the linear scaling method proposed by (Lenderink *et al.* 2007)is used for bias correction of RCM data.

Table 3.1: Description of RCMs used in the research work

Acronym	Full Name	Driving GCM	Contributing Institute
CCAM(ACCESS)	Australian Community and Earth System simulator	ACCESS1.0	CSIRO Marine and Atmospheric Research, Melbourne, Australia
CCAM(CNRM)	Centre National De Recherché Meteorologiques	CNRM-CM5	
CCAM(CCSM)	Community Climate System Model	CCSM4	
CCAM(MPI)	Max Plank Institute Earth System Model at Base Resolution	MPI-ESM-LR	

Source: *http://cccr.tropmet.res.in/home/ftp_data.jsp*

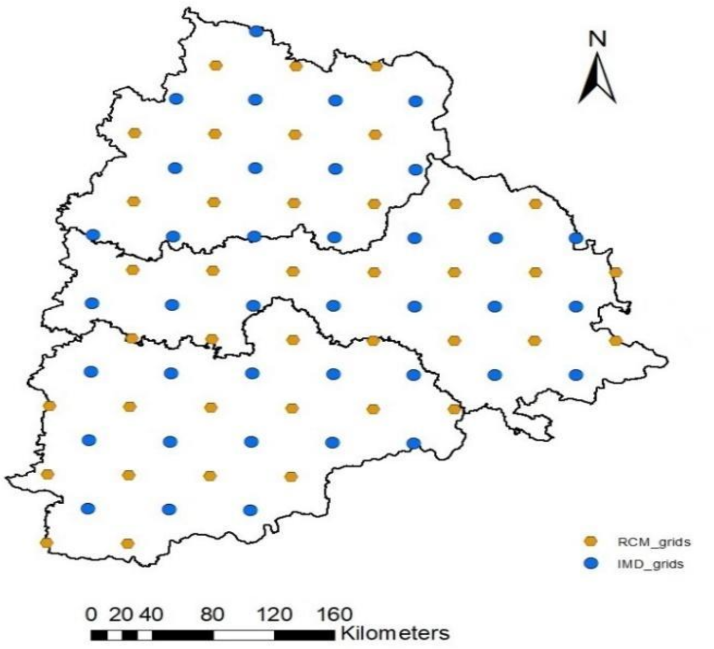


Figure 3.2. IMD and RCM climate grid points in the study area.

3.4 Methodology

To evaluate the precipitation and temperature variability, the coefficient of variation (CV %) at each grid point is calculated for observed and model data. Trend analysis is done using both linear regression (parametric) and Mann-Kendall test (non- parametric). Linear regression approach is used to determine the trends in climate variables parametrically. Each grid point is subjected to the non-parametric Mann-Kendal and Sen's slope test to identify potential trends and their sizes.

3.4.1 Climate Variability

Climate variability is examined by calculating the coefficient of variation (CV) at spatial and temporal scales for both observed IMD data and future projections from RCM's under RCP 4.5 and 8.5. A greater value of CV is an indicator of higher variability and vice versa which is computed as:

$$CV = \frac{\sigma}{\mu} \times 100 \tag{3.1}$$

Where, CV is the coefficient of variation; σ is the standard deviation and μ is the mean precipitation.

3.4.2 Mann-Kendall Test

In the present study Mann–Kendall trend test (Mann 1945, Sen 1968) was applied to detect the existing trend in annual, monthly and daily trends in climate variables. The trend test is applied to both observed and RCM data for all the three climate variables (PCP, TMAX and TMIN). The Mann-Kendall test *S* statistic and sign are calculated as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(xj - xi) \tag{3.2}$$

$$sgn(xi - xj) = \{+1, \quad xj < xi \quad 0, \quad xj = xi \; -1, \quad xj > xi \tag{3.3}$$

Where *n* is the length of the time series, *x* is the data values at times *i* and *j* (*j* > *i*). The variance of S is as follows:

$$Var(S) = \frac{n(n-1)(2n+5)}{18} \tag{3.4}$$

For *n* larger than 10, the standard test statistic *Z* is computed as follows:

$$Z = \{\frac{S-1}{\sqrt{Var(S)}} \; if\ S < 0 \qquad 0 \qquad if\ S = 0 \; \frac{S+1}{\sqrt{Var(S)}} \; if\ S > 0 \tag{3.5}$$

The presence of a statistically significant trend is evaluated using the *Z* value at the α level of significance. In the present study, 5% significance level i.e. α=0.05 is used for testing the null hypothesis, which is rejected if |*Z*| > 1.96. Z values that are positive represent increasing trends, whereas Z values that are negative suggest decreasing trends.

3.4.3 Sen's Slope Estimator

If the temperature and precipitation time series showed a trend after the Mann-Kendall test at α=0.05, Sen's Slope Estimator (Sen 1968) is calculated which gives the linear rate of change.

First, a set of linear slopes is calculated as follows:

$$d_k = \frac{x_j - x_i}{j - i} \; for \; (1 \leq i < j \leq n) \tag{3.6}$$

where n is the length of time series, d_k is the slope at k=1, 2, . . ., n, x denotes the climate variable values at i and j times. Sen's slope (b_{Sen}) is then calculated as the median from all the linear slopes obtained from Eq. (3.6) and it is referred to as "trend magnitude" (Kormann *et al.* 2015). A positive value of b_{Sen} indicates an increasing trend and a negative value indicates a decreasing trend in the time series.

3.5 Analysis of Observed Climate Variables

The spatial distribution plots for annual CV for IMD precipitation and temperature are shown in figure 3.3, which are plotted using the kriging interpolation technique. According to Asfaw *et al.* 2018, degree of variability of precipitation can be classified based on the annual CV value as less if CV < 20, moderate if 20 < CV < 30, and high for CV > 30. For IMD precipitation data the annual CV values in the region are observed between 22% –31.5%, suggesting that the precipitation variability is ranging from moderate to high. Highest precipitation variability can be observed in NTZ and STZ. The annual CV for maximum temperature ranges from 1.3% – 1.52 %, with the highest CV in STZ. Annual CV for minimum temperature ranges from 1.38% – 1.98, with the highest variability in NTZ. The spatial distribution plots for monthly CV of PCP, TMAX and TMIN for IMD data are shown in figure 3.4. For PCP, highest monthly CV values can be observed in NTZ indicating a significant rainfall uncertainty in that region. TMAX and TMIN show lesser monthly CV values ranging from 1% –22% indicating a lower monthly variability.

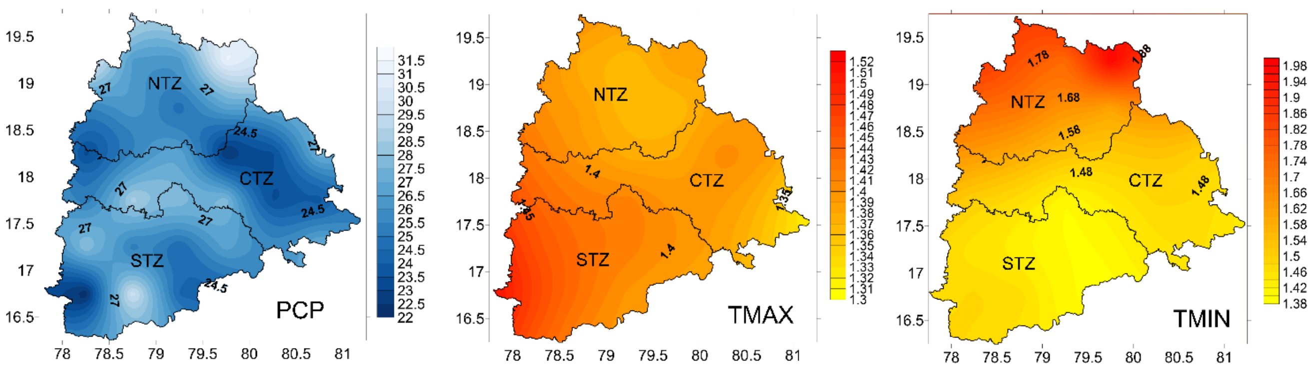


Figure 3.3 Spatial distribution plots for annual CV of PCP, TMAX and TMIN for IMD data (1951-2013).

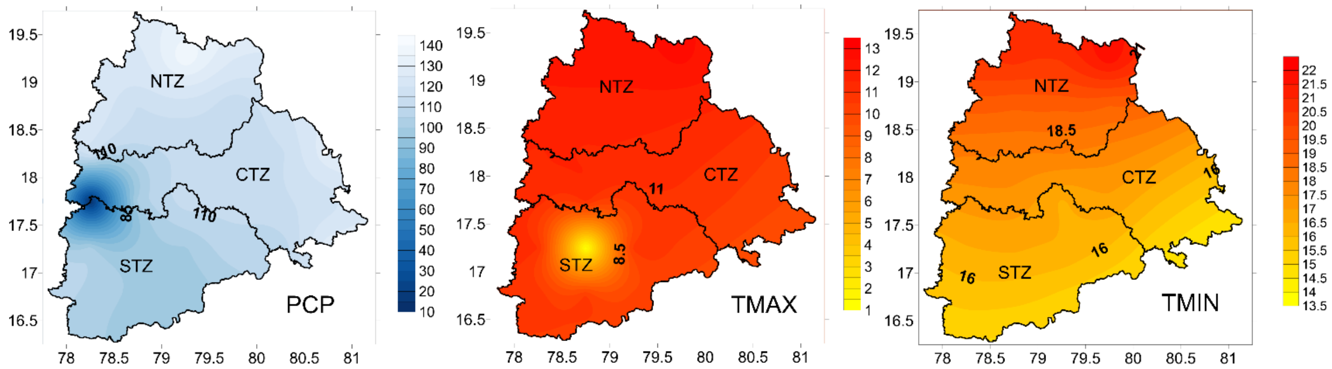


Figure 3.4. Spatial distribution plots for monthly CV of PCP, TMAX and TMIN for IMD data (1951-2013).

The linear regression analysis results for climate data averaged over each zone are shown in figure. 3.5, from which the rate of change can be defined by the slope of the regression line. In this case, the rate of change in annual PCP is 0.825 mm/year, 0.808mm/year and 0.115 mm/year for NTZ, CTZ and STZ respectively. The results indicate an increasing trend in precipitation in all the three zones of the region. The linear regression results for both TMAX and TMIN show a significant increasing trend in all the three zones with the highest rate of change of 0.014 ^{o}C/year for TMAX in STZ and highest rate of change of 0.004 ^{o}C/year for TMIN.

The results of the Mann-Kendall trend test exhibit an increasing trend in daily maximum and minimum temperature for IMD at all grid points. Daily precipitation from IMD exhibits no significant trend (NT), increasing trend (IT) at some grid points and decreasing trends (DT) at the other. TMAX and TMIN show increasing trends throughout the state. The results of the Mann-Kendall trend test for daily PCP, TMAX and TMIN are shown in figure 3.6. Further Sen's slope estimator results are plotted in figure 3.7, which show the spatial variation of slope (trend magnitude) for the three variables. From the Sen's slope plots, it can be observed that the highest and the lowest slopes in PCP can be observed in CTZ. For TMAX, lower magnitude slopes are observed in NTZ and CTZ, while higher slope magnitudes are observed in STZ. In the case of TMIN, the highest slope value is observed in CTZ and lowest slope value is in STZ.

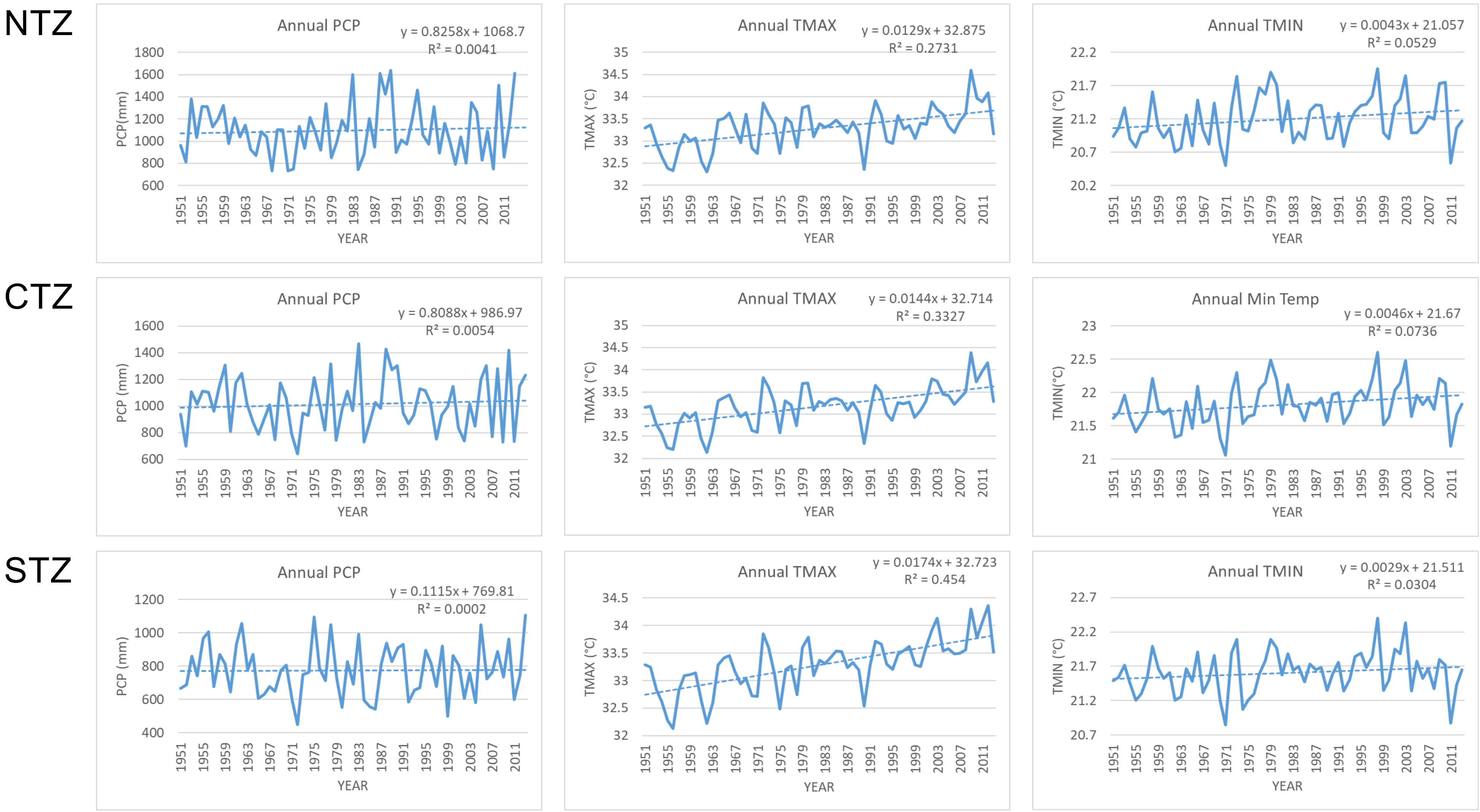


Figure 3.5 Linear Regression Analysis Results for IMD data (1951-2013)

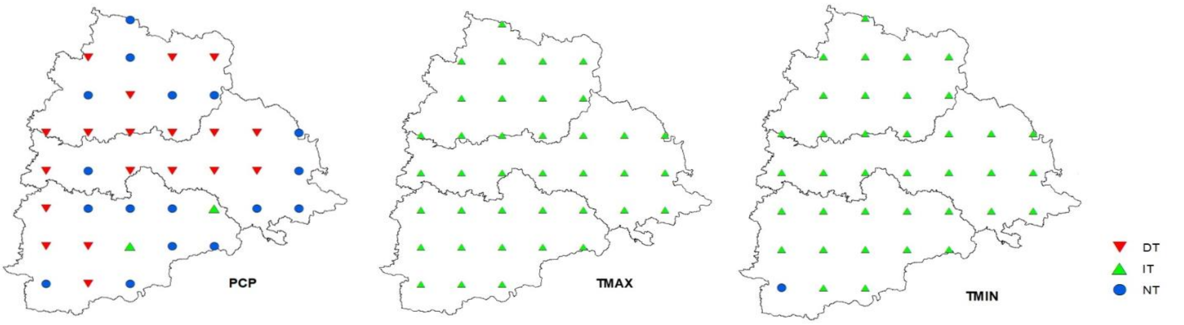


Figure 3.6. Daily PCP, TMAX and TMIN Trend at IMD Grid Points 1951-2013)

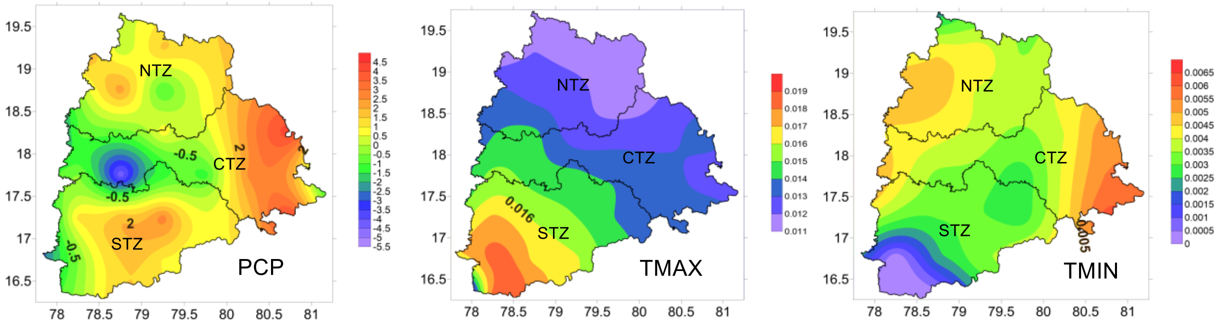


Figure 3.7. Sen’s slope for PCP, TMAX and TMIN for IMD data (1951-2013)

3.6 Analysis of RCM Simulated Climate Variables

The spatial distribution plots for annual and monthly CV for RCP 4.5 precipitation and temperature are shown in figures 3.8 and 3.9. The annual CV for PCP ranges between 14.2%–19.4%, suggesting a moderate variability throughout the state. High PCP variability is observed in NTZ. The CV for TMAX ranges between 2.85% - 3.5% with highest TMAX variability in NTZ and CTZ. CV range of TMIN is 1% -1.95% with maximum variability in STZ. The results of CV for TMAX and TMIN suggest that the temperature variability is not significant. The monthly precipitation variability range is 81% - 98%, suggesting high monthly variability. The monthly variability range for TMAX and TMIN is 9.2% -14.4 %.

RCP 8.5 annual and monthly CV results are plotted in figure 3.10 and 3.11. The annual CV for PCP ranges between 9% - 21.1%, suggesting a moderate variability. High PCP variability is observed in CTZ and low variability is observed in NTZ. The CV for TMAX ranges between 1.73% and 2.01% with highest TMAX variability in CTZ. CV range of TMIN is 1.45% -2.25% with maximum variability in NTZ. The results of CV for TMAX and TMIN suggest that the temperature variability is not significant. The monthly precipitation is varying in the range of 62% - 94%, indicating high monthly variability and whereas for TMAX and TMIN it is 10.2%

-16 %. RCP 4.5 and RCP 8.5 scenarios show a similar result for PCP variability whereas for TMAX and TMIN, RCP8.5 shows higher variability than RCP 4.5. Both RCP 4.5 and RCP 8.5 ensemble simulation results for the future period show a lesser PCP variability, while TMAX and TMIN show higher variability when compared to IMD past observations.

The linear regression analysis results for RCP 4.5 and RCP 8.5 future climate data averaged over each zone are shown in fig. 3.12. In the case of RCP4.5, the rate of change in annual PCP is 5.75mm/year, 6.31mm/year and 4.82mm/year for NTZ, CTZ and STZ respectively, suggesting a significant increase in future PCP in the region. The linear regression results for both TMAX also show an increasing trend in all the three zones with the highest rate of change of 0.096 ^{o}C/year for TMAX in STZ and there is a significant decreasing trend in TMIN. In case of RCP 8.5 the rate of change of annual PCP is observed to be negative with a magnitude of 2.52 mm/year, 4.71 mm/year and 4.04 mm/year in NTZ, CTZ and STZ, which suggests a significant decreasing trend in PCP. While TMAX and TMIN rate of change is positive, indicating an increasing trend.

The results of the Mann-Kendall trend test for daily PCP, TMAX and TMIN for RCP 4.5 and RCP8.5 are shown in figure 3.13 and 3.14. The results of the Mann-Kendall trend test for RCP 4.5 exhibit an increasing trend for PCP and TMAX. While TMIN exhibits no significant trend in NTZ and parts of CTZ, a decreasing trend in STZ. The results of the Mann-Kendall trend test for RCP 8.5 exhibit an increasing trend for TMIN and TMAX. While PCP exhibits no significant trend at all grid points except one which is showing an increasing trend. Sen's slope estimator results for RCP 4.5 and RCP 8.5 are plotted in figure 3.15 and 3.16, which show the spatial variation of slope (trend magnitude) for the three variables.

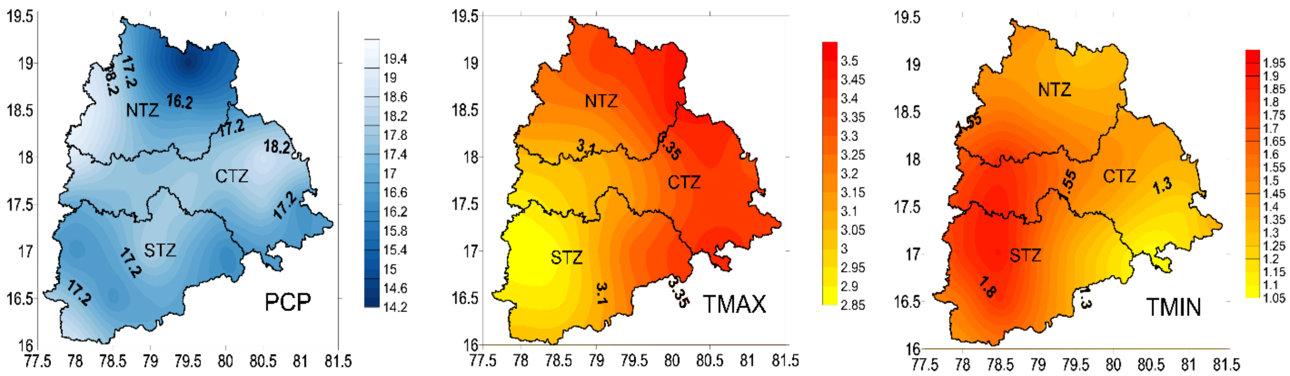


Figure 3.8. Spatial distribution plots for annual CV of PCP, TMAX and TMIN for RCP 4.5 (2020-2050).

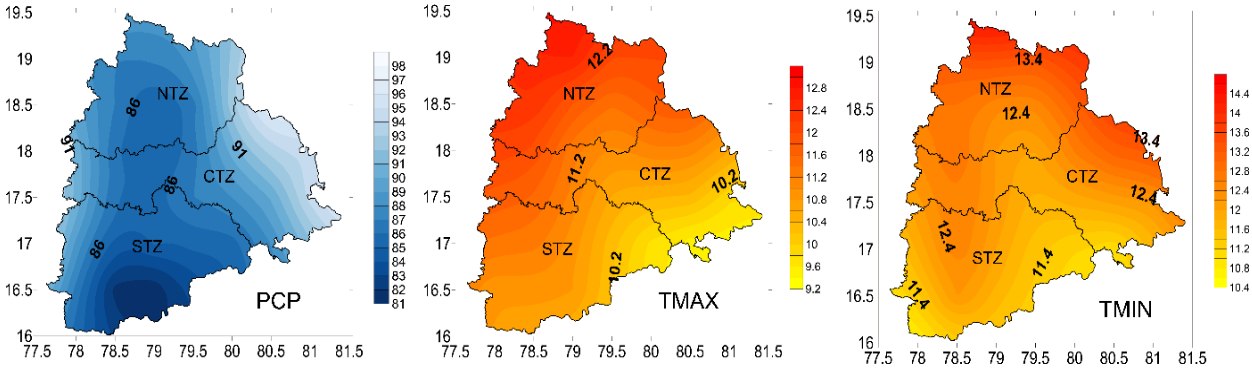


Figure 3.9. Spatial distribution plots for monthly CV of PCP, TMAX and TMIN for RCP 4.5 (2020-2050).

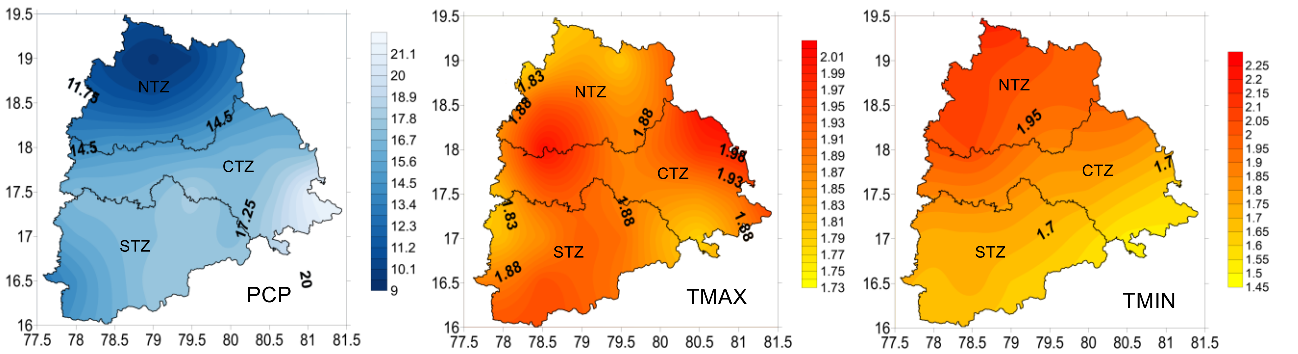


Figure 3.10. Spatial distribution plots for annual CV of PCP, TMAX and TMIN for RCP 8.5 (2020-2050).

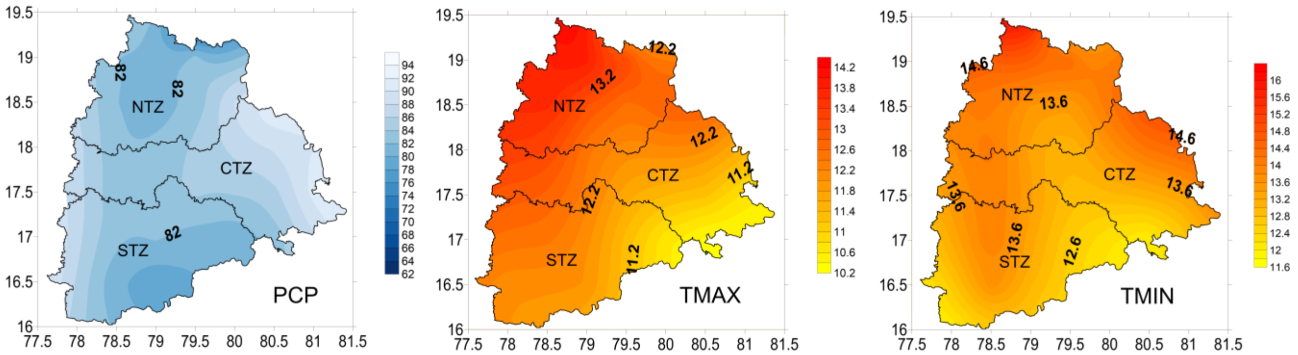


Figure 3.11. Spatial distribution plots for monthly CV of PCP, TMAX and TMIN for RCP 8.5 (2020-2050).

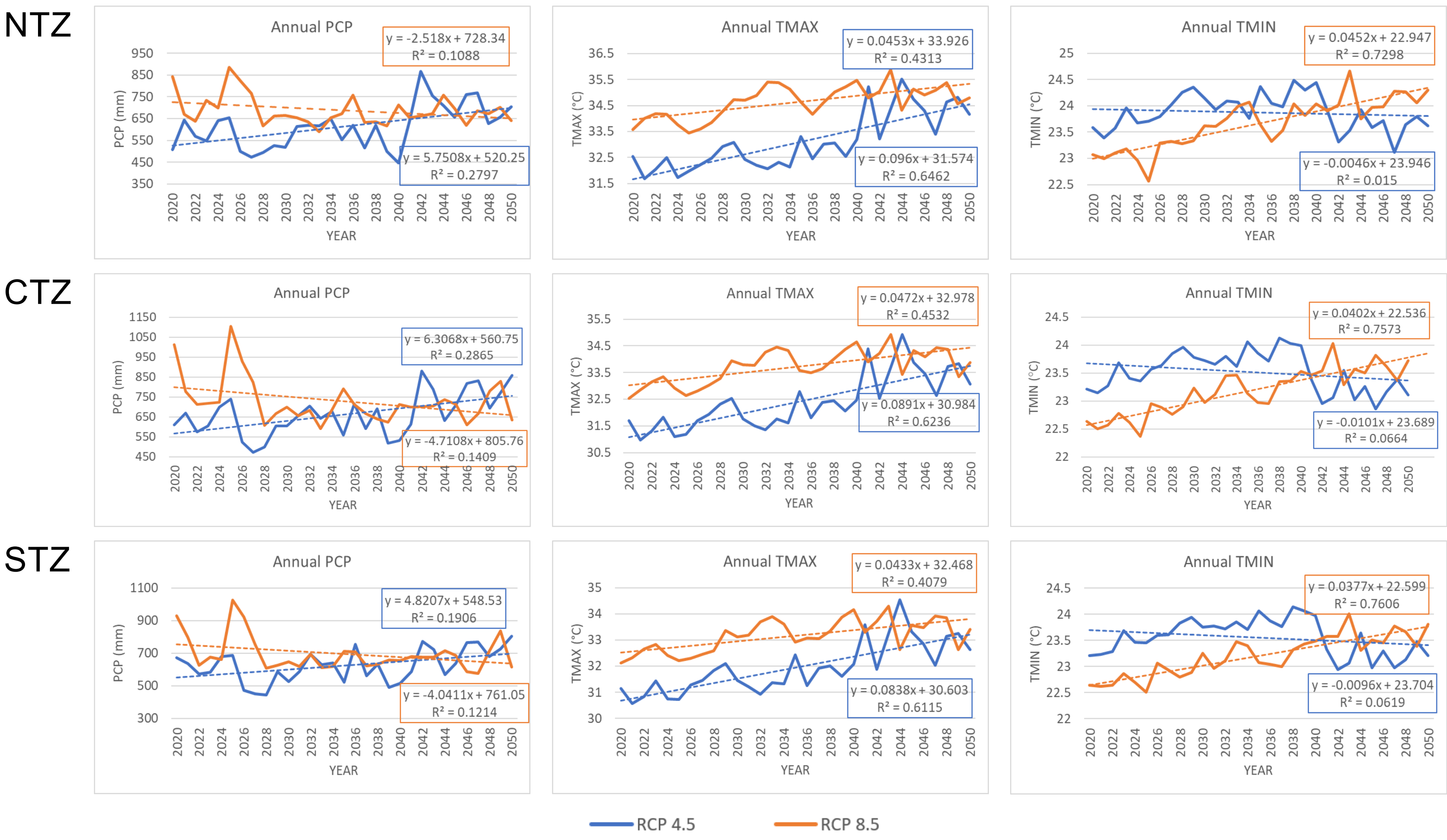


Figure 3.12. Linear Regression Analysis Results for RCM data (2020-2050)

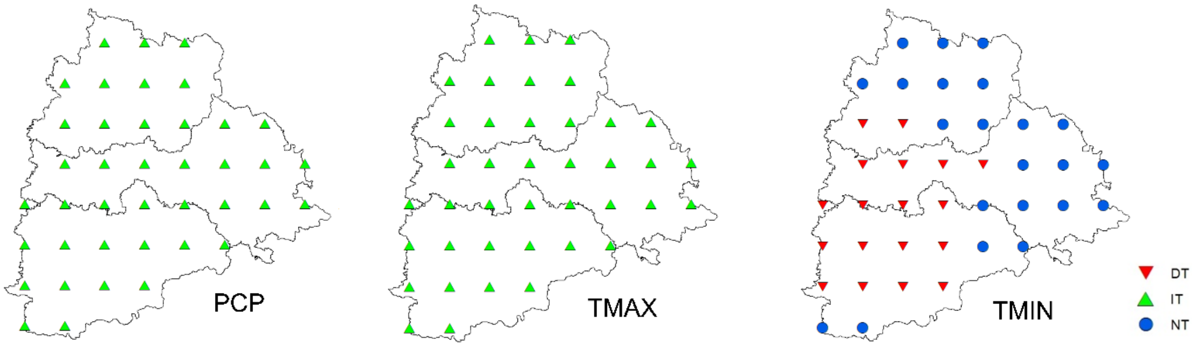


Figure 3.13. Daily PCP, TMAX and TMIN trend at RCP 4.5 grids for (2020-2050)

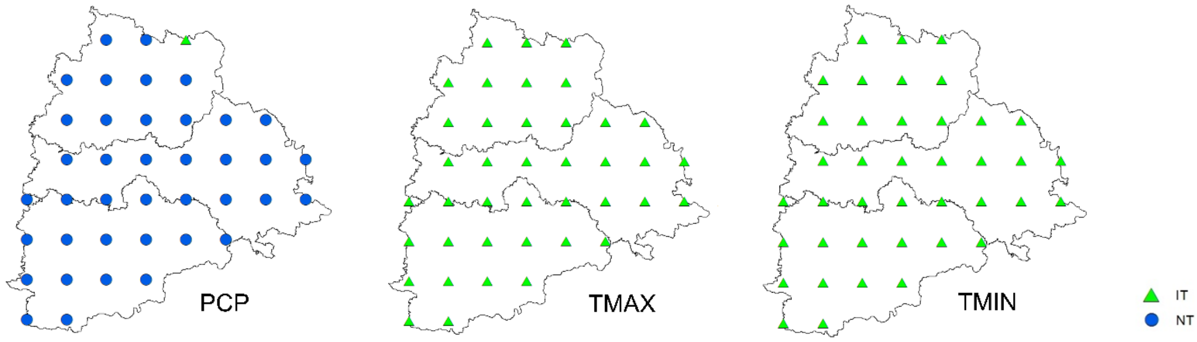


Figure 3.14. Daily PCP, TMAX and TMIN trend at RCP 8.5 grids for (2020-2050)

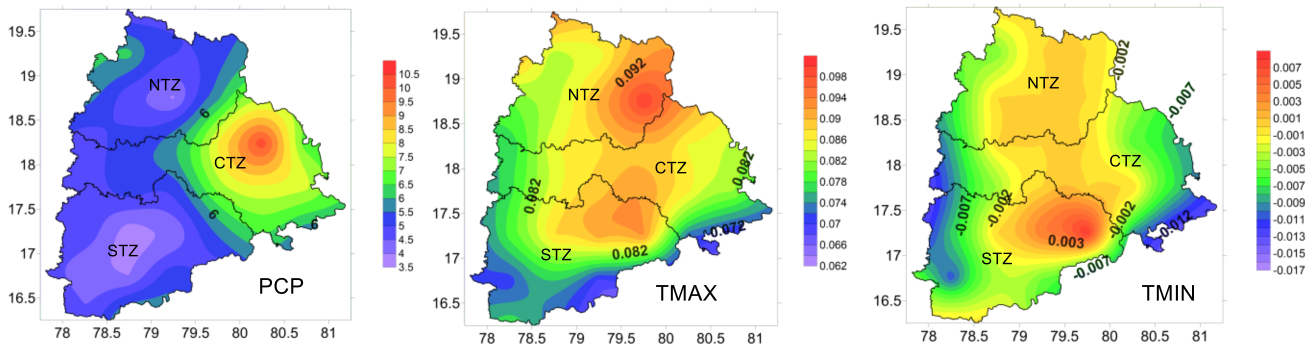


Figure 3.15. Sen's slope for PCP, TMAX and TMIN for RCP 4.5 data (2020-2050)

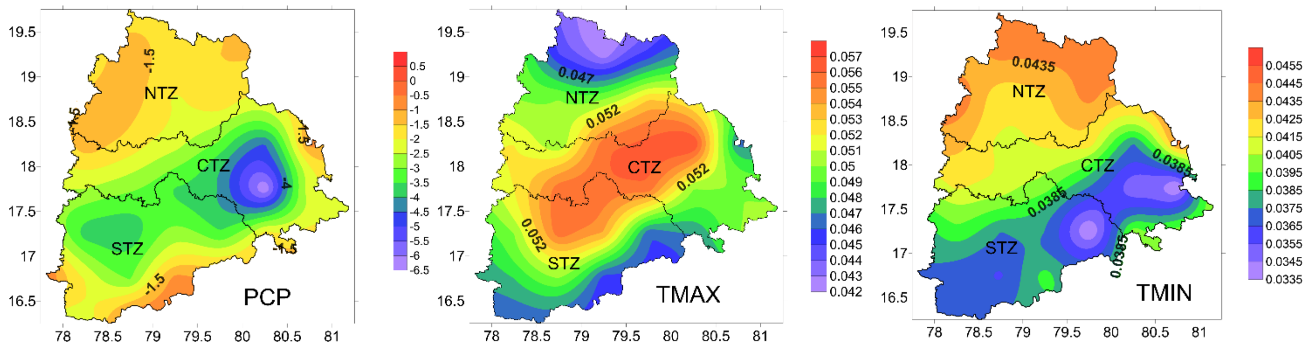


Figure 3.16. Sen's slope for PCP, TMAX and TMIN for RCP 8.5 data (2020-2050)

3.7 Closure

In this chapter, the observed (IMD) and simulated (RCM) climate variability and trend are analysed for historic and future periods, for Telangana, India which is a semi-arid region. Coefficient of variation (CV) is used to estimate the variability in climate variables. To comprehend the trend and its magnitude, parametric (linear regression) and non-parametric tests (Mann-Kendall and Sen's Slope) are performed at each grid point. For the observed IMD data, the results of both parametric and non-parametric tests suggest a substantial upward trend in the daily maximum and minimum temperature. While the daily precipitation has no discernible pattern, this indicates precipitation uncertainty. The maximum and minimum temperatures have increased significantly, which will have an impact on the precipitation patterns. The results of RCP 4.5 ensemble exhibited an increasing trend for PCP and TMAX, while TMIN showed no significant trend in NTZ and parts of CTZ, decreasing trend in STZ. Future scenario of RCP8.5 ensemble results scenarios projected a decrease in rainfall and an increase in daily maximum and minimum temperatures. The variability and trend examination of the climate parameters showed a considerable change in the climate that demands some specific measures for the management and planning of Telangana's water resources. Agricultural sustainability of the region is greatly impacted by the annual precipitation trend, which is declining, compared to the growing trend in TMAX and TMIN. This suggests that evaporation is increasing and that water resources are becoming less available. As chain tank systems are one of the major sources of irrigation in the Telangana region, itis important to study how the water resources of tank systems influence due to changing climate patterns of the region. Hence, the next chapter deals with the analysis of climate change impact on water resources of a selected semi-arid tank system – Phakal Lake, which is an important source of agricultural water situated in Telangana State.

Chapter 4

Hydrologic Modeling of Tank System under Climate Change

4.1 General

Climate change and its variability can change the hydrological cycle and hydrological regime of the region and these changes can cause significant impacts on water resources of the region (Dibike and Coulibaly 2005). The increasing rate of the global climate changes pose a significant impact on local hydrological regimes and water resources, particularly in semi-arid regions. This signifies that the assessment of the climate change impacts is a prerequisite for managing any water-related issues in the semi-arid regions, since these regions are already facing major water and agriculture-related issues (Sivakumar *et al.* 2005). Therefore, there is a need for climate change analysis that can determine its impacts on various aspects of water resources availability in these regions. Further, there is an increasing demand for best use and sustainable management of water resources.

Water resource management in semi-arid areas is significantly aided by irrigation tanks. These tanks play a vital role not only in the irrigation but also in the local ecosystem balance (Palanisami *et al.* 2010). Over the centuries, traditional tank systems have become a major source of irrigation which helped in the sustainable agricultural production in the semi-arid zones of Asian countries like India, Sri Lanka and Japan (Palanisami and Easter 1987, Unami *et al.* 2005, Arumugam *et al.* 2009). In India, these tanks are concentrated in the semi-arid region of Deccan plateau due to the terrain and soil conditions that are existent in the region (Narayanamoorthy 2007). About 60% of tank irrigation in the country is accounted by Andhra

Pradesh, Telangana, Karnataka and Tamil Nadu (Palanisami and Nanthakumaran 2000, Krishna Kumar *et al.* 2011). As one-third of the country's irrigation is still accounted for by tanks, they remain a significant traditional source of irrigation in India. So it is necessary to analyse the potential climate change impacts on hydrology and water resources availability of irrigation tanks in semi-arid regions. Impact assessment is usually carried by setting up a calibrated and validated hydrologic model for the watershed and estimating the future stream flow (inflow into the tank) for different climate change scenarios.

This often requires measured historical stream flow data (gauge data), which most of the watersheds lack (Razavi *et al.* 2013). Accurate estimation of stream flow for ungauged watersheds can be achieved by regionalization (Gitau and Chaubey 2010, Razavi *et al.* 2013). Regionalization is the process of transferring the information from gauged to ungauged catchments that have similar geology, climate, topography, vegetation and soils. Model parameter regionalization is performed by developing regionalized model parameters values for ungauged watersheds by extending or extrapolating the calibrated values from gauged watersheds located within the same region (Gitau and Chaubey 2010). The regionalization of parameters can be done by various methods such as simple transfer of parameters based on physical similarity, spatial proximity method, ratio method, global averaging method, regression method or interpolation methods like krigging or inverse distance weighting (IDW) (Gitau and Chaubey 2010, Razavi *et al.* 2013, Kim *et al.* 2016).

In this chapter, the effects of climate change on water resources have been evaluated for the Phakal watershed in the semi-arid zone of Krishna River Basin, Telangana, India. This watershed is essential for the study because it serves as the catchment for Phakal Tank, a significant medium irrigation project in Telangana's semi-arid region. The Soil and Water Assessment Tool (SWAT) model has been used to analyze the potential effects of climate change on the Phakal tank catchment. The NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset and the Coordinated Regional Climate Downscaling Experiment (CORDEX) climate data repositories are used to generate the meteorological data for the present and future time periods. Due to the lack of a gauge station at Phakal Lake, the Konduru catchment, which is downstream of the present study area, was used to run the SWAT Model utilizing the necessary geospatial layers and weather data from the IMD (Indian Meteorological Department) between the years 1985 and 2005. Utilizing observed stream flow data from the Purushothamagudem gauging station located in the Konduru catchment, SWAT model calibration and validation is conducted for monthly simulated stream flow and a simple regionalization technique is employed in order to transfer the model parameters to the Phakal watershed. The calibrated and validated SWAT model was used for Phakal tank catchment in order to estimate the inflows for future time periods and the climate change impact on the water resources availability is studied.

4.2 Description of Study area

Phakal lake is situated in the border region of Warangal and Mehabubabad Districts, Telangana, India. It is approximately 50 km east of Warangal city and it is well connected by a road passing through Narsampet which is 12 km away. Pakhal Lake is a Medium Irrigation Project constructed across Munneru vagu near Ashoknagar Village, Khanapur Mandal, Warangal District. The original project as envisage in the year 1902 by the Nizam PWD by restoring the existing Project constructed long back by the Kakatiya Dynasty in the year 1213 AD. The total catchment area of the lake is 264 sq km. The annual rainfall is about 1000 mm. Almost three lakh acres of agricultural area is surviving under the lake. Phakal lake watershed does not have any gauge stations for measuring inflows. Hence, Konduru Watershed which is downstream of the Phakal lake watershed is chosen for hydrological model application and parameters estimation. Konduru watershed has discharge measuring station at Purushothamagudem. The location map of the Phakal lake watershed and Knoduru watershed are shown in Figure 4.1. The landcover of the Phakal watershed predominantly consists of shrub land and agricultural land growing both Kharif and Rabi crops. The major crops grown in the area are cotton and paddy. Other minor growing crops include groundnut, maize and castor oil. The soil present in the watershed consists of sandy clayey loams with mixed red and black soils (Biswas *et al.* 2015).

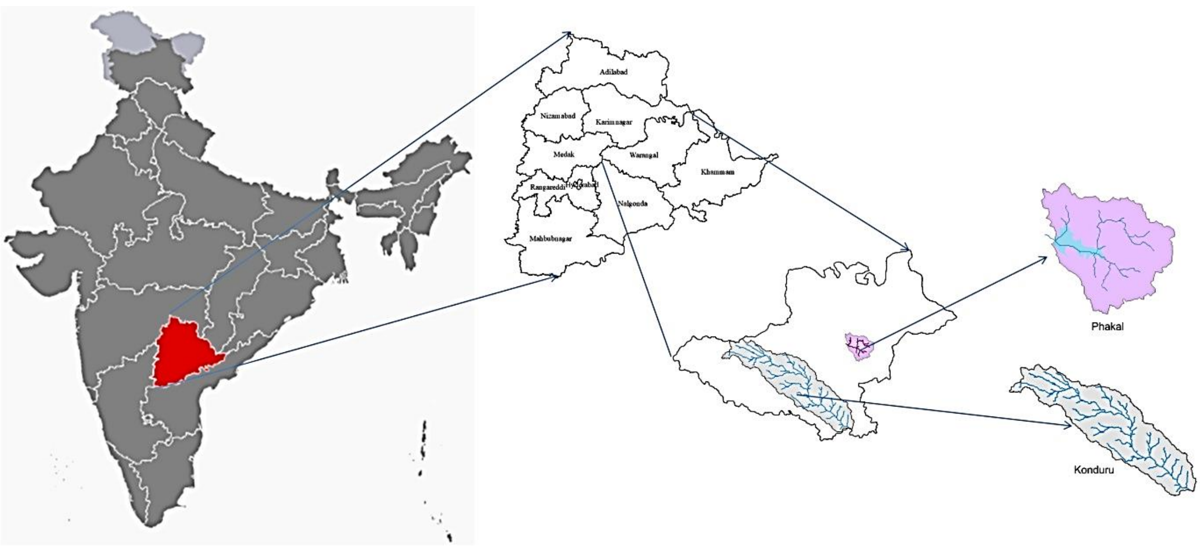


Figure 4.1. Study Area – Phakal Watershed (Ungauged) and Konduru Watershed (Gauged)

4.3 Data Used

4.3.1 Climate Data

Daily weather data for precipitation and minimum and maximum temperature have been collected from Indian Meteorological Department (IMD), Pune, India, for a period of 33 years (1986–2018) and used in the SWAT model. Observed climate variable data with grid cell size of 0.25°×0.25° for precipitation and 0.5°×0.5° for temperature are available. Climate model data generated by the CORDEX under RCP4.5 and RCP8.5 scenarios are obtained from Indian Institute of Tropical Meteorology (IITM), Pune (http://cccr.tropmet.res. in) and were classified as a baseline (1986–2018), early century (2020–2050), mid-century (2051–2080) and end century (2081–2099) data in the present study. The climate models under CORDEX project which are selected for the study are listed in Table 3.1. In addition to CORDEX data, the National Aeronautics and Space Administration (NASA) Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset contains downscaled climate scenarios derived from the GCM simulations of the Coupled Model Intercomparison Project Phase 5 (CMIP5) data are also used. The NEX-GDDP dataset based on two out of the four greenhouse gas emission scenarios known as Representative Concentration Pathways, i.e., RCP4.5 and RCP8.5. The spatial resolution of the dataset is 0.25° (~ 25 km × 25 km). NEX-GDDP data under baseline (1986–2018), early century (2020–2050) time periods is considered for the study. These datasets provide a set of global, high-resolution, bias- corrected and spatially disaggregated climate change projections that can be used to evaluate climate change impacts on finer scales. Table 4.1 describes the RCP4.5 and RCP8.5 scenarios and Table 4.2 shows the 21 GCM models used that were downscaled to obtain NEX-GDDP. Observed stream flow in the Purusottamgudem gauge station is obtained from Central Water Commission (http://www. india-wris.nrsc.gov.in), Ministry of Water Resources, and Government of India (GOI).

Table 4.1: Description of Representative Concentration Pathway RCP4.5 and RCP8.5.

RCP	Description
RCP4.5	Radiative forcing increased to 4.5 W/m2 (~650 ppm CO2 -eq) by 2100
RCP8.5	Radiative forcing is stable at 8.5 W/m2 (~1370 ppm CO2 -eq) by 2100

Table 4.2. List of the 21 Coupled Model Intercomparison Project 5 (CMIP5) general circulation models (GCMs) used in the study.

Model	Country and Institution
ACCESS	Commonwealth Scientific and Industrial Research Organization and Bureau of Meteorology, Australia
BCC-CSM1	Beijing Climate Center, China Institute of global change and Earth System Sciences, Beijing Normal University, China
BNU-ESM	Institute of global change and Earth System Sciences, Beijing Normal University, China
CCSM4	National Center for Atmospheric Research, America
MIROC5	Atmosphere and Ocean Research Institute, Japan Atmosphere
MIROCESM	Atmosphere and Ocean Research Institute, Japan Atmosphere
MIROCHEM	Atmosphere and Ocean Research Institute, Japan Atmosphere
CanEsm	Canadian Centre for Climate Modelling and Analysis, Canada
CESM1-BGC	National Center for Atmospheric Research, America Centre National de Recherches Meteorologiques, Centre.
CNRM-CM5	Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique, France Commonwealth Scientific and Industrial Research
CSIRO-MK3	Organization/Queensland Climate Change Centre of Excellence, Australia
GFDL-CM3	Geophysical Fluid Dynamics Laboratory, America
GFDL-ESM2G	Geophysical Fluid Dynamics Laboratory, America
GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory, America
INMCM4	Institute of Numerical Calculation, Russia
IPSL-CM5A-LR	Institut Pierre-Simon Laplace, France
IPSL-CM5A-MR	Institut Pierre-Simon Laplace, France
MPI-ESM-LR	Max Planck Institute for Meteorology, Germany
MPI-ESM-MR	Max Planck Institute for Meteorology, Germany
MPRI-CGCM3	Max Planck Institute for Meteorology, Germany
NORESM1-M	Norway Consumer Council, Norway

4.3.2 Geospatial Data

The geospatial data necessary for the SWAT model were prepared for both Phakal and Konduru Watersheds. The spatial input data layers such as land use data, digital elevation model (DEM) and soil data are required to run the model along with gridded weather data. Shuttle Radar Topography Mission (SRTM) 30 m × 30 m DEM, which is available from the United States Geological Survey (USGS) (https://earthexplorer.usgs.gov), was used to delineate the boundaries of both the watersheds and analyse the drainage patterns in the catchment areas. The DEM for both Phakal and Konduru Watersheds are shown in Figure 4.2. Slope gradient of the terrain and stream network have been derived from DEM for both the watersheds (Figure 4.3). The land use map of the study area has been obtained from USGS and reclassified as per SWAT model Land Use/Land Cover (LULC) classes which is shown in Figure 4.4. It consists of LULC classes of Dryland Crop land and Pasture, Crop land/grass land mosaic, Irrigated crop Pasture, Savanna and Water. Various soil physio-chemical and textural properties like soil texture, available moisture content, bulk density, hydraulic conductivity and organic carbon content for different sub-layers for each type of soil are required as SWAT model input (Gosain *et al.* 2006). The soil data is obtained from Food and Agricultural Organization (FAO). The watersheds consist of prominently Chromic Luvisols soils which are shown in Figure 4.5. Combined land use and soil data are incorporated for the definition of the hydrological response units (HRUs). The stream network is created with ArcGIS Spatial analyst tool using flow accumulation raster as an input which is prepared using DEM which are shown in Figure 4.6. Slope map is also prepared by using DEM as input by ArcGIS Spatial analyst tool in that surface tool.

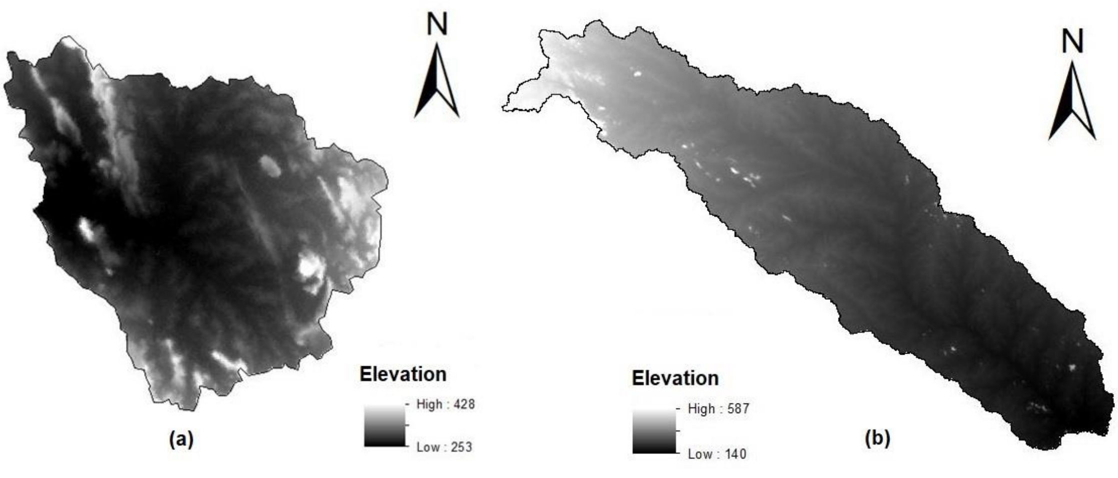


Figure 4.2. DEM of the watersheds (a) Phakal (b) Konduru

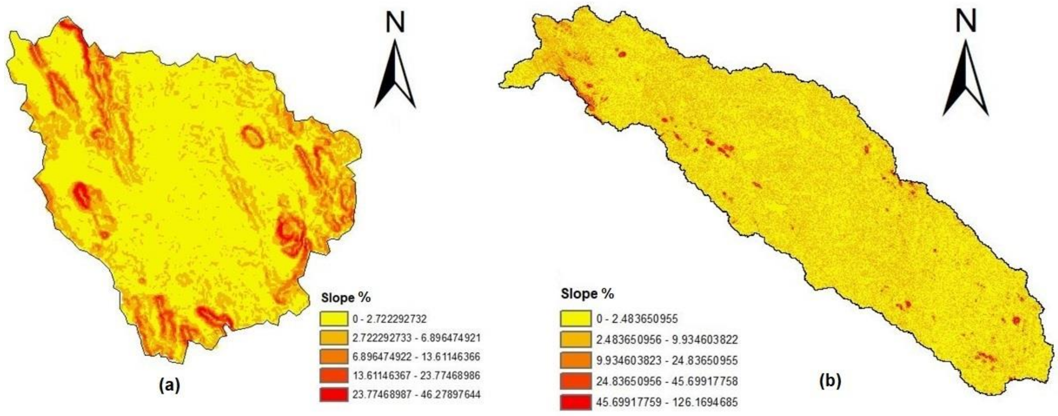


Figure 4.3. Slope map of the watersheds (a) Phakal (b) Konduru

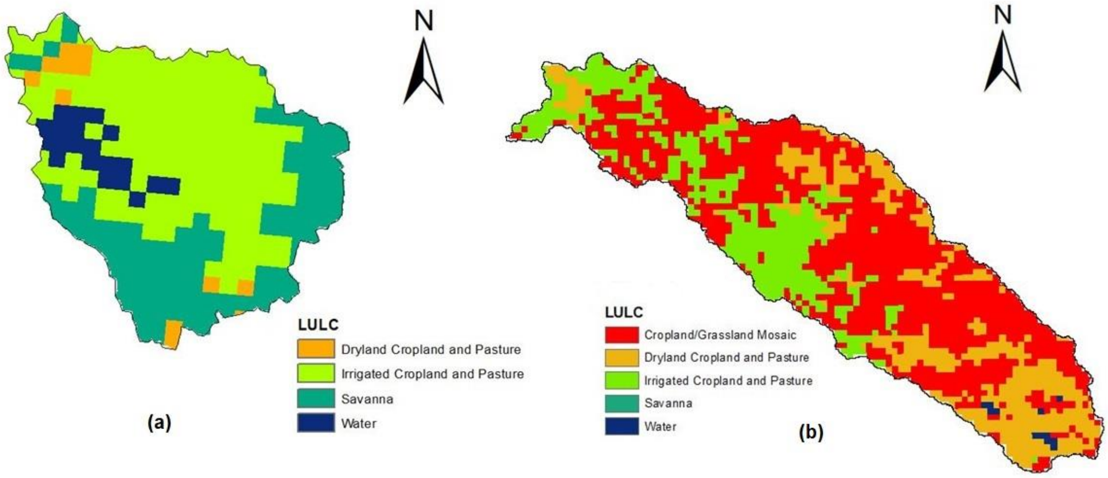


Figure 4.4 LULC map of the watersheds (a) Phakal (b) Konduru

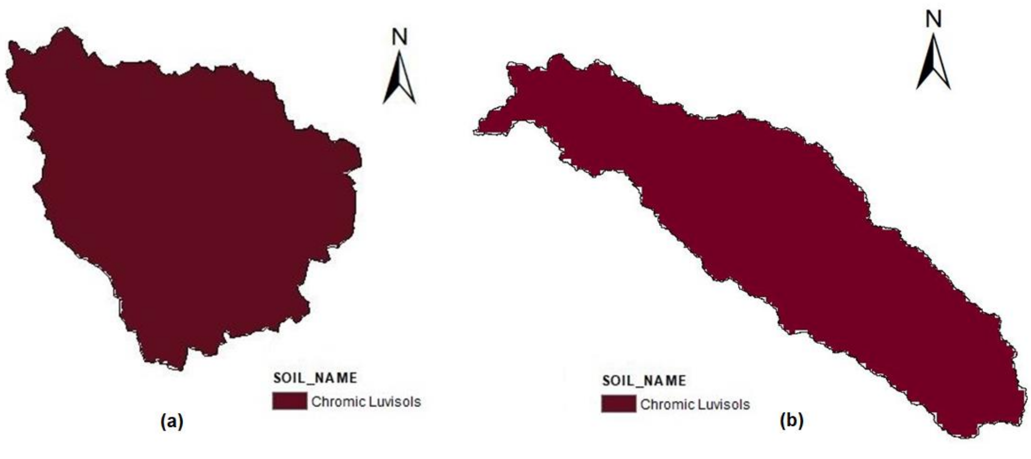


Figure 4.5 Soil map of the watersheds (a) Phakal (b) Konduru

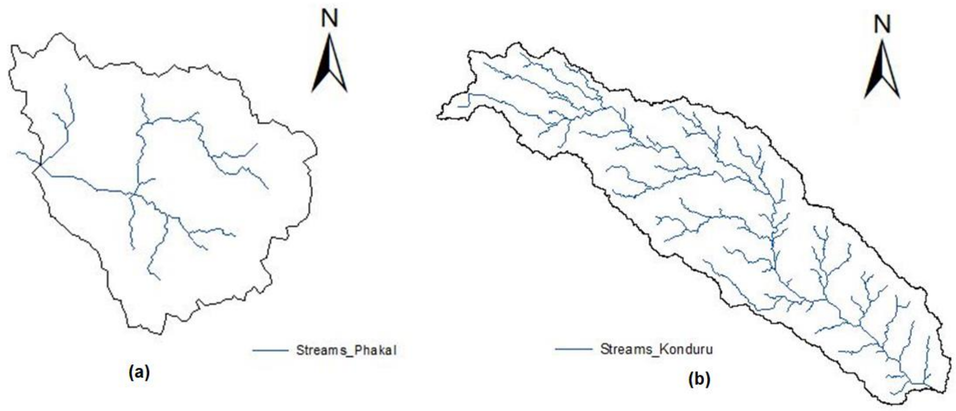


Figure 4.6 Drainage map DEM of the watersheds (a) Phakal (b) Konduru

4.4 Methodology

Methodology followed for the present study is shown in Figure 4.7. The climate data from CORDEX RCM have been extracted and bias-corrected using R programming language and input climate data files are prepared in SWAT input format. The bias correction of CORDEX RCM data is carried out using nonparametric quantile mapping method (Gudmundsson *et al.* 2012). Concurrently, the SWAT model was run for the watershed using geospatial data along with gridded weather data as inputs. SWAT CUP (Sequential Uncertainty Fitting version.2 - Sufi-2 algorithm) was used to calibrate and validate the model with the observed streamflow data (Abbaspour *et al.* 2004). To analyse the climate change impact on lake inflow, the simulations were performed in the calibrated and validated SWAT model using the bias-corrected climate data.

4.5 Non-parametric Quantile Mapping Method for Bias Correction

RCM simulated precipitation and temperature should be handled with caution as they contain significant biases. They cannot be used directly for assessing climate change impact at local scale and need bias correction. Many bias correction approaches have been developed which are ranging simple scaling methods to complex distribution mapping techniques (Teutschbein and Seibert 2012). Many studies were conducted to compare the performance of existing bias correction methods and concluded that quantile mapping method is most efficient in removing the biases (Jakob Themeßl *et al.* 2011, Fang *et al.* 2014). Gudmundsson et al. (2012) compared three different types of quantile mapping techniques (distribution derived quantile mapping, parametric transformations and nonparametric transformations) and suggested nonparametric quantile mapping is ideal for bias correction. Therefore, in the present study, the authors applied the quantile mapping for bias correction. Quantile mapping uses the distribution-based transformations to match the distribution of a modelled variable (P_m) with the distribution of an observed variable (P_o). The distribution-based transfer function is defined in Equation 4.1:

$$P_o = F_o^{-1}\left(F_m(P_m)\right) \quad (4.1)$$

where, F is a CDF and F^{-1} is the respective quantile function (inverse CDF). The subscripts o and m represent the parameters of the distribution, which correspond to the observed and modelled data respectively. A correction table of the two CDFs (simulated and observed data) is used to apply nonparametric quantile mapping, and a linear interpolation is applied between the two percentiles.

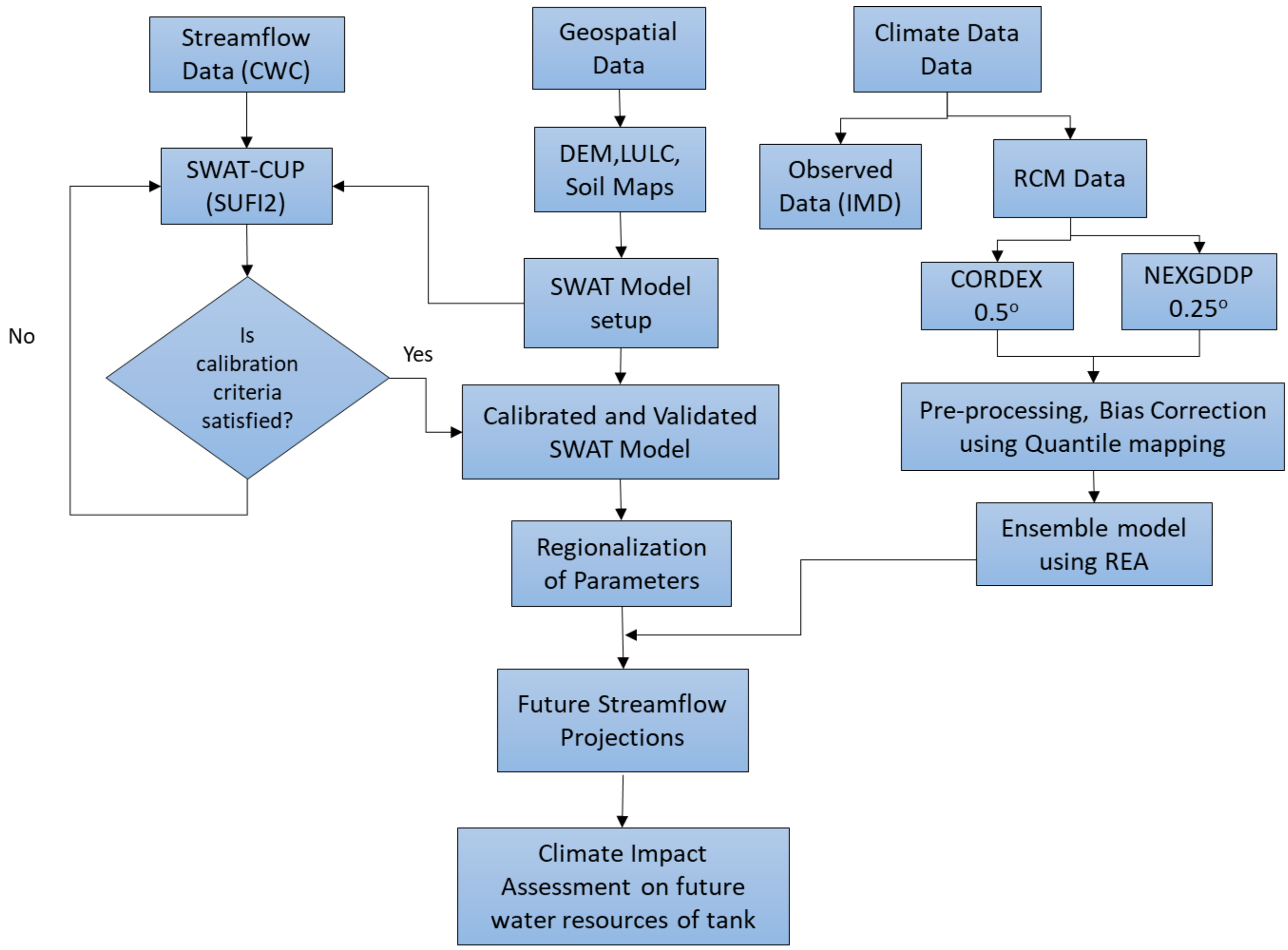


Figure 4.7 Methodology followed for the climate change impact study on water resources of Phakal lake watershed.

4.6 Reliability Ensemble Averaging (REA)

In the present study, the uncertainty due to the usage of multiple GCMs is treated using the Reliability Ensemble Averaging (REA) method. Giorgi and Mearns (2003) developed a probability-based Reliability Ensemble Averaging (REA) approach that provides the best estimate and reliable climate model data with a limited range of uncertainty. REA method is a quantitative method that assigns weights to GCMs based on their ability to represent observed data and convergence of the simulated changes across GCMs (Mujumdar and Ghosh 2008). Moreover, by reducing the impact of outlier and underperforming models, REA allows the uncertainty range in the simulated series to be reduced, making it possible to quantify the consistency of the simulated series by satisfying the model performance and convergence criteria. Unlike the simple ensemble averaging (SEA) method, which gives equal weight to all models, the REA method gives more weight to more reliable models (Xu *et al.* 2010). This method enables to minimize the higher uncertainty associated with the less reliable models during multi-model analysis. The REA approach developed by (Chandra *et al.* 2015) for climate variables (precipitation, minimum and maximum temperature) is used in this work. The methodology of REA approach is given in figure 4.8.

Two of the reliability criteria employed in REA are model performance, or the model's ability to effectively represent the original series, and model convergence, or the convergence of the model simulation for a certain forcing scenario. Model performance is measured based on errors produced from the deviation of Cumulative Distribution Functions (CDFs) between GCM simulated and original series, whilst model convergence is examined with regard to weighted mean CDF formed from repeated GCM future simulations. The convergence criterion also evaluates how well one model's forecast of the future corresponds with that of another model (Chandra et al. 2015). Initial weights are determined in REA using the root mean square error (RMSE) (Eq. 4.2), which establishes the performance criterion, as a measure of the GCMs' capacity to reproduce historical observations.

$$RMSE = \frac{1}{N}\sum_{i=1}^{N}(Observed_i - RCM_i)^{1/2} \tag{4.2}$$

$$w_{ini} = \frac{\left({}^{1}/_{RMSE_i}\right)}{\left(\sum_{i=1}^{N} {}^{1}/_{RMSE_i}\right)} \tag{4.3}$$

The step by step procedure used to evaluate the climate model's reliability and obtain the reliability ensemble mean are as follows:

1. With respect to the observed series, 10 identical intervals (N) of CDF that cover the whole range of atmospheric variables are used to determine the RMSE for each GCM. The proportionality of the weights is based on the inverse values of the RMSE, and the total number of GCM weights (n) is equal to one. Better models get heavier weights assigned to them.
2. To perform model convergence, the model performance criteria weights are utilized as initial weights for the respective GCMs.
3. To determine the weighted mean CDF (F_{wm}), the appropriate initial weights (w_{int}) are multiplied with the CDF of a future simulated ith GCM (F_{GCMi}).

$$F_{wm} = \sum_i w_{int(i)} \times F_{GCMi} \tag{4.4}$$

4. The same process as in step 1 is repeated, but the RMSE for the weighted CDF and future GCM projection is computed, and the weights obtained will be applied to the relevant GCMs in the subsequent iteration, resulting in a new weighted CDF with changed weights.
5. The model convergence requirement is fulfilled when the new weights and prior weights are the same by repeatedly performing steps 2-4.

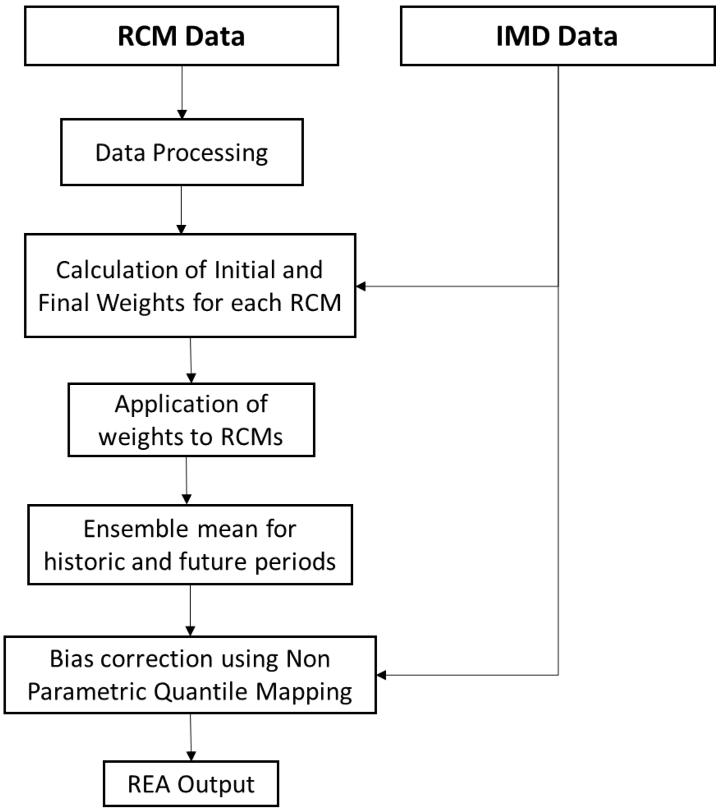


Figure 4.8 Flow Chart of Reliability Ensemble Averaging method

The aforementioned technique is repeated for all grid points falling in the study area and three meteorological parameters (precipitation, maximum temperature, and minimum temperature) due to the diversity of GCMs for the various grids and weather parameters. The final weights obtained for the GCMs are multiplied by the meteorological variable values at a particular grid, and the 'mean' of the resultant values after multiplication is regarded as the ensemble average of that particular climate parameter for that grid. As a result, rather than providing input for each GCM separately, after evaluating model uncertainty, an ensemble weighted mean of each meteorological parameter for the all the grids is provided as an input to the hydrologic model.

4.7 SWAT model

The SWAT is a physically based distributed hydrological model for analyzing the effects of environmental changes on hydrology (Neitsch *et al.* 2002). It is used to assess streamflow response to climate change. SWAT is an eco-hydrological model that can simulate regional-scale watersheds for several decades with reasonable temporal (daily) and spatial resolution without requiring excessive computational power It is utilized to assess how a gauged or ungauged watershed will be affected by land management practices and climate change (Luo *et al.* 2017). Specific data on topography, meteorological parameters (such as precipitation and maximum/minimum temperature), soil textural and physicochemical qualities, and land use are required as input for the SWAT model. SWAT distributes a watershed in to several sub watersheds, which are then divided into hydrological response units, which are units of distinct soil/land use characteristics (HRUs). These HRUs are described as homogeneous spatial units with similar geomorphologic and hydrological characteristics (Flugel, 1995). When modelling hydrologic processes, the SWAT gives numerous alternatives that users may choose based on their data availability(Li *et al.* 2009). The SWAT model's hydrological components are governed by the water balance equation as follows:

$$SW_{ti} = SW_o + \sum_{i=1}^{t}(R_{dayi} - Q_{surfi} - E_{ai} - w_{seepi} - Q_{gwi}) \tag{4.5}$$

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),

$Q_{surf\,i}$ 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).

4.7.1 Model Setup

The necessary geo-spatial layers and weather database inputs were prepared for running the SWAT model. SRTM 30m DEM was used for watershed delineation, sub-basin definition and topographic parameterization. Based on unique landuse and soil type, the sub basins have been further divided into HRU's. The HRU's are defined by considering 10 % threshold value of landuse, slope and soil area. SWAT model was set up by using observed weather data obtained from IMD from 1985-2005. Because there is no gauge station at Phakal Lake, the SWAT model is run for Konduru catchment, which is downstream of the research region. From the geospatial data of both Phakal and Konduru catchment areas it can be observed that they have a physical similarity. Hence, utilizing observed streamflow data from the Purushothamagudem gauging station located in Konduru watershed, the SWAT model calibration and validation is undertaken for monthly simulated streamflow. In order to stabilize the model, the starting three years of simulation have been regarded as a spin-up period.

4.7.2 Calibration, Validation and Uncertainty Analysis

The model calibration and validation are evaluated using sensitivity analysis and uncertainty analysis. Because the SWAT model has a huge number of input parameters, calibration and validation of the model is a very sophisticated, difficult, and thorough procedure. SWAT-CUP (SWAT Calibration Uncertainty Procedures) is a dynamic SWAT edit software that handles all SWAT parameters such as multiple soil layers and management rotation operations, precipitation data, and so on, which is used for model calibration and validation. The model parameters in SWAT-CUP can be manually adjusted repeatedly between auto-calibration runs. When employing Sequential Uncertainty Fitting (SUFI-2), a semi-automated process related to SWAT-CUP, the set of parameters must be analysed for sensitivity before calibration to aid in finding and ranking factors that have a substantial influence on certain model outputs (Abbaspour *et al.* 2017).

In SUFI-2 algorithm, all uncertainties (input, parameter, conceptual model, etc.) are accounted by parameter uncertainty(Abbaspour *et al.* 2004, 2009). The overall uncertainty is quantified by 95% PPU (95 percentage prediction uncertainty). In this study, the p-factor and the r-factor of the SUFI-2 algorithm were considered to assess the extent to which the calibrated model accounted for the uncertainties. Nash Sutcliff Efficiency (NSE) and coefficient of determination (R^2) are used for evaluation of performance of the model (goodness fit). The NSE and R^2 values are computed using equations 4.6 and 4.7 respectively. The r-factor is calculated by dividing the width of the 95 PPU band by the standard deviation of the measured data, whereas the p-factor is the proportion of data captured by the 95PPU. Ideally, p-factor should be close to 1 and r-factor narrowing down to 0. Roth *et al.* 2016 suggested that the p-factor > 0.60 and r-factor < 1.3 are acceptable. The R^2 and NSE values range from -∞ to 1, and 0 to 1, respectively with an ideal value of 1. In general, for the performance of the model can be considered "satisfactory" if NSE > 0.5 and $R^2 > 0.6$ for flow simulations (Moriasi *et al.* 2007, 2015).

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)}{\sum_{i=1}^{n}(O_i - \bar{O})} \quad 4.6$$

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2 (P_i - \bar{P})^2}}\right] \quad 4.7$$

where, n is the total number of observations, *Oi* and *Pi* are the observed and simulated discharges at ith observation, respectively, $\overline{O}$ is the mean of observed data over the simulation period.

In the present study, SWAT-CUP with SUFI-2 algorithm was utilized for the model calibration, validation and uncertainty analysis (Abbaspour *et al.* 2004). SWAT model for Konduru watershed was calibrated and validated using monthly river discharge available at Purushothamagudem. The optimized parameters of the Konduru watershed are very important as they represent the entire watershed. The Purushothamagudem has the discharge data for complete period of 18 years i.e. 1988-2005 without any missing values. The model was simulated for 1985-2005, using the first 3 years as warm-up period which were excluded from the analysis to mitigate the effect of uncertainties occurring due to initial conditions. Hence, the discharge data is divided into calibration (1988–1998) and validation (1999–2005) periods. The built-in sensitivity analysis tool in SWAT-CUP is used for sensitivity analysis (Neitsch *et al.* 2002). Subsequently, 9 most sensitive parameters are identified and other 6 parameters also being important for SWAT simulation in the Konduru watershed were also considered, which are listed in Table 4.3.

4.7.3 Regionalization of Parameters

Proximity method is used to transfer the parameters from Konduru watershed to Phakal watershed (Gitau and Chaubey 2010, Razavi *et al.* 2013, Emam *et al.* 2016, Rizzi 2017). This method can be applied if the gauged watershed is similar to ungauged watershed. The comparison of catchment characteristics of Konduru and Phakal watersheds are given in Table 4.4. The hypsometric curves for both the watersheds are shown in Fig 4.9. Based on the comparison, the watersheds are found similar. Hence, parameter transfer is carried out from Konduru watershed to Phakal watershed for SWAT model simulation.

Table 4.3 Sensitive parameters and their best fitted values and range

V__CH_K2.rte	Effective channel hydraulic conductivity, mm/hr	9.166	5.00	22.00
R__CN2.mgt	Curve Number	0.006	-0.007	0.007
A__OV_N.hru	Manning's N	0.189	0.18	0.2
A__REVAPMN.gw	Threshold depth for revaporation to occur, mm	72.16	0.00	500
V__ESCO.bsn	Soil evaporation compensation factor	0.91	0.8	1.0
V__CH_N2.rte	Manning's N	0.181	0.15	2.0
R__SOL_K (...).sol	Saturated hydraulic conductivity	-0.556	-0.6	-0.57
R__SOL_AWC (...).sol	Available water capacity, m/m	0.339	0.33	0.4
R__SOL_BD (...).sol	Moist bulk density (Mg/ $m^{3)}$	-0.087	-0.04	-0.1
A__GWQMN.gw	Threshold depth for ground water flow to occur, mm	1355.70	1350	1390
V__GW_REVAP.gw	Ground water revaporation coefficient	1.86	1.8	1.9
v__GW_DELAY.gw	Ground water delay, days	58.903	42	60
V__EPCO.bsn	Plant uptake compensation factor	0.86	0.00	1.00
V__ALPHA_BF.gw	Base flow recession factor, days	0.063	0.00	1.0

Table 4.4: Comparison of Catchment characteristics of Konduru and Phakal Watersheds.

Physical Characteristic	Konduru Watershed	Phakal Watershed
Area(km^2)	2177.4	264.5
DEM mean (m)	263.3	285.6
Hypsometric integral	0.275	0.231
Average Slope (%)	4	5.6

4.8 Results and Discussion

4.8.1 Results of bias correction

Nonparametric quantile mapping is used for bias correction. The results of bias correction for ACCESS model at grid point (18, 80) are shown in Figure 4.9 (a and b). The plot shows the comparison of quantile plots between uncorrected and corrected data. It can be observed that the nonparametric quantile mapping method for bias correction performs well as the data falls on the x = y line after bias correction (Figure 4.10(b)). The same procedure of bias correction is applied for all the climate models for both CORDEX and NEX-GDDP data.

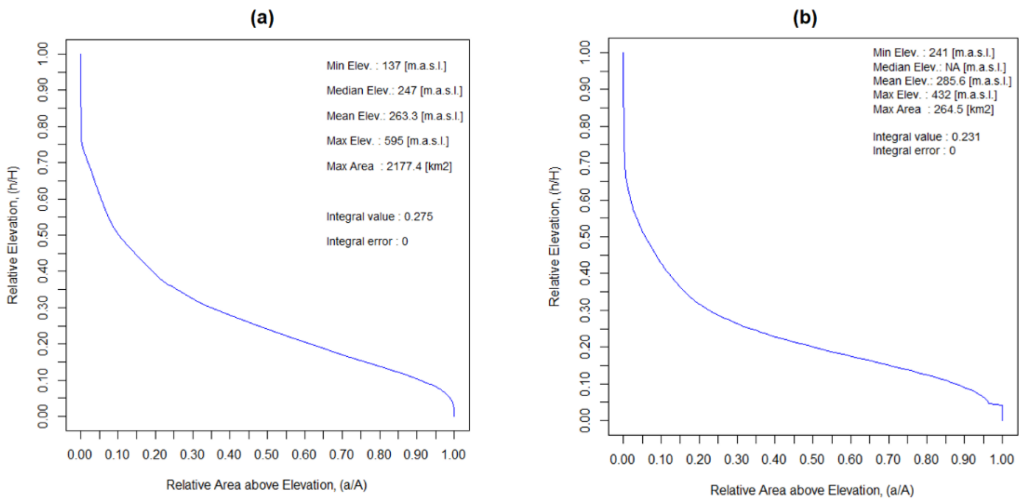
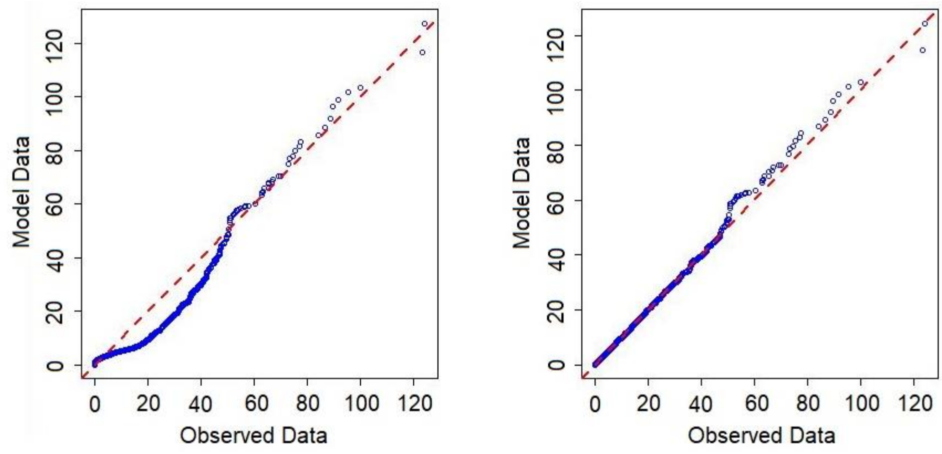


Figure 4.9. Hypsometric curve for the watersheds (a) Konduru and (b) Phakal



(a) Before Bias Correction (b) After Bias Correction

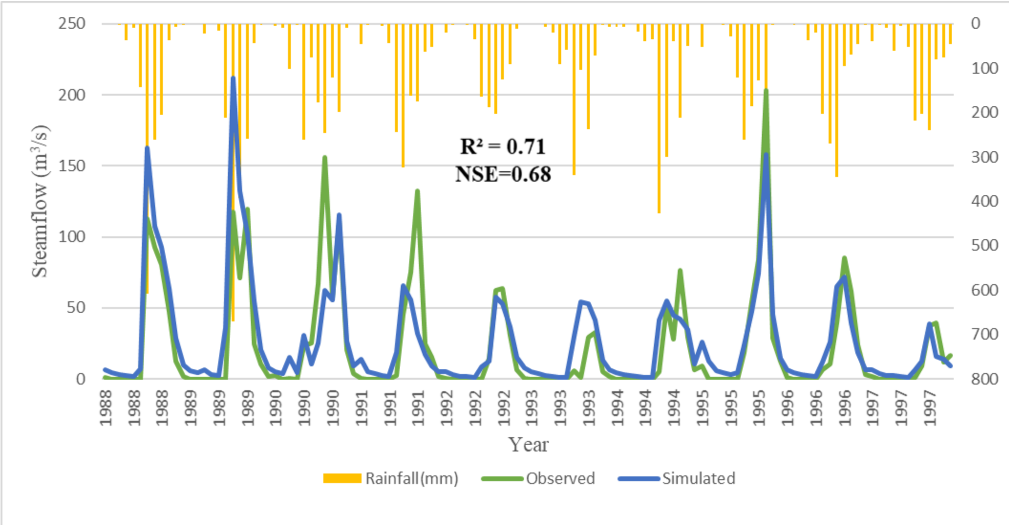
Figure 4.10. Quantile plots showing the results before and after bias correction at (18, 80) grid point

4.8.2 SWAT model calibration and validation results

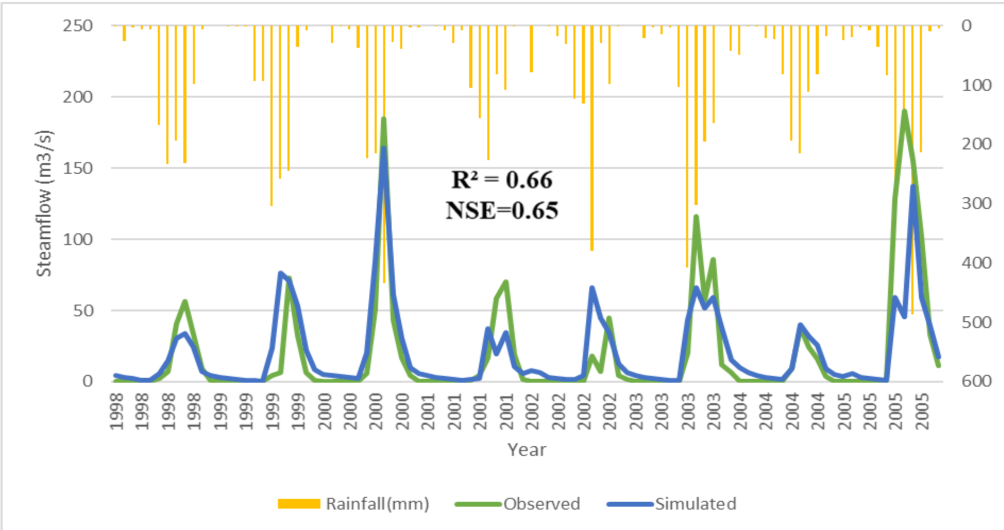
The model performance was evaluated by comparing the SWAT simulated monthly flows with observed monthly flows during calibration and validation. The calibration and validation plots are shown in Figures 4.11 (a) and (b), respectively. The efficiency of the model to simulate flows is evaluated using four performance indicators: NSE, R^2, p-factor and r-factor. These performance indicators were observed to be 0.71, 0.66, 0.65, and 0.52, respectively, during the calibration period (Table 4.5). R2, NSE, p-factor, and r-factor were observed to be 0.68, 0.65, 0.62, and 0.55 correspondingly during validation. These statistics suggest that the SWAT model performed satisfactorily during calibration and validation.

Table 4.5: Model Performance Indicators during Calibration and Validation

Index	Calibration	Validation
R^2	0.71	0.68
NSE	0.66	0.65
p-factor	0.65	0.62
r-factor	0.52	0.55



(a)



(b)

Figure. 4.11 Observed and simulated flows for (a) calibration period (b) for validation of Konduru Watershed

4.8.3 Historic and Future CORDEX Climate Data Analysis

The hydrologic components of the Phakal Watershed were simulated for the Baseline (1986-2018), Future-1 (2020-2050), Future-2(2051-2080), and Future-3 (2081-2099) periods using SWAT model after calibration and validation. For simulating the future hydrologic conditions, four CORDEX-RCM outputs under RCP 4.5 and 8.5 scenarios are used. For the analysis of climate change, the simulated hydrologic conditions are compared with the observed data. The CORDEX-simulated temperature and precipitation are compared with IMD data for the baseline period. The average monthly values of maximum and minimum temperatures from IMD and the four CORDEX models, i.e. ACCESS, CCSM, CNRM, MPI-ESM, are shown in Figure 4.12.

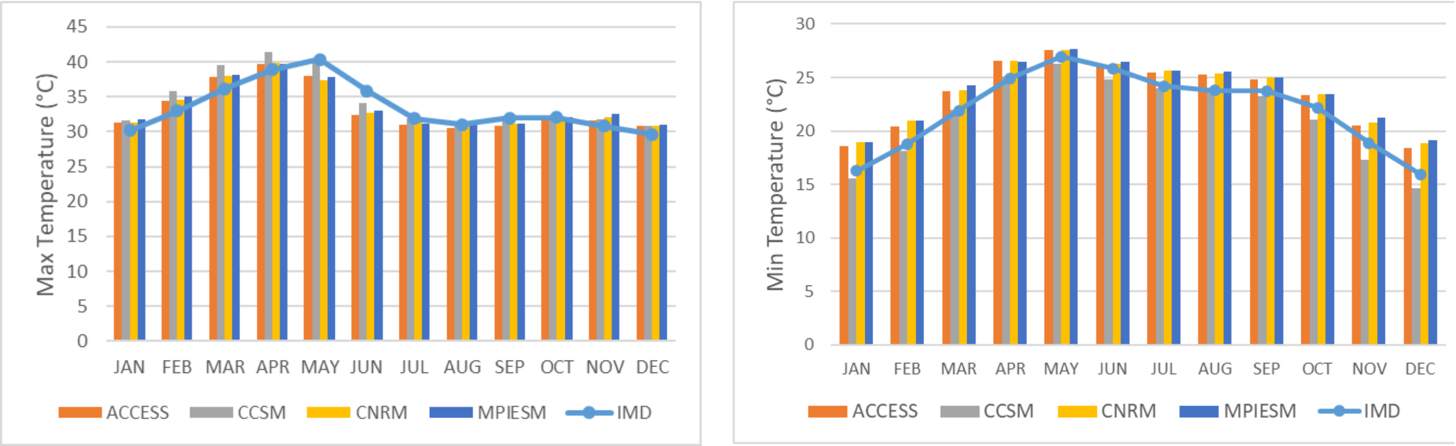


Figure 4.12. Comparison of average monthly temperature for model and observed data during baseline period (1986–2018).

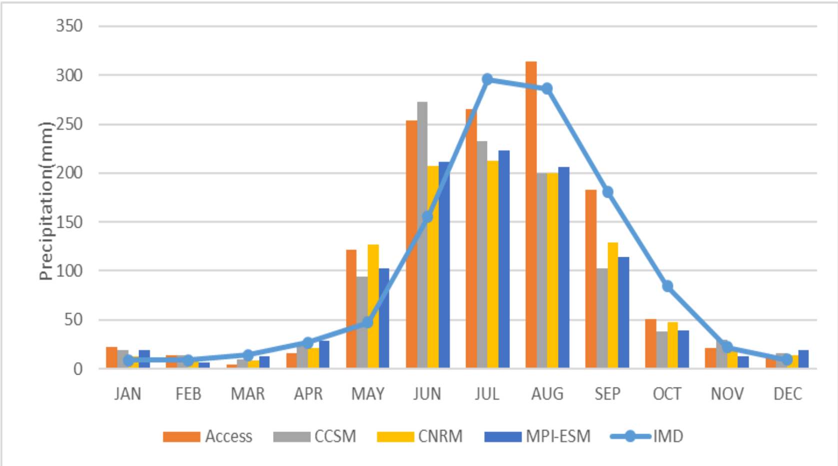


Figure 4.13. Average monthly precipitation for climate model and observed data during baseline period (1986–2018).

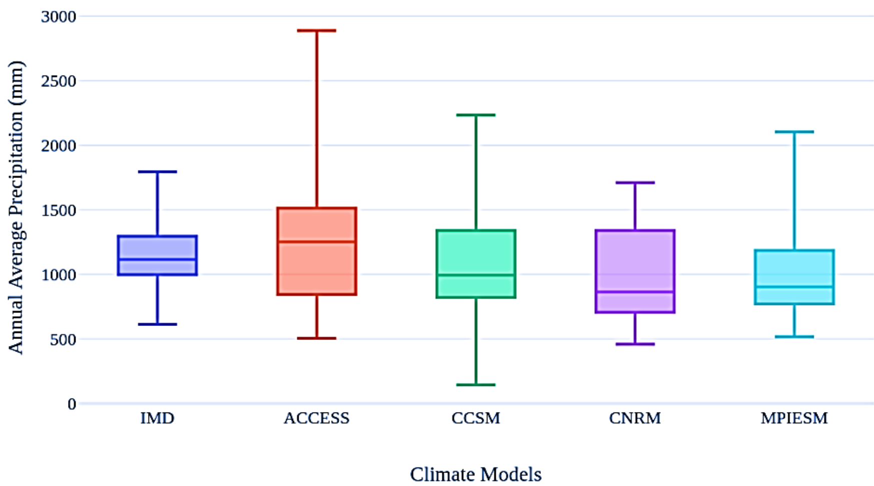


Figure 4.14. Comparison of annual precipitation of observed data and four climate models during historic period (1986–2018).

It is indicated that CCSM model predicts both maximum and minimum temperatures similar to observed data. ACCESS, CNRM and MPI-ESM overestimated the maximum temperature during January, February, March, April, November and December, while these models underestimated during May, June and July months. In case of minimum temperature estimation, all the RCM models are over predicted. The mean monthly precipitation with respect to CORDEX models and observed data are shown in Figure 4.13. It is observed that CCSM, CNRM and MPI-ESM models overestimated the precipitation from January to July and underestimated during the rest of the months. The ACCESS model simulated the precipitation similar to observed data. The CCSM model is the better predictor among the four models in simulating monthly maximum, minimum temperature and while MPI-ESM model shows good correlation with observed data in case of monthly precipitation than the other three models. The comparison of IMD annual average precipitation with 4 RCM models is shown in figure 4.14. The CCSM model simulates the precipitation similar to observed data. The MPI-ESM model is the better predictor among the four models in simulating annual mean precipitation than the other three models.

Figure 4.15 shows the comparison of SWAT simulated streamflow (tank inflow) using IMD data and CORDEX climate model data. It can be observed that the CCSM model predicts streamflow similar to IMD during July and August months. No particular model is in good match with the observed data, either they under predicted or over predicted. The box-plots for annual streamflow simulated using IMD and climate model data are shown in Figure 4.16. The CCSM model data predicted the mean annual streamflow close to IMD data.

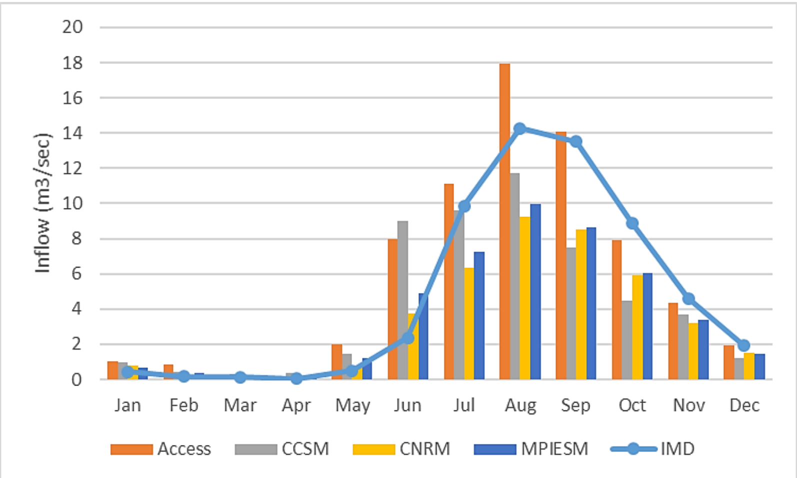


Figure 4.15. Comparison of average monthly tank inflow for model and observed data during historic period (1986–2018).

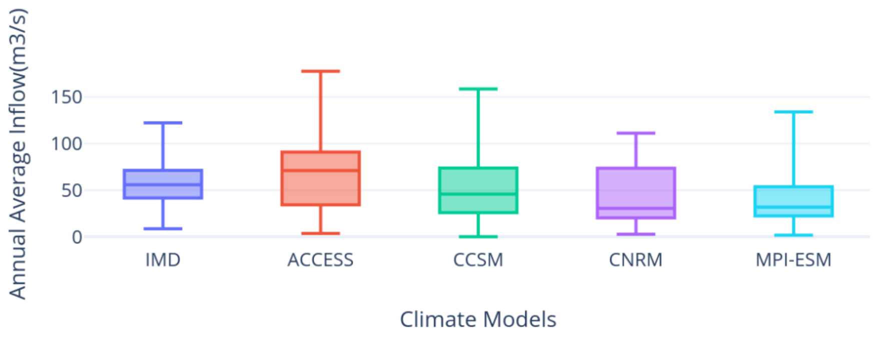


Figure 4.16. Comparison annual streamflow of observed data and four climate models during baseline period (1986–2018).

It can be observed that no particular model have good correlation with IMD data, so REA ensemble model is developed using all the four RCM's in order to account of the model uncertainty. The REA results for each of the RCM for historic and future time periods are given in table 4.6. The initial weights for the models are shown under historic column, which suggest that the precipitation from ACCESS model has good correlation (0.69) with IMD compared rest of the models. The min and max temperature estimates from the RCM's don't have good match with IMD with initial weights less than 0.38. Thus, there is a need for an ensemble model. The final weights for the future time periods are calculated using the CDF's for each of the time period which are shown in table 4.5. The REA mean precipitation for historic time (1986-2018) period is calculated by applying the initial weights to the RCM model precipitation. The scatter plot for REA data and IMD daily precipitation is shown in figure 4.17. It can be observed that the REA model has a good match with observed data with correlation coefficient (R^2) value of 0.899. The average monthly precipitation from REA and IMD is shown in figure 4.18. The REA model monthly precipitation is similar to IMD data. The R^2 value for REA temperature and observed temperature is 0.87 and 0.93 for maximum and minimum temperature respectively. REA model is able to capture the annual average precipitation also with R^2 of 0.6 and the correlation for monthly precipitation is 0.99. Figure 4.19 shows the comparison of annual average precipitation between REA and IMD.

Table 4.6 REA weights for the three climate variables at grid point (18, 80)

	Precipitation						
		RCP4.5			RCP8.5		
Model	***Historic***	***Future-1***	***Future-2***	***Future-3***	***Future-1***	***Future-2***	***Future-3***
ACCESS	0.6917	0.2871	0.3169	0.1976	0.2356	0.2062	0.2668
CCSM	0.3024	0.2065	0.2021	0.2377	0.2647	0.3496	0.3039
CNRM	0.0029	0.2901	0.2525	0.2911	0.2679	0.1924	0.1622
MPIESM	0.0029	0.2163	0.2285	0.2736	0.2319	0.2518	0.2672

	Maximum Temperature						
		RCP4.5			RCP8.5		
Model	***Historic***	***Future-1***	***Future-2***	***Future-3***	***Future-1***	***Future-2***	***Future-3***
ACCESS	0.3641	0.2562	0.2541	0.2474	0.2476	0.2500	0.2521
CCSM	0.0185	0.2278	0.2241	0.2293	0.2481	0.2506	0.2507
CNRM	0.3632	0.2608	0.2642	0.2617	0.2514	0.2437	0.2487
MPIESM	0.2542	0.2552	0.2576	0.2616	0.2529	0.2557	0.2485
	Minimum Temperature						
		RCP4.5			**RCP8.5**		
Model	***Historic***	***Future-1***	***Future-2***	***Future-3***	***Future-1***	***Future-2***	***Future-3***
ACCESS	0.3240	0.2499	0.2559	0.2520	0.2515	0.2537	0.2562
CCSM	0.1830	0.2399	0.2362	0.2317	0.2474	0.2511	0.2522
CNRM	0.2536	0.2547	0.2517	0.2598	0.2510	0.2524	0.2482
MPIESM	0.2394	0.2555	0.2562	0.2564	0.2500	0.2428	0.2434

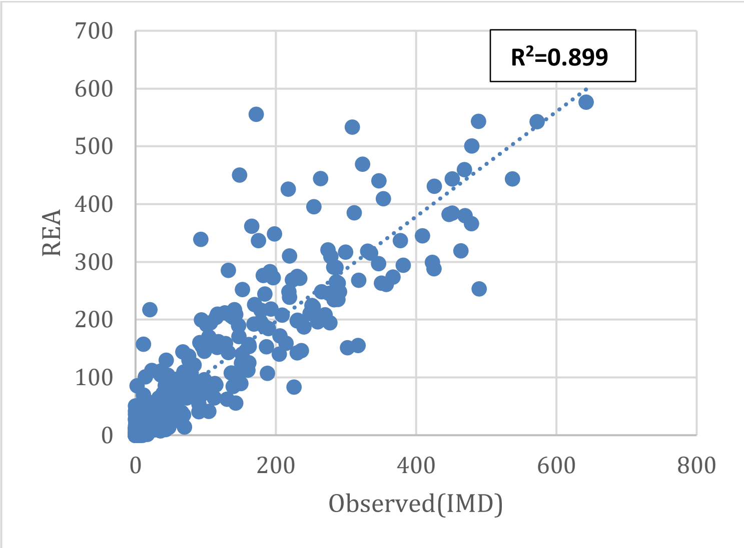


Figure 4.17 Scatter plot between REA and IMD daily precipitation for (1986-2018)

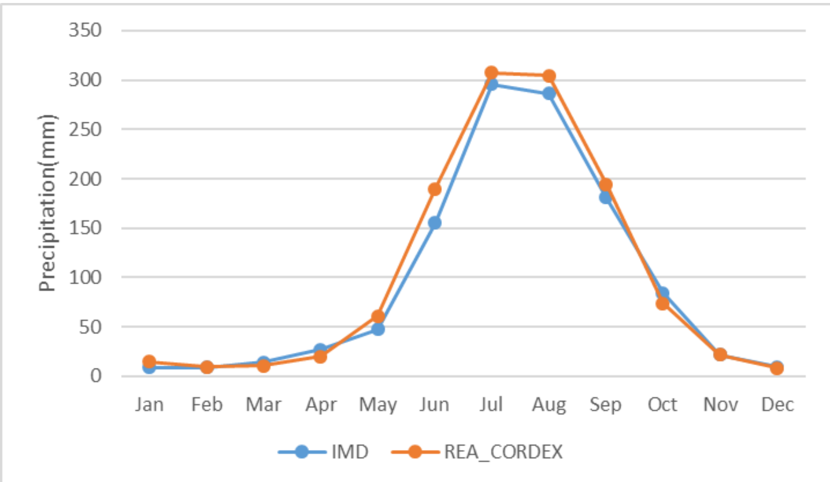


Figure 4.18. Average monthly precipitation for REA model and observed data during historic period (1986–2018).

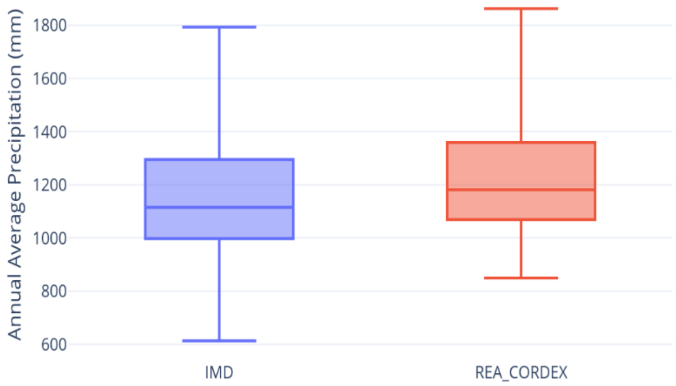


Figure 4.19 Comparison of annual average precipitation between REA and IMD.

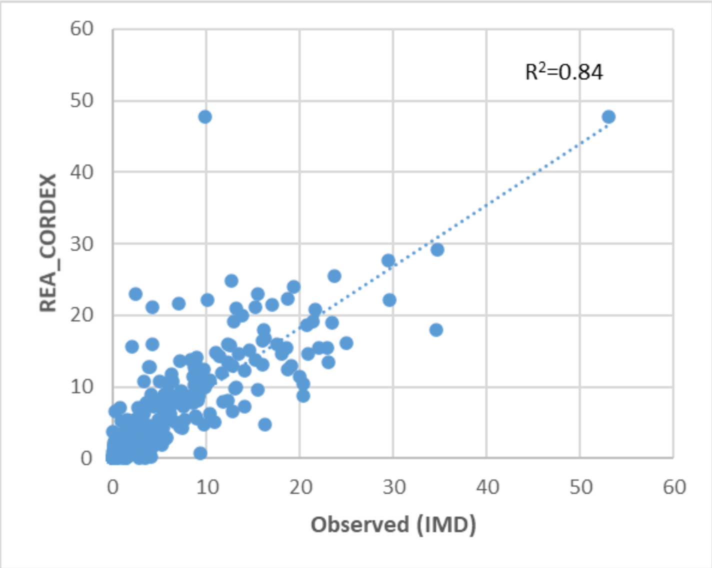


Figure 4.20 Scatter plot between REA and IMD streamflow (inflow) for (1986-2018)

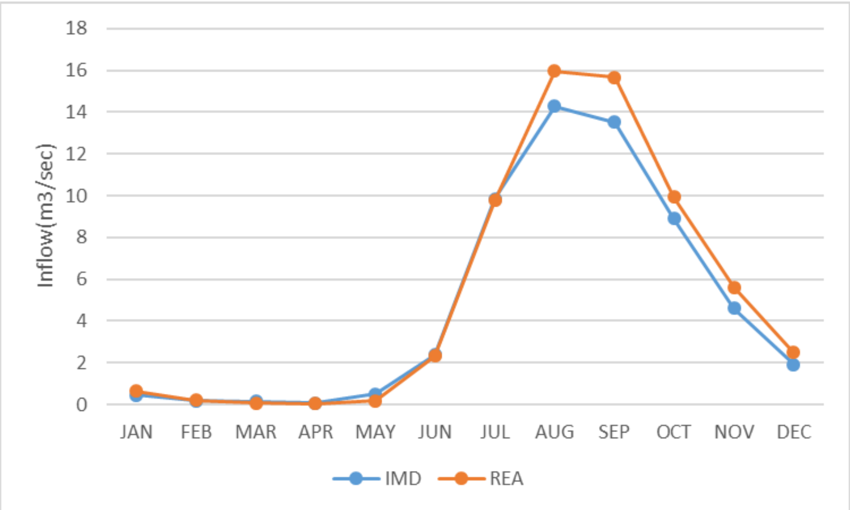


Figure 4.21. Average monthly simulated tank inflow with REA model and IMD observed data during baseline period (1986–2018).

The scatter plot for REA and IMD monthly streamflow (tank inflow) is shown in figure 4.20. It can be observed that the REA model has a good match with observed data with correlation coefficient (R^{2-}) value of 0.84. The average monthly precipitation from REA and IMD is shown in figure 4.21. The REA model monthly streamflow is similar to IMD data. The annual streamflow from REA model is also in good correlation with IMD with R^2 value of 0.62.

The changes in CORDEX simulated climate variables for future time periods with respect to observed climate data is shown in table 4.7. The percentage change in precipitation and temperature changes under RCP4.5 and RCP 8.5 are calculated for historic, future-1, future-2 and future-3. Under RCP4.5 scenario, ACCESS and CCSM models over predicted the precipitation during historic period by 12.2% and 29.7% respectively, while the other two models under predict by 11.4% and 12.6%. During future-1 all the models indicate a decrease in precipitation under both RCP 4.5 and 8.5 scenarios. CCSM model shows an increase in precipitation during future-2 under RCP4.5 scenario, while rest of the model show a decrease in precipitation. During future -3, all the models exhibit a decrease in precipitation except ACCESS model.

The changes in minimum and maximum temperatures are shown in table 4.7. During historic period, ACCESS and CNRM show similar maximum temperature values with IMD. CCSM model predicts minimum temperature similar to IMD. While, rest of the three models over predicted. It can be observed both maximum temperature and minimum temperature shown a significant increase during future time periods under RCP 4.5 and 8.5. During future-1, CCSM model indicates decrease in maximum temperature by 1.25^{o}C under RCP 4.5, while it indicates an increase by 1.51^{o}C. All the other models indicate an increase in maximum temperature. Similar pattern is followed in future-2 and during future-3 all the models show a raise in maximum temperature ranging from 0.13- 3.15^{o}C. The minimum temperature changes in future show significant raise relative to IMD, ranging from 0.04^{o}C – 6.95^{o}C. The relative changes from Table 4.7 imply that changes in temperature are more significant under RCP 8.5 than under RCP 4.5.

Table 4.7 Change in CORDEX-simulated climate variables relative to observed variable

	Precipitation							
	RCP 4.5				RCP8.5			
	ACCESS	CCSM	CNRM	MPI-ESM	ACCESS	CCSM	CNRM	MPI-ESM
Historic (1986-2018)	12.2%	29.7%	-11.4%	-12.6%				
Futue-1 (2020-2050)	-19.3%	-40.2%	-21.1%	-13.0%	-16.8%	-27.2%	-23.5%	-15.1%
Future-2 (2051-2080)	-8.5%	4.1%	-6.9%	-10.6%	-6.83%	-22.9%	-10.9%	-15.7%
Future-3 (2081-2099)	19.4%	-10.6%	-4.0%	0.1%	1.6%	-23.6%	-10.4%	-19.1%
	Maximum Temperature							
	RCP 4.5				RCP8.5			
	ACCESS	CCSM	CNRM	MPI-ESM	ACCESS	CCSM	CNRM	MPI-ESM
Historic (1986-2018)	-0.12	0.94	0.04	0.23				
Futue-1 (2020-2050)	1.19	-1.25	0.95	0.72	1.34	1.51	1.01	1.08
Future-2 (2051-2080)	1.21	-0.47	0.71	1.13	2.14	1.85	1.49	2.29
Future-3 (2081-2099)	0.93	0.13	0.81	0.99	3.03	2.52	2.54	3.15
	Minimum Temperature							
	RCP 4.5				RCP8.5			
	ACCESS	CCSM	CNRM	MPI-ESM	ACCESS	CCSM	CNRM	MPI-ESM
Historic (1986-2018)	1.45	-0.61	1.65	1.79				
Futue-1 (2020-2050)	4.14	0.61	4.38	4.50	4.33	4.67	4.50	4.71
Future-2 (2051-2080)	4.56	-0.03	4.69	4.96	5.52	5.43	5.27	5.90
Future-3 (2081-2099)	4.83	0.04	4.87	4.93	6.68	6.31	6.34	6.95

Table 4.8: Percentage Change in simulated streamflow with CORDEX data relative to IMD data simulated to streamflow

Change in Streamflow (%)								
	RCP4.5				RCP8.5			
	ACCESS	CCSM	CNRM	MPI-ESM	ACCESS	CCSM	CNRM	MPI-ESM
Historic (1986-2018)	22%	-11%	-22%	-29%				
Futue-1 (2020-2050)	-40%	-57%	-43%	-30%	-37%	-53%	-48%	-34%
Future-2 (2051-2070)	-23%	8%	-19%	-23%	-25%	-49%	-28%	-40%
Future-3 (2071-2099)	29%	-17%	-16%	-5%	-12%	-50%	-30%	-45%

The future flow simulation results under RCP 4.5 and RCP 8.5, for early, mid and end centuries are shown in figure 4.22 (a), (b), (c) respectively. The streamflow exhibited a decreasing trend in future period when compared to baseline. In future-1, MPI-ESM model predicted peak streamflow of 9.5m^3/s, while the other models predicted 8m^3/s in RCP 4.5 scenario. The peak flows by the four models during future-2 are around 11m^3/s, while in end century the peak flows are in the range of 9 –14 m^3/s. During the three future time periods the mean monthly streamflow under RCP 8.5 is less than RCP 4.5. Under RCP 8.5 scenario, the peak flows are ranging from 8-10 m^3/s during future time periods. The peak streamflow is observed in the month of August in RCP 4.5, while in RCP 8.5 the peaks flow is shifted to September.

The average annual streamflow results are shown in Figure 4.23. The box plots indicate the maximum, minimum and median flows of the annual average streamflow during the three future time periods for both RCP4.5 and RCP8.5. It can be observed that during early century, expect CCSM all the models predicted the flows similar under RCP4.5 and RCP8.5 scenarios. During mid and end centuries, the models under RCP8.5 predicted low flows when compared to RCP4.5. It is observed that during early century the average streamflow predicted by all the models is decreased by 42% under RCP 4.5 and 43% under RCP8.5 scenario (Figure 4.24). The average decrease in streamflow during mid-century is observed to be 14.3% under RCP4.5 and 35.6% under RCP 8.5 scenario. During end century the decrease in streamflow is 2.3% under RCP4.5 and 34.3% under RCP 8.5. Overall, it can be concluded from the aforementioned findings that fluctuations in precipitation values and changes in temperature are the main causes of changes in streamflow. The decrease in streamflow imply that the inflows in the tank are going to decrease in future. The highest decrease in streamflow is observed in future-1 compared to future-2 and future 3(table 4.8).

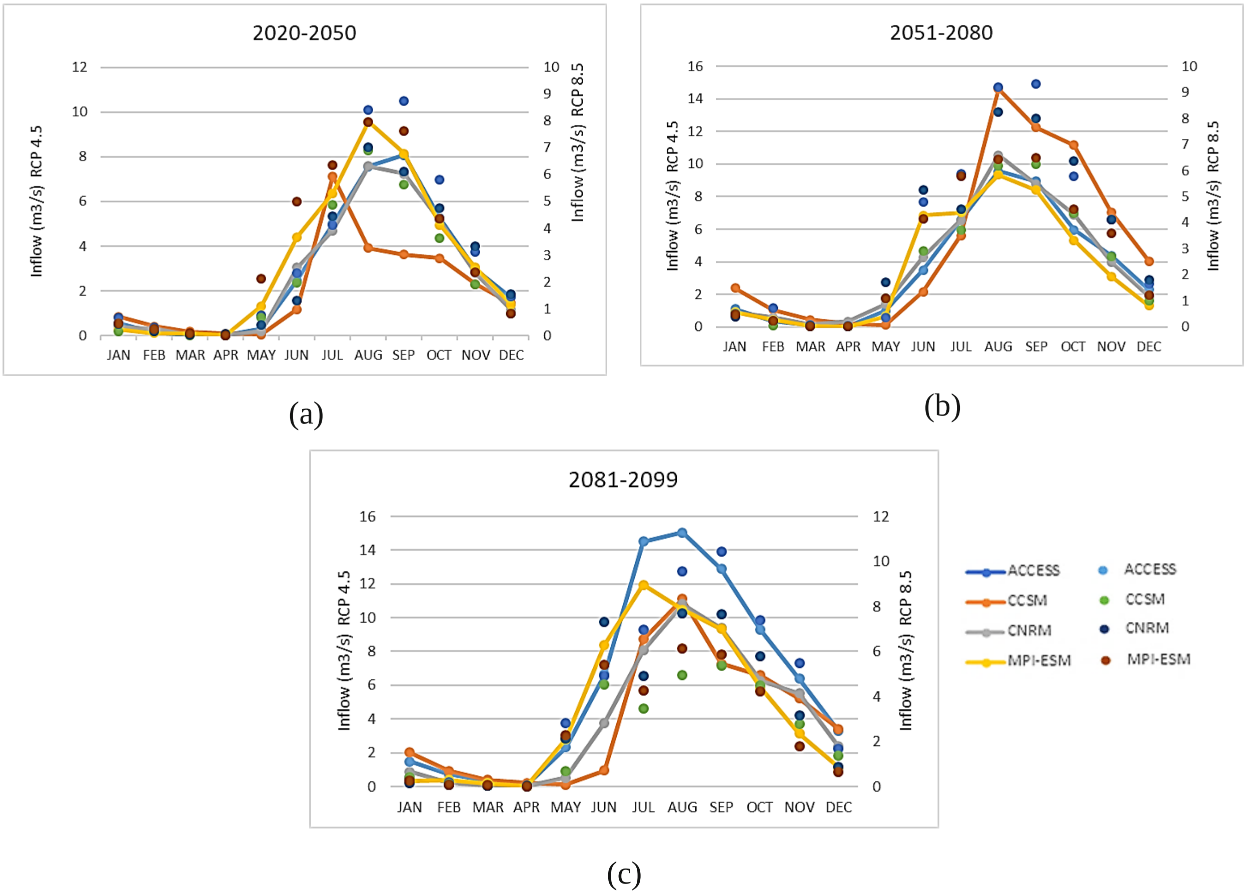


Figure 4.22 Future monthly streamflow under RCP4.5 and RCP8.5 using four CORDEX models.

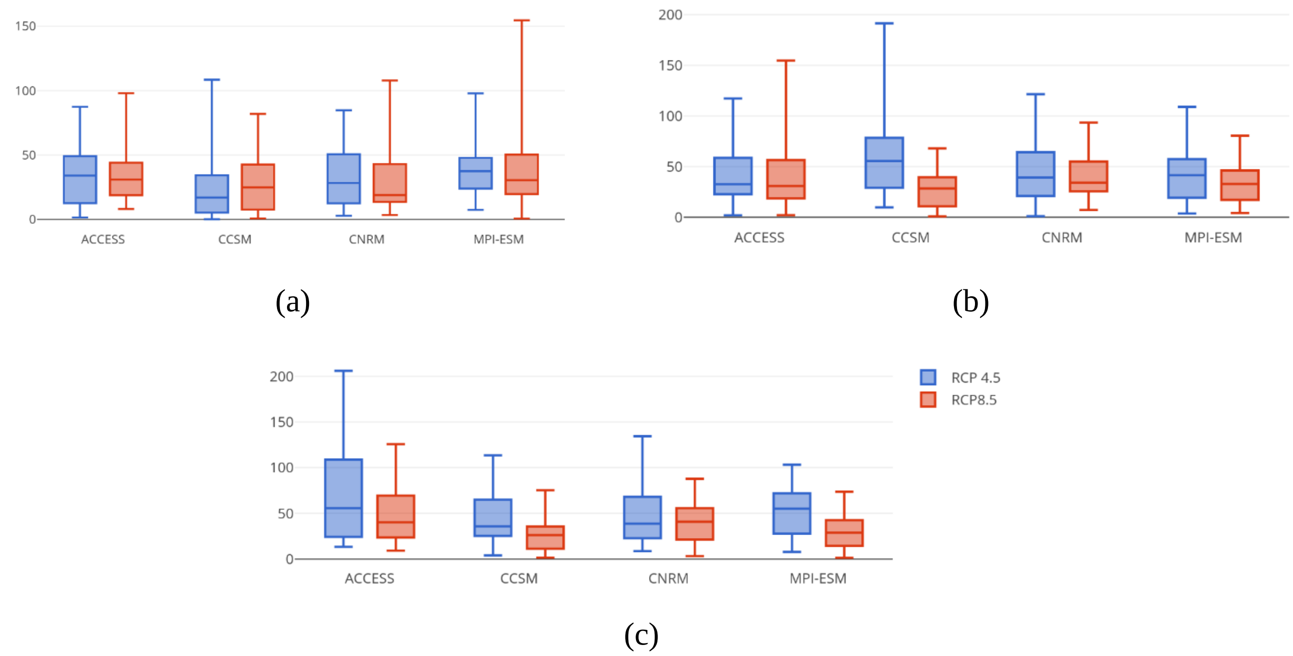
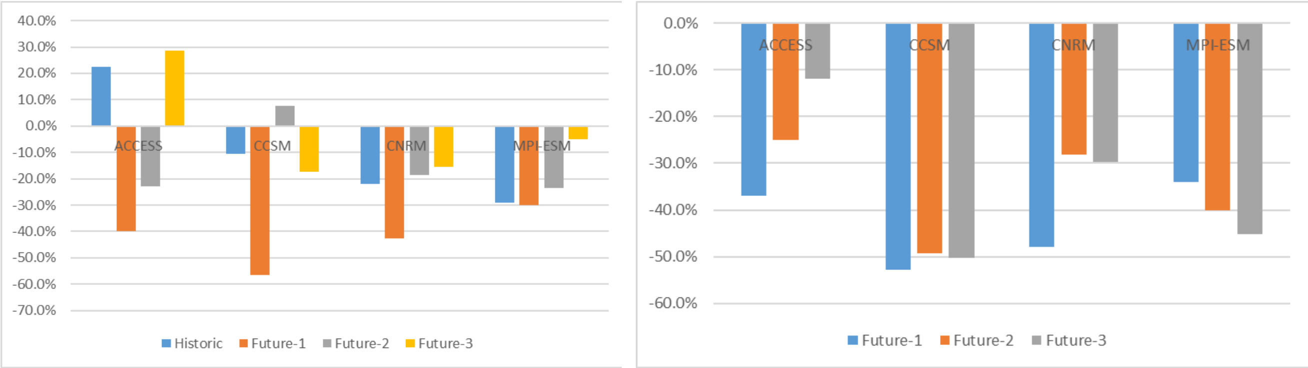


Figure 4.23. Future average annual streamflow under RCP4.5 and RCP8.5 using four CORDEX models.



(a) (b)

Figure 4.24. Percentage change in CORDEX annual streamflow relative to IMD simulated streamflow. (a) RCP4.5. (b) RCP8.5.

The changes in REA model future climate variables relative to observed are shown in table 4.9. It can be observed that highest change in precipitation is projected in future-1 compared to future-2 and future-3 under both RCP 4.5 and RCP 8.5. The precipitation under RCP 4.5 scenario is decreased by 26%, 18% and 1% during future-1, future-2 and future -3 respectively. Under RCP 8.5 it is observed that the decrease in precipitation is 21%, 15% and 14% during future-1, future-2, and future-3. Similar pattern observed in case of streamflow with 59% under RCP 4.5 and 52% under RCP 8.5. The historic and future monthly flow simulation results using REA climate data is shown in figure 4.25.

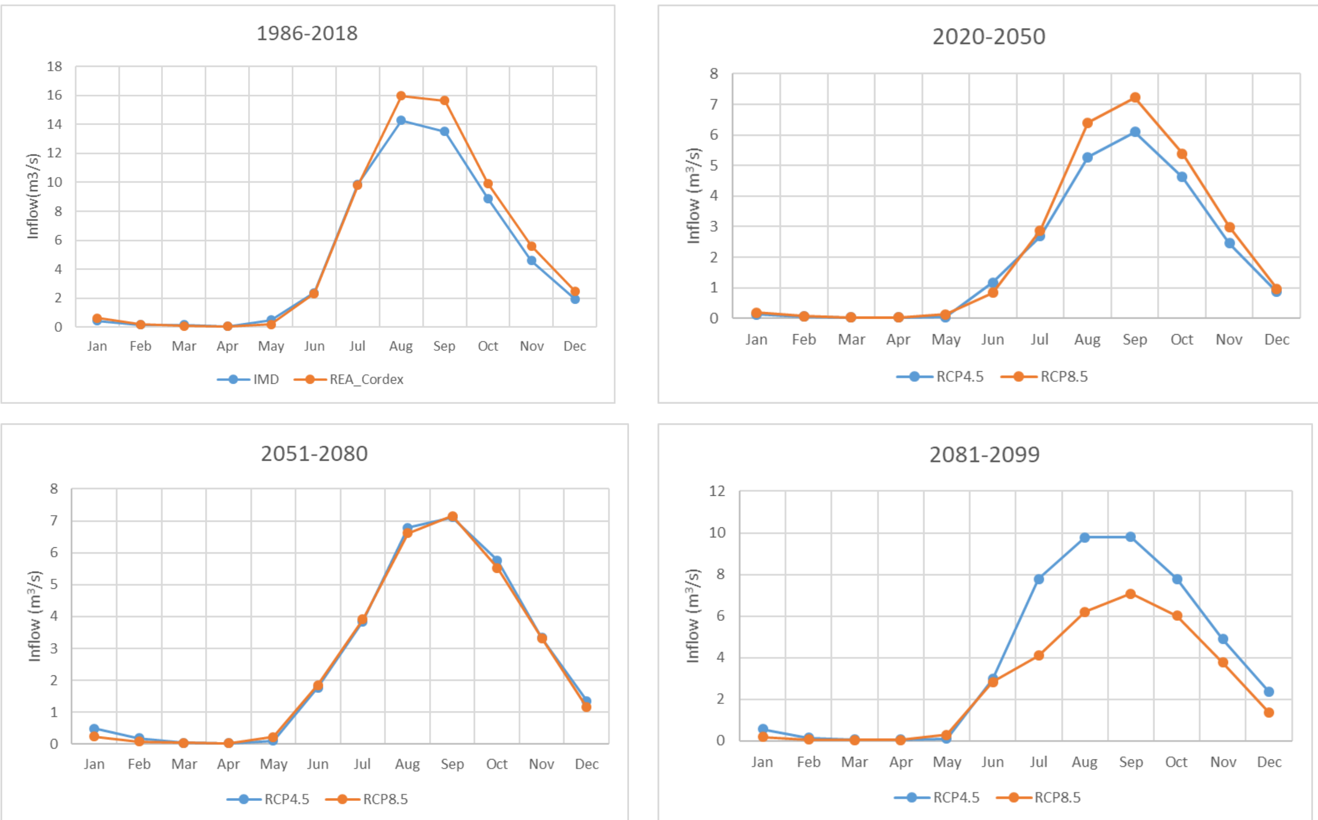


Figure 4.25. Monthly streamflow for historic and future under RCP4.5 and RCP8.5 using REA model.

Table 4. 9 Change in REA climate variables relative to IMD

	Precipitation		Streamflow		Maximum Temperature		Minimum Temperature	
	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
Historic(1986-2018)	7%		11%		0.51		0.05	
Future-1 (2020-2050)	-26%	-21%	-59%	-52%	3.45	4.55	0.45	1.23
Future-2(2051-2080)	-18%	-15%	-46%	-47%	3.61	5.52	0.68	1.95
Future-3(2081-2099)	-1%	-14%	-18%	-44%	3.75	6.57	0.73	2.81

4.8.4 Historic and Future NEX-GDDP Climate Data Analysis

The calibrated and validated SWAT model was applied to simulate the hydrologic components of Phakal Watershed for Baseline (1986–2018), Future-1 (2020–2050), using REA ensemble of 21 NEX-GDDP models. For the analysis of climate change, the simulated hydrologic conditions are compared with the observed data. The NEX-GDDP models are at a higher spatial resolution than CORDEX models with a resolution of 0.25°. The CORDEX model results exhibited a significant change in hydroclimatic variables in Future-1 when compared to other future time periods. Hence, future-1 is considered for simulation using NEX-GDDP data for comparison between the two data sets.

The precipitation and temperature from 21 NEX-GDDP models are compared with the IMD data to find the correlation. It was observed that the R^2 values for the climate variables are less than 0.5 indicating that none of the models show good correlation with observed data. In order to account for the mode uncertainty, the data is bias corrected using quantile mapping approach and reliability ensemble averaging (REA) is done for obtaining an ensemble model. REA ensemble initial (historic) and final weights (future) for the climate models corresponding to each climate variable are tabulated in table 4.10. The table shows the weights corresponding to one grid point. Similar procedure is applied for all the grids points in the study area. The obtained weights are applied to the climate data and REA mean is calculated for each climate variable and then used for SWAT model simulation.

The scatter plot for REA and IMD monthly precipitation is shown in figure 4.26. It can be observed that the REA model has a good match with observed data with correlation coefficient (R^2) value of 0.74. The average monthly precipitation from REA and IMD is showing in figure 4.27. The R^2 value for REA temperature and observed temperature is 0.94 and 0.96 for maximum and minimum temperature respectively. The scatter plot for REA and IMD monthly streamflow (tank inflow) is shown in figure 4.28. It can be observed that the REA model has a good match with observed data with correlation coefficient (R^2) value of 0.67. The average monthly precipitation from REA and IMD is showing in figure 4.29. The REA model monthly streamflow is similar to IMD data.

Table 4.10 REA results for the three climate variables.

	Precipitation			Maximum Temperature			Minimum Temperature		
Model	**Historic**	**RCP 4.5**	**RCP 8.5**	**Historic**	**RCP 4.5**	**RCP 8.5**	**Historic**	**RCP 4.5**	**RCP 8.5**
ACCESS1-0	0.0848	0.0379	0.0091	0.0531	0.0470	0.0454	0.0356	0.0480	0.0480
BCC-CSM1-1	0.0229	0.0527	0.0575	0.0437	0.0482	0.0475	0.0438	0.0469	0.0469
BNU-ESM	0.0272	0.0560	0.0612	0.0492	0.0481	0.0483	0.0398	0.0484	0.0484
CanESM2	0.0166	0.0640	0.0424	0.0392	0.0479	0.0472	0.0332	0.0472	0.0472
CCSM4	0.0309	0.0355	0.0480	0.0542	0.0472	0.0475	0.0576	0.0483	0.0483
CESM1-BGC	0.1612	0.0543	0.0255	0.0409	0.0466	0.0454	0.0427	0.0449	0.0449
CNRM-CM5	0.0403	0.0390	0.0427	0.0508	0.0480	0.0486	0.0439	0.0483	0.0482
CSIRO-Mk3-6-0	0.0322	0.0360	0.0353	0.0541	0.0484	0.0487	0.0799	0.0486	0.0485
GFDL-CM3	0.0311	0.0424	0.0420	0.0445	0.0473	0.0483	0.0592	0.0468	0.0468
GFDL-ESM2G	0.0362	0.0439	0.0555	0.0525	0.0494	0.0486	0.0420	0.0498	0.0498
GFDL-ESM2M	0.1678	0.0361	0.0450	0.0413	0.0477	0.0483	0.0408	0.0479	0.0479
INMCM4	0.0613	0.0467	0.0330	0.0518	0.0485	0.0479	0.0703	0.0490	0.0491
IPSL-CM5A-LR	0.0281	0.0535	0.0613	0.0426	0.0478	0.0476	0.0498	0.0493	0.0493
IPSL-CM5A-MR	0.0400	0.0392	0.0493	0.0462	0.0474	0.0484	0.0365	0.0482	0.0481
MIROC5	0.0285	0.0441	0.0657	0.0473	0.0478	0.0485	0.0719	0.0475	0.0475
MIROCESM	0.0222	0.0740	0.0786	0.0452	0.0473	0.0474	0.0363	0.0470	0.0471
MIROCHEM	0.0285	0.0572	0.0720	0.0459	0.0473	0.0473	0.0297	0.0467	0.0467
MPI-ESM-LR	0.0328	0.0454	0.0312	0.0502	0.0469	0.0473	0.0415	0.0464	0.0464
MPI-ESM-MR	0.0220	0.0499	0.0412	0.0535	0.0472	0.0464	0.0348	0.0462	0.0462
MRI-CGCM3	0.0637	0.0411	0.0456	0.0478	0.0471	0.0477	0.0612	0.0469	0.0469
NorESM1-M	0.0219	0.0511	0.0578	0.0460	0.0468	0.0477	0.0497	0.0478	0.0478

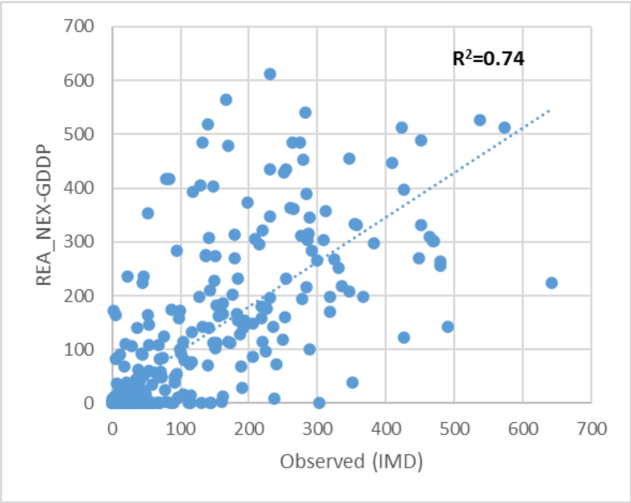


Figure 4.26 Scatter plot between REA and IMD monthly precipitation for (1986-2018)

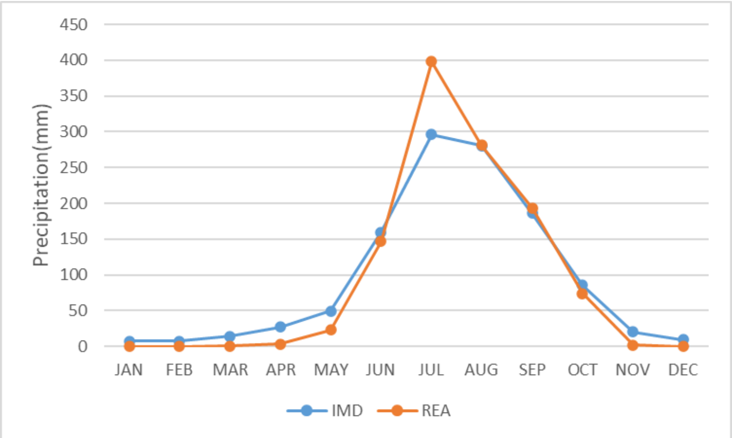


Figure 4.27. Average monthly precipitation for REA model and observed data during historic period (1986–2018).

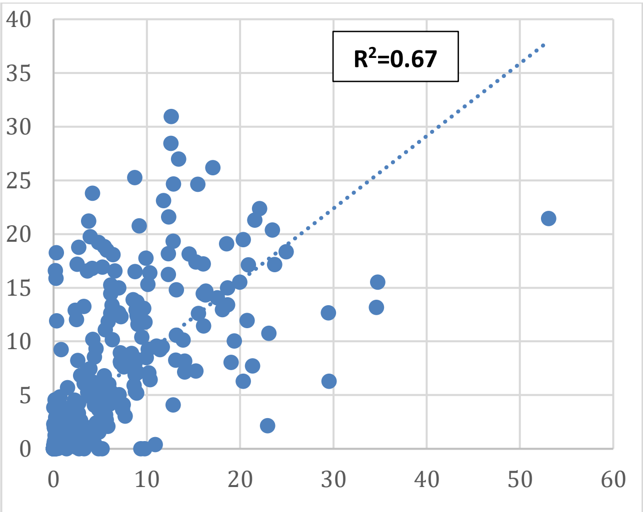


Figure 4.28 Scatter plot between REA and IMD monthly tank inflow for (1986-2018)

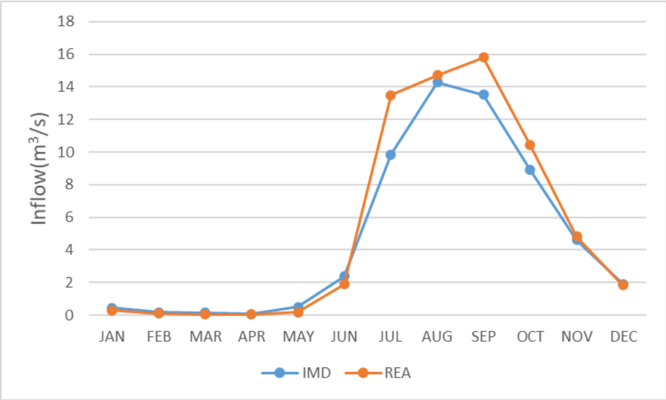


Figure 4.27. Average monthly streamflow for REA model and observed data during historic period (1986–2018).

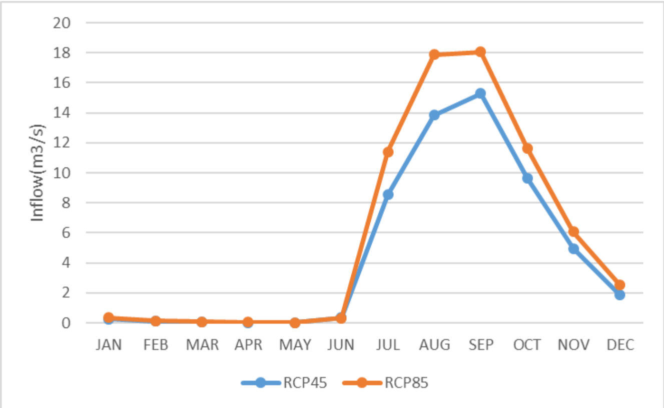


Figure 4.28 Average monthly streamflow under RCP4.5 and RCP8.5 using REA model for 2021-2050

The changes in NEX-GDDP hydroclimatic variables with respect to observed data under historic and future time periods are shown in table 4.11. It can be observed that the precipitation is under predicted in historic period by 2%. While the streamflow is over prediction by 12% during historic period. During future time period (2020-2050), both precipitation and streamflow are decreased when compared to observation data under RCP 4.5 and an increase is observed under RCP 8.5. The minimum and maximum temperature changes are shown in ^{o}C. During historic period they are similar to observed data. In future period, the maximum temperature is increased by 1.21^{o}C and minimum temperature is decreased by 1.19^{o}C under RCP 4.5. Under RCP 8.5, the changes are 1.42^{o}C and 0.26^{o}C for minimum and maximum temperature respectively. The results show that the RCP 4.5 is vulnerable to climate change due to a decrease in precipitation and streamflow. In comparison, the RCP 8.5 scenario results show an increase in precipitation and streamflow. Temperature and evapotranspiration changes are comparable in both RCP scenarios. Figure 4.28 show the average monthly variations in tank inflows, which suggest that the peak flows are shifted to the month of September during the future time period, while the observed peak flows are found during the month of August.

Table 4. 11 Change in NEX-GDDP simulated climate variables relative to observed

	Precipitation	Streamflow	Maximum Temperature	Minimum Temperature
Historic	-2%	12%	-0.07	0.03
Future RCP4.5	-10%	-3%	1.21	1.19
Future RCP8.5	3%	21%	1.42	0.26

From the results of both CORDEX and NEX-GDDP data, it can be observed that there is a significant decrease in precipitation during future period and increase in temperature. The future tank inflow simulation results also exhibit a significant decrease. Out of the three future periods, Future-1(2020-2050) is the most vulnerable as it experiences highest decrease in tank inflow. This will affect the water availability in the Phakal lake during this period, which suggests that the tank water resources should be maintained effectively.

4.9 Closure

Tank irrigation is predominant in southern part of India and contribute significantly in meeting the agricultural water demand in semi-arid regions. With tank irrigation the water is used to irrigate an area immediately downstream of the tank (tank command area) unlike in reservoirs where water is carried to long distances. Although the tank irrigation proved effective, due to climate change the tank performance may be at stake. Hence, adaptive management of tank irrigation will augment the water resources of the region even in extreme climatic conditions. Present research is focused to study the impact of climate change on the medium irrigation system.

The study revealed that SWAT model performs satisifactory for the simulation of flows to the tank systems of semi-arid regions of Telangana, India. Through regionalization, the model parameters are transferred to the Phakal lake catchment. The results of this study reveal, surface runoff amounts are going to be affected by the impact of climate change. The findings suggest that tank inflows could decline by as much as 59% between the historic and future time periods.

The rainfall and lake inflow indicate a significant decreasing trend in the Phakal Watershed. For better understanding of the water budget SWAT model simulation with the tank daily water level data using both RCP 4.5 and 8.5 scenarios, is advisable. In this research study, proximity method is used for regionalization of the parameters and the results are presented. The results from this research work are useful to plan the adaptation policies for different stakeholders of the tank system. The results are useful for making decisions related to tank rejuvenation in order to achieve tank sustainability under changing climate.

Chapter 5

Integration of SWAT and Support Vector Regression (SVR) Method for Predicting of Lake Water Levels

5.1 General

In the previous chapter, the SWAT model has been set up for Pakhal Lake in order to evaluate the climate change impact on the tank inflows. The projected results indicated a significant decrease in the streamflow future time period under both RCP 4.5 and RCP 8.5 scenarios. The rainfall and lake inflow indicate a significant decreasing trend in the Phakal Watershed. In addition to the future projection of rainfall and streamflow, it is also essential to determine the future water availability (i.e. water level fluctuations) from water resources planning perspective. Analysis of water level fluctuations in Pakhal Lake using the integrated results from a physical-based hydrological model and machine learning approach in view of changing climate scenarios is provided in this Chapter.

Apart from studying the impact of climate change on the lake water balance components, estimating lake level fluctuations under future climate scenarios is important for developing sustainable water management policies (Bucak et al., 2017). The natural water exchange between the lake and its catchment affects the level of lake water, hence the water level fluctuations reflect regional climatic variations (Kisi et al., 2015). Recently, machine learning-based Support Vector Machine (SVM) algorithms has been used effectively for predicting changes in water levels (Buyukyildiz, Tezel, & Yilmaz, 2014; Mohammadi et al., 2020). Khan and Coulibaly (2006) investigated the utility of SVM in predicting lake water levels in Lake Erie over the long term. They observed that SVM outperformed multi-layer perceptron (MLP).

Cimen and Kisi (2009) found that Support Vector Regression (SVR) outperformed Artificial Neural Networks (ANN) techniques in modeling the monthly lake levels. Hipni et al. (2013) found that the ν-SVR model outperformed the other SVM techniques in forecasting daily water levels in Klang reservoir, Malaysia, and concluded that the SVR model was the best regression type for lake water predictions (Hipni et al., 2013). Kisi et.al (2015) used the SVM technique coupled with the firefly algorithm for forecasting daily lake water levels in Lake Urima. Bucak et.al (2017) integrated SWAT model outputs with the SVR model to project the future water availability in Beyşehir Lake and concluded that climate change leads to the drying up of the lake by the end of the century.

The previous studies mainly focused on the assessment of climate change on the water balance components like runoff, streamflow, and evapotranspiration in the lake catchments. Most of the studies on the applicability of SVM techniques for lake level predictions were carried out based on the past lake levels, without considering the water balance components that influence the water availability. Very few studies addressed the integration of catchment hydrology and lake water level changes. Pakhal lake is a major source of water for agriculture, poor and marginal farmers of this region largely depend on the lake for their agricultural water needs. It is essential to study the impact of climate change on this lake system for future planning and management of water resources to provide sustainable livelihood to the farmers. Hence, water availability and lake water fluctuations for present and future climate change scenarios for Phakal lake are studied in the present research work.

5.2 Support Vector Regression (ν-SVR)

Support Vector Machine (SVM) is a popular machine learning technique for solving classification and regression problems (Yang et al., 2017). Support Vector Regression (SVR) is characterized by the use of kernels, sparse solutions, and control of the margin and the number of support vectors. SVR is considered as a nonparametric technique because it relies on kernel functions. SVR has established itself as a reliable technique for estimating real-value functions. The main benefit of SVR is that it incorporates the principle of minimization of the structural risk (Hipni et al., 2013; Khan & Coulibaly, 2006). It also has excellent generalization capabilities and high prediction accuracy (Mohammadi et al., 2020). Recently, SVR has been used in a variety of water resources research areas, which include the prediction of water level changes. There are two types of SVM regression with a generalized formula which is given in Eq. (4.1)

$$y = f(x) + Z \tag{4.1}$$

where, y is dependent variable, f(x) is a function independent variable(s) and Z is the additive noise. The first type of SVM regression is known as Epsilon (ξ). In this type, the error function is given by the following formula:

$$\frac{1}{2}w^T w + C\sum_{i=1}^{N} \xi_i + C\sum_{i=1}^{N} \xi_i^* \tag{4.2}$$

where, w is the vector of coefficients, C denotes the capacity constant, the distances of the training data sets' points from the region where errors smaller ε than are ignored are designated as ξi and ξi *, respectively. The index *i* labels the *N* training cases. The subject is then minimized to obtain the following:

$$w^T \emptyset(x_i) + b - y_i \leq \varepsilon + \xi_i^* \tag{4.3}$$

$$y_i - w^T \emptyset(x_i) - b \leq \varepsilon + \xi_i \tag{4.4}$$

$$\xi_i \xi_i^* \geq 0, i = 1, \ldots., N$$

Where b is a constant, y ∈ ± 1 is the class labels and x_i is the independent variable(s). The kernel function Ø assists in transforming the input (independent) data to the feature space. As the C value increase, higher errors are penalized. Thus, to avoid over fitting, C should be chosen with caution. The second type of regression is Nu (ν) regression. The error function for Nu(ν) regression is given by Eq.(7).

$$\frac{1}{2}w^T w - C\left(\nu\varepsilon + \frac{1}{N}\sum_{i=1}^{N}(\xi_i + \xi_i^*)\right) \tag{4.5}$$

Similarly, the subject is minimized to obtain the following:

$$(w^T \emptyset(x_i) + b) - y_i \leq \varepsilon + \xi_i^* \quad (4.6)$$

$$y_i - (w^T \emptyset(x_i) - b) \leq \varepsilon + \xi_i \quad (4.7)$$

$$\xi_i \xi_i^* \geq 0, i = 1, \dots, N$$

In this study, Nu (ν) SVR with the radial basis function (RBF) kernel was used:

$$K(X, X') = \exp(-\gamma ||X - X'||^2) \quad (4.8)$$

where, γ denotes the spread of the RBF kernel function (Bucak et al., 2017; Buyukyildiz et al., 2014; Mohammadi et al., 2020).

5.3. Linking SWAT with ν-SVR

In, the present study area, the prediction future water levels by calculating of the water balancing components of the lake is difficult because observational data (precipitation and inflows) from Pakhal Lake is scarce and water abstraction is non-systematic. In order to address the challenge of predicting future lake water levels, the SWAT model outputs are linked with SVR (Bucak et al., 2017). Precipitation, monthly outflow volume, and potential evapotranspiration (PET) and inflows from SWAT outputs, are the considered inputs for the *ν*-SVR model. The *ν*-SVR model was trained from 2003 to 2015, and data from 2016 to 2018 were used for testing the model's water level (validation). While applying the *ν*-SVR model, e1701 package from R (Version 3.6.2) programming software is used for obtaining the optimized values of error term (ε), configuration factor (C), and gamma parameter (γ). The performance of *ν*-SVR model is evaluated by using the root mean square error (RMSE), the mean absolute error (MAE) and the coefficient of determination (R^2). In order to determine the lake's water level in response to the future climate change scenarios RCP 4.5 and 8.5, the calibrated and validated v-SVR model was run for the time period 2021–2050.

5.4 Performance of the ν-SVR model

The best fit between the projected and actual water level change was given by the parameter set of C = 34, v = 0.5, and γ = 0.91 with the RBF kernel (Figure 5.1). The value of R^2 was 0.79, MAE was 0.018 m, and RMSE was 0.13 m during the training period. The scatter plot between the observed and SVR model generated tank water levels during the training period is shown in Figure 5.2. In the validation period, the R^2, MAE and RMSE values obtained are 0.72, 0.6 m and 0.25 m, respectively. The scores of the three metrics (R^2, MAE and RMSE) during the training and validation periods suggest that the model performance is satisfactory in capturing the observed lake water level trends. The time series plot of observed and SVR model monthly lake water level changes suggests that the model performance is good (Figure 5.3).

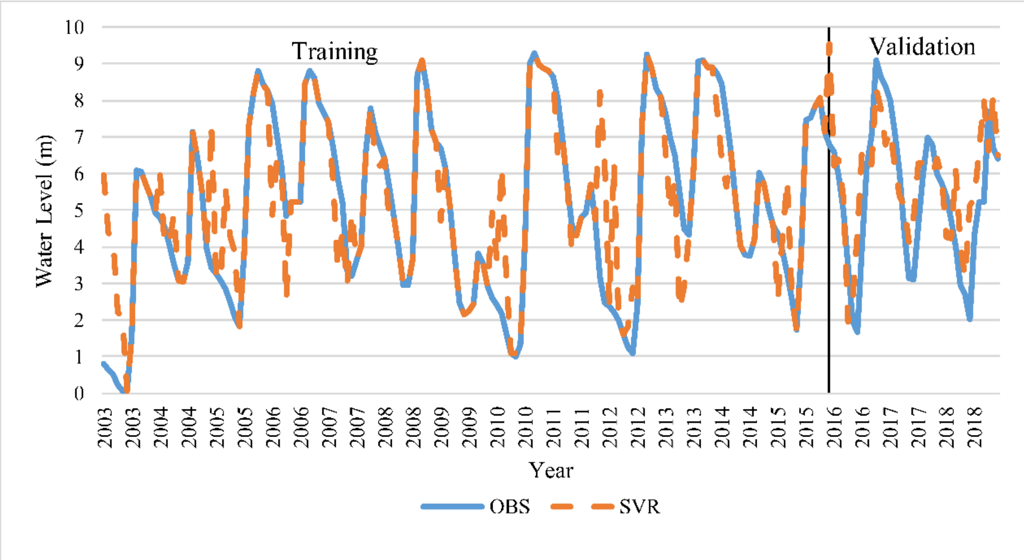


Figure 5.1. Observed and modelled water level changes in the ν –SVR model during the training and validation periods.

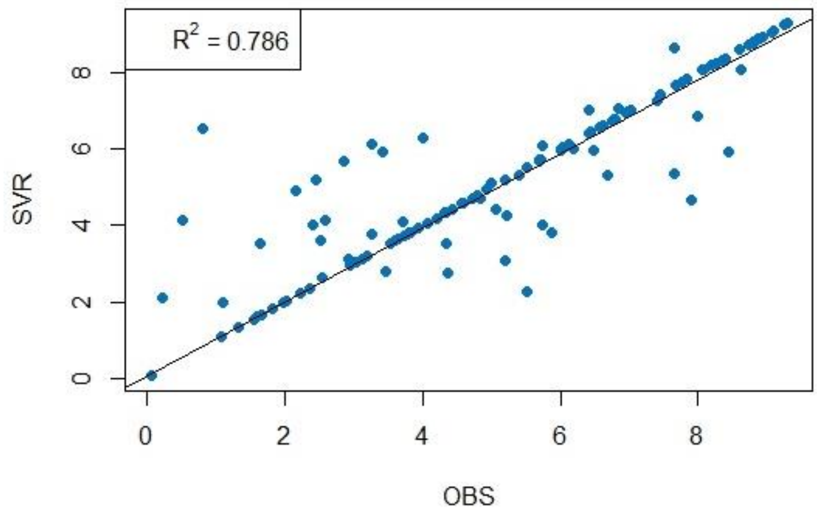


Figure 5.2. Scatter Plot between observed and SVR simulated tank water levels during the training period.

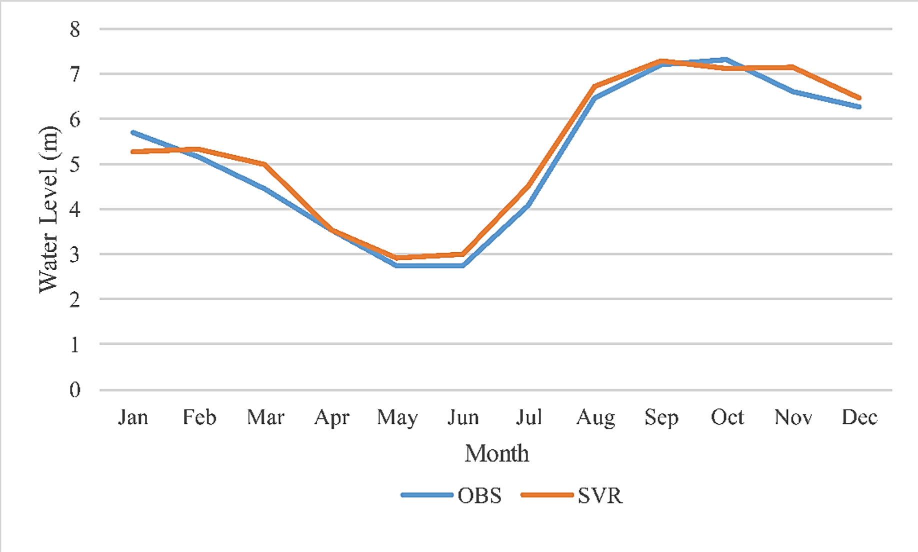


Figure 5.3. Observed and SVR model average monthly lake water level changes for the period 2003-2018.

5.5. Effect of climate change on water availability

The calibrated and validated SVR model is used to make monthly tank water level predictions under RCP 4.5 and RCP 8.5 scenarios for the period 2021-2050. The changes in predicted monthly lake water level is shown in Figure. 5.4 and 5.5. The lake water level ranges during the observation period (2003-2018) are 0.05–9.3m. The future lake water level ranges under RCP 4.5 and RCP 8.5 are 0.0–9.2m, 0.35–9.8m, respectively. The average water level observed during the SVR modeling period (2003-2018) is 5.2m. Whereas, the average water level range during future scenarios was between 5.6m and 5.8m under both RCPs. The average lake water levels for the future scenarios are similar to the historic trends.

Seasonal analysis is performed for assessing the water level changes during rabi and kharif seasons. Three crop growth seasons are considered for the analysis are rabi (July-October), kharif(October- April) and summer(May -June). The average changes in water levels during each season are shown in figure 5.6. The results under RCP 4.5 signify an increase water levels in rabi and kharif season, while a decrease in water levels in summer season. Under RCP 8.5, the water levels showed an increase in water levels in kharif while a significant decrease in levels can be seen in the rabi season. High increase in water levels can be observed in summer under RCP 8.5. These changes can be attributed to changes in the climate variables.

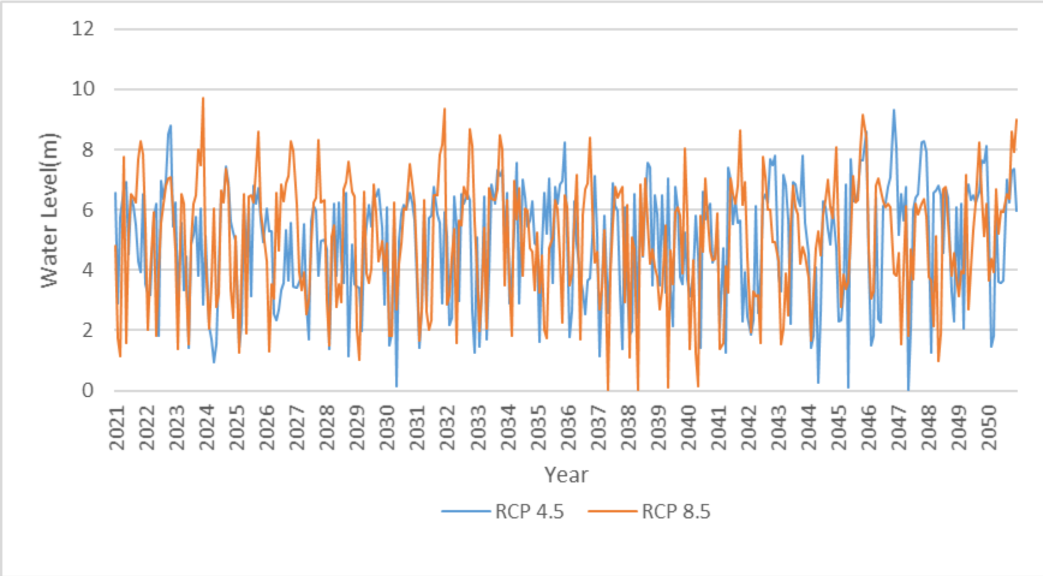


Figure 5.4. Changes in predicted monthly lake water level during 2021-2050 under CORDEX climate change scenarios

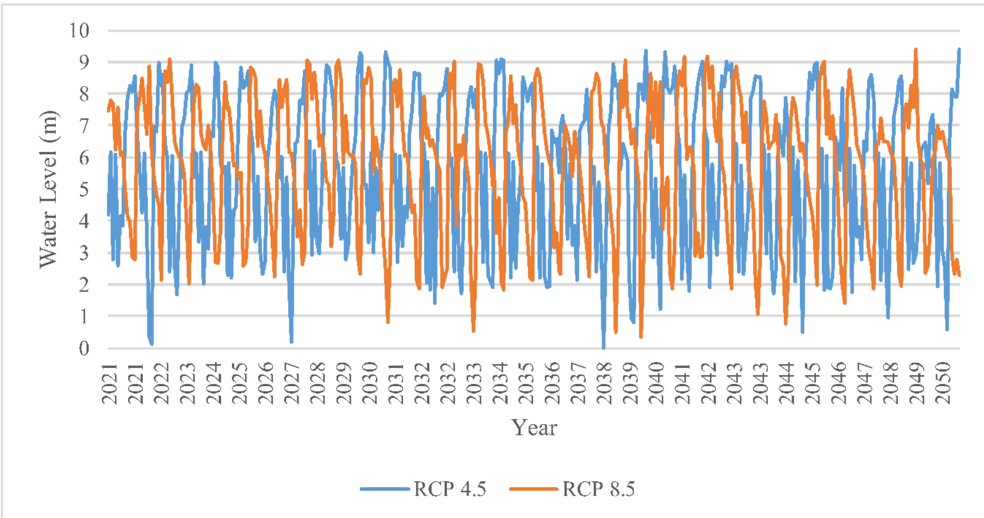


Figure 5.5. Changes in predicted monthly lake water level during 2021-2050 under NEXGDDP climate changes scenarios.

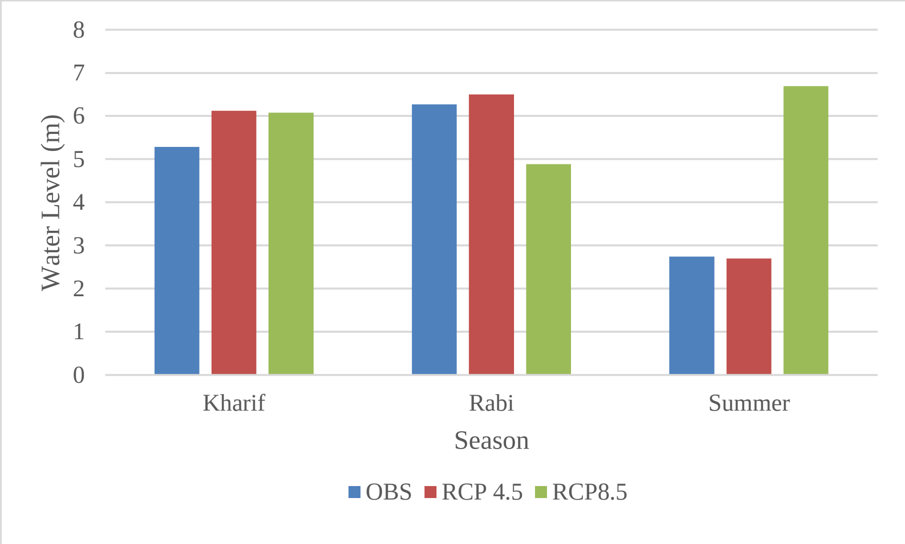


Figure 4.6. Changes in water levels during each season compared to observed levels under RCP climate change scenarios.

The linking of SWAT outputs with the SVR model proved effective in predicting the lake water levels as the performance metrics are satisfactory. The predicted lake water levels indicate a similar pattern under both the climate scenarios when compared to observed levels. From, the results it can be concluded that the lake level fluctuations are highly dependent on the evapotranspiration in the lake catchment. Further, investigation is needed in order to correlate the catchment water balance components and lake levels at the monthly and seasonal scale. The results of the monthly water levels in the both RCP 4.5 and 8.5, show almost zero values at some instances (Fig 4.5). Hence, the study on the extreme event analysis is needed in order to identify the events where the lake dries up completely.

5.6. Closure

In the present study, an integrated approach of linking SWAT model outputs with support vector regression (v-SVR) has been developed for the prediction of future lake water levels of a tank located in a semi-arid region. The climate datasets from REA ensemble of CORDEX and NEXGDDP are used as input in future water level prediction of Pakhal Lake. A decrease in streamflow is observed in both CORDEX RCP scenarios and NEXGDDP RCP 4.5 which can be attributed to decreased precipitation and enhanced potential evapotranspiration (PET). An increased streamflow is predicted in NEXGDDP RCP 8.5. Precipitation, outflow volume, PET and inflows from SWAT can be used as input variables in SVR to estimate lake water level when direct estimation of surface evaporation from the lake is not possible. This method can be an effective way for estimating water levels, since the changes in future lake area information is unavailable. The predicted lake water levels indicate a similar pattern under both the climate scenarios when compared to observed levels. Seasonal analysis suggests a decrease in water availability in the rabi season under RCP 8.5 scenario. Significant extreme events are observed in the RCP 4.5 scenario. As majority of the lake waters are used for agricultural purpose, adaptation strategies are required for sustainable management of water resources. In view of the changing climate, this study assists in developing the essential water management strategies for Pakhal Lake. The seasonal analysis aids in developing policies for water augmentation from the lake linking project in order to sustain agriculture during periods of water scarcity. The methods proposed in this research study can be extended to other semi-arid lake systems with limited observable data.

Chapter 6

Adaptation Strategies for Water Management in the Tank System

6.1 General

Climate change can have a negative effect on agriculture productivity across agroecological regions both due to temperature rise and changes in water availability, hence reservoir operation for agricultural irrigation has to be modified (Zhang *et al.* 2017). Since most rural communities still rely heavily on agricultural production for their income, it will be crucial to adapt the agricultural sector to the negative consequences of climate change in order to guarantee food security (Vibhute *et al.* 2016). By improving rural populations' capacity to adapt to climate change and unpredictability, reducing possible damages, and assisting them in coping with negative effects(Yang *et al.* 2017). In addition to assisting farmers in managing agricultural water without having a detrimental impact on crop yields and profitability, adaptation can greatly lower risk of climatic change (Holzkämper 2017, He *et al.* 2020).

In order to increase irrigation productivity and achieve effective water resource planning and management, precise information on crop water requirements, the type of soil, and climatic conditions are needed (Sunil *et al.* 2021). Traditionally irrigation releases from tanks are done based on constant or fixed demand. This is done without considering the crop water requirement. Climate change is going to affect crop water demand because the major part of the available water is used for irrigation (Masia *et al.* 2018, Le Page *et al.* 2021, Poonia *et al.* 2021). For efficient use of tank water resources, it is essential to estimate the irrigation water demand based on climate change. In order to meet the changing water demand, decisions have to be made on the tank operational policy and water management strategies. In the previous chapter, the climate change impact on the tank water availability of Pakhal lake is assessed and it was found that there is a significant decrease in the water availability, especially under the RCP 4.5 CORDEX climate change scenario. In, this chapter, the Irrigation Water Requirement (IWR) is estimated using the CROPWAT model for the command are of the Pakhal lake. The changes in the irrigation water demand with respect to future climate change scenarios are evaluated for the tank system. The ensemble climate model data of the RCP 4.5 scenario (CORDEX) is used to simulate the streamflow in the lake and for developing adaptation strategies. Climate change impact on irrigation systems and its performance criteria (reliability with respect to volume, resilience, and vulnerability) are evaluated using the r package "reservoir". The performance criteria obtained are studied initially with the Standard Operating Policy (SOP). The performance indices projected with the SOP for future scenarios show a decrease in reliability and resilience, while the vulnerability is likely to increase because of climate change. Hence, Stochastic Dynamic Programming (SDP) is used to develop adaptive policies for the optimal monthly operation of the Pakhal Lake. Three demand-side adaptation strategies are applied and the tank performance indices are measured in order to obtain the best fit strategy.

6.2 Estimation of IWR using CROPWAT

Crop Water Requirement (CWR) vary greatly and it is influenced by crop type, soil properties, weather conditions, and so on. Crop evapotranspiration (ETc) is the measure of water lost by the crop, while crop water requirement (CWR) is the additional amounts of water required for crop growth. The total amount of water applied to the land surface in addition to the water supplied by rainfall and soil profile to meet the water needs of crops for optimum growth is referred to as Irrigation Water Requirement (IWR). In essence, it is the discrepancy between CWR and effective precipitation. The estimation of IWR in the Pakhal command area for present and future climate scenarios is carried out using the CROPWAT model.

6.2.1 CROPWAT model

CROPWAT is an Food and Agricultural Organization (FAO) model for crop simulation developed by Smith (1992) which incorporated climate, crop, and soil related data to estimate reference evapotranspiration (ETo), crop evapotranspiration (ETc), and IWR. The main advantage of the model is that it requires a smaller number of inputs compared to other crop simulation models. The Penman-Monteith equation recommended by the FAO was used to calculate the potential evapotranspiration. Numerous input data modules are needed by the model, including meteorological, crop, soil, and crop pattern data. Precipitation, minimum and maximum temperatures, wind speed, relative humidity, sunshine hours are the climate related data, that are used as initial input for calculation of ET_o. Using the location's latitude, longitude, altitude, maximum and minimum temperatures, CROPWAT can calculate ET_o in the absence of relative humidity and daylight. In addition to climate data, the crop module also needs crop data, such as maximum rooting depth, crop description, crop factor, rooting depth, growing days, etc. Additionally, the soil module receives inputs for properties including initial soil moisture depletion, maximum penetration rate, maximum rooting depth, and soil moisture availability. The CWR is computed using Eq. 6.1.

$$ET_c = K_c \times ET_o \tag{6.1}$$

The crop coefficient, or K_c, is influenced by a number of parameters, including the soil, crop height, albedo, wind speed, and wind direction. Depending on the crop variety and growth stage, K_c has a different value. Effective rainfall (Peff), which is determined using the fixed percentage approach, is used to determine the Crop Irrigation Requirement (CIR). It is advisable to consider 50-80% of the total rainfall in India's conditions as effective for rice crops, and 70% for non-rice crops (Dastane 1974). Based on the geography of the study area, 70% of the total rainfall is considered effective precipitation in the current study. By deducting the expected effective rainfall from the estimated agricultural water requirement, the quantity of crop irrigation needed is determined (Eq. 6.2). The total IWRis calculated from Eq. 6.3, where the CIR is calculated for each crop 'i' and multiplied by corresponding irrigated area denoted by A_i.

$$CIR = CWR - P_{eff} \tag{6.2}$$

$$IWR = \sum_{i}^{n} CIR_i \times A_i \tag{6.3}$$

6.2.2 Simulation of Irrigation Water Demand

In the present study, monthly mean values of precipitation, and maximum and minimum temperature from IMD gridded data are used to estimate the reference crop evapotranspiration for the historic period (2003-2018). The soil information for the Pakhal command area is obtained from the maps provided by Telangana State Remote Sensing Center (TRAC), India. Red soil is predominant in the study area. The cropping pattern information is obtained from the I&CAD Department, Warangal Rural District. Rice is the major crop grown in both the kharif and rabi seasons. Minor crops include maize and cotton. Additional soil and crop characteristic data are adopted from the literature (Thirupathi and Shashikala 2017). For future simulations, climate data with CORDEX and NEXGDDP scenarios are considered for the years

2025 to2050. Two different future cropping patterns are chosen for the study. The workflow for the estimation of IWR in the Pakhal command area is shown in Figure 6.1. The following scenarios are used for the study:

- Climate change RCP 4.5 and same cropping pattern (Mixed crop: Rice -75%, Maize-13%, Cotton-12%)
- Climate change RCP 8.5 and same cropping pattern (Mixed crop: Rice -75%, Maize-13%, Cotton-12%)
- Climate change RCP 4.5 and100% Rice in both seasons
- Climate change RCP 8.5 and 100% Rice in both seasons

For ease of analysis, the eight scenarios considered in the study are given codes, the details of which are given in table 6.1.

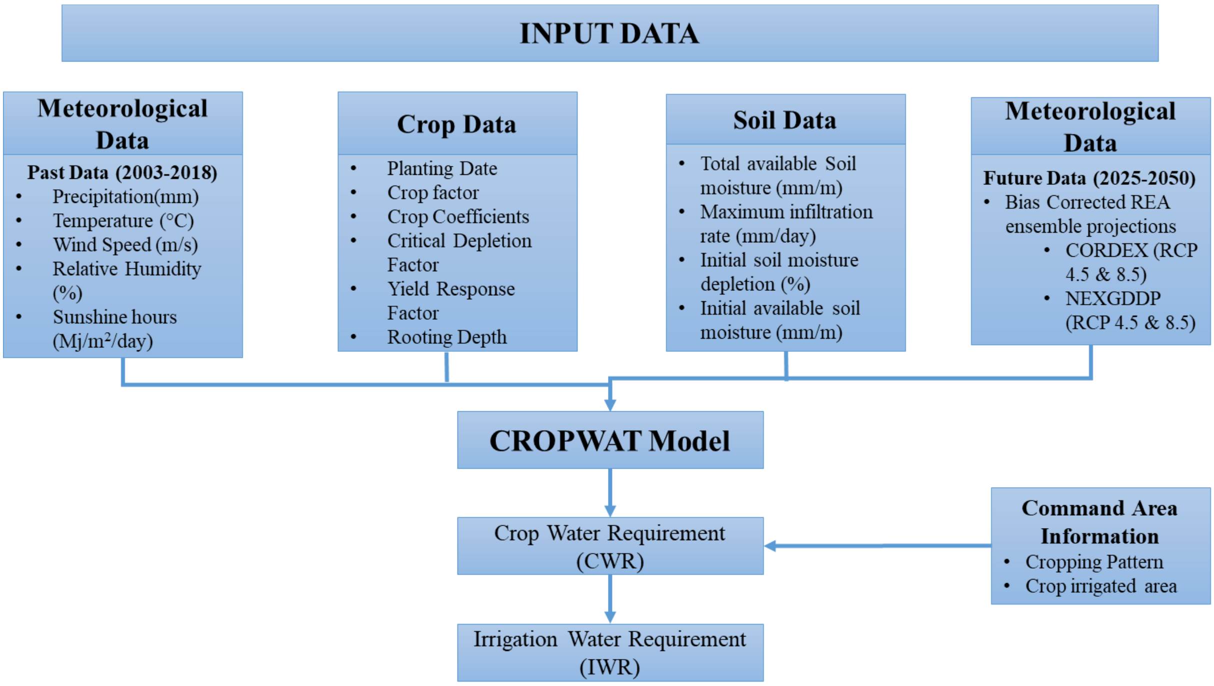


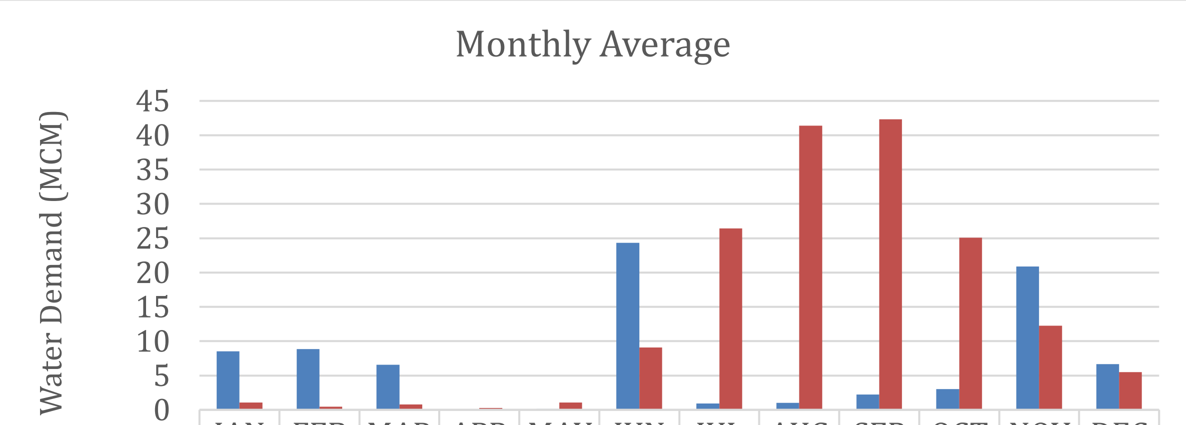
Figure 6.1 Workflow flowchart for the estimation of Irrigation Water Requirement (IWR)

Table 6.1 Details of the Scenarios used and their respective codes.

CODE	***Scenario***
S1	CORDEX 4.5 (MIXED CROP)
S2	CORDEX 8.5 (MIXED CROP)
S3	CORDEX 4.5 (100% 100% RICE)
S4	CORDEX 8.5 (100% 100% RICE)
S5	NEXGDDP 4.5 (MIXED CROP)
S6	NEXGDDP 8.5 (MIXED CROP)
S7	NEXGDDP 4.5 (100% 100% RICE)
S8	NEXGDDP 8.5 (100% 100% RICE)

The average monthly irrigation water demand and inflow in Pakhal irrigation tank during 2003-2018 is shown in figure 6.2. It can be observed that the available tank water at the start of Kharif season is inadequate to meet the command area's irrigation demand. The annual IWR in the Pakhal command area shows an increase in all the future scenarios considered for the study. The percentage changes in average annual IWR in future scenarios with respect to observed time period is shown in figure 6.3. The scenarios S1, S7and S8 are shown highest increase in IWR with 8.9%, 16.7%, and 16.8% respectively. The irrigation requirement has increased as a result of the decreasing trend in the predicted rainfall in the Kharif season for the future scenarios. The results imply that the effective rainfall in the command area significantly impacts the IWR of the Kharif season. The Rabi season's irrigation needs were determined by projected increases in temperature, evapotranspiration losses, and rainfall patterns, which led to slightly increased irrigation requirements for the NEXGDDP RCP 8.5 scenario compared to the NEXGDDP RCP 4.5 scenario. Further, the increase in IWR can be attributed the shift in peak monsoon precipitation from the month of August to September. The results demonstrate that even if future precipitation is expected to increase, agricultural water needs will not be met by the precipitation that falls just before monsoon season due to an increase in evaporation and transpiration losses.

Figure 6.4 displays the monthly fluctuation in the overall irrigation water demands (MCM) as well as the tank water that is available to satisfy the water requirements under various scenarios.



	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Demand	8.5	8.86	6.55	0	0.12	24.3	0.93	1	2.21	3.04	20.9	6.64
Inflow	1.05	0.46	0.76	0.28	1.05	9.06	26.4	41.4	42.3	25.1	12.2	5.51

Figure. 6.2 Average monthly water demand and Inflow in Pakhal study area during 2003-2018

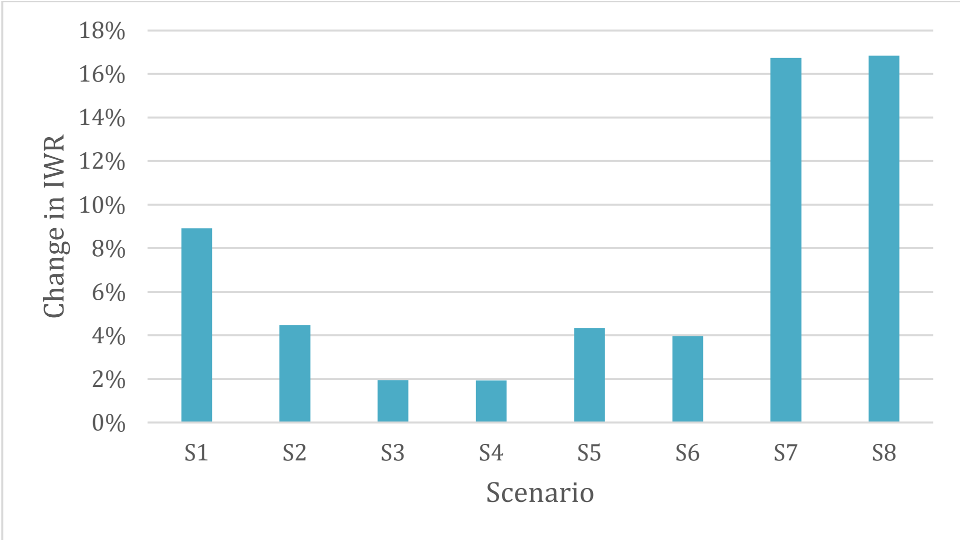


Figure 6.3. The percentage change in average annual IWR with respect to observed during future scenarios.

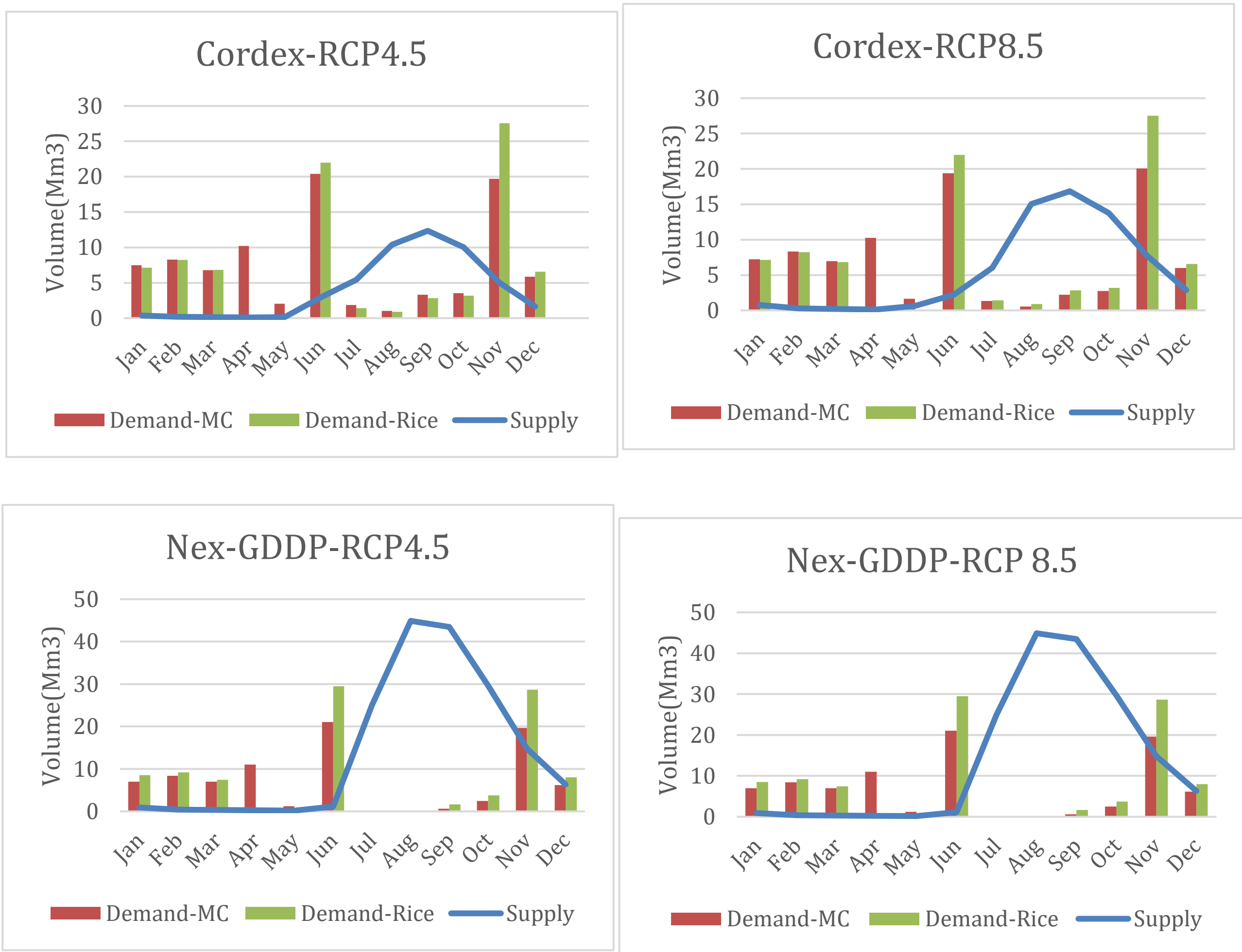


Figure 6.4. Average monthly demand and tank water available for the future period 2025-2050.

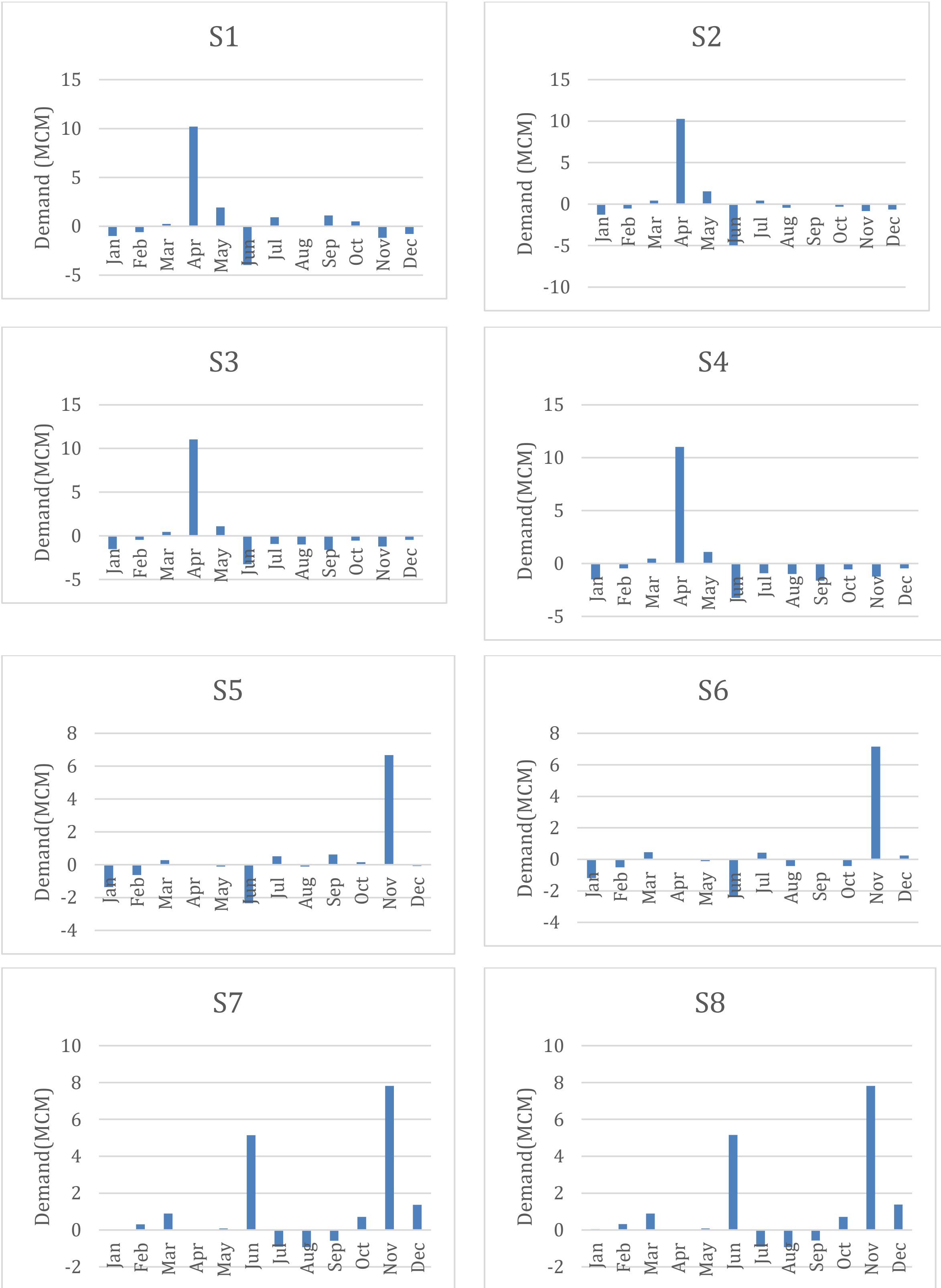


Figure 6.5 Monthly deviations of total irrigation demand in future scenarios from the historic period in the Pakhal command area. *Note: S1, S2, S3… S8 are described in table 6.1*

The monthly fluctuations in the total irrigation demands across the historical period for both RCP scenarios are shown in Figure 6.6. The warmer months of April and May will see the highest water demand in the future, according to CORDEX climate estimates. The increased irrigation needs projected for the peak summer season should be taken into consideration for the development of better irrigation techniques in the future. The Rabi months showed greater monthly fluctuations in irrigation demand, compared to the Kharif months, which showed less deviation. When the command area is assumed to be entirely irrigated with rice crop (100%) during the Kharif season (June–October), the future irrigation demand estimates for the CRODEX scenarios show a decrease. While, the NEXGDDP scenarios show a significant increase in future irrigation demands in Rabi season. The maximum deviation can be observed during the month of November, when mixed crop cultivation is considered. When 100% rice crop is irrigated, the irrigation demand is higher during month of June (pre-monsoon) and November (start of Rabi season). The future irrigation demand fluctuations can be met by optimizing the irrigation tank releases by considering the changes in the water demand. Stochastic Dynamic Programming (SDP) can be implemented for optimizing the irrigation tank releases by taking irrigation demand variability into account.

6.3 Stochastic Dynamic Programming (SDP)

Irrigation system operation for meeting the agricultural water demand require optimizing the use of water over time. In the present study, irrigation tank performance is measured for the standard operating and adaptive policy using SDP. Standard Operating Policy (SOP) attempts to meet the target at all times unless constrained by available water in the reservoir plus incoming flows. In SDP, a variation of dynamic programming algorithm, reservoir inflows are treated as random variables underlying probability distributions. This type of a stochastic description of inflow aids in calculating the anticipated benefits associated with the each release decision. 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 is the release vector for period t, and et(S_t, St+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) which is given as follows:

$$St+1= St+ Qt-Rt-(St,St+1) \tag{6.4}$$

The reservoir storage, represented by St, and frequently some variable that indicates the hydrologic status of the river basin can be used to explain the system's state at each stage t. A water release Rt is selected for each stage and state that maximizes the sum of the current benefit of that release B_t (Rt) and the future benefit $\boldsymbol{ft{+}1}(\boldsymbol{St{+}1})$, which depends on the storage generated as a result in the subsequent period $\boldsymbol{St{+}1}$ in the following period, with an assumption that the system operates optimally from that point forward. A backward recursive function is used in the model 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 Qt, the functional equation is evaluated using Eq 6.5 (Faber and Stedinger 2001).

$$f_t(\mathbf{S}_t) = \max_{\mathbf{R}_t^*} \; \underset{\mathbf{Q}_t}{E} \{B_t(\mathbf{S}_t, \mathbf{Q}_t, \mathbf{R}_t) + \alpha f_{t+1}(\mathbf{S}_{t+1})\}$$
$$\forall \mathbf{S}_t \text{ and } t \in \{1, \ldots, T\} \tag{6.5}$$

Where, T is the final time period in the model, (B_t) the benefit function for period t and α denotes the discount factor. The transition probabilities provide the information on inflow characteristics in order to decide 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 (6.6). Eq (6.7) is used to compute the reservoir storage capacity with minimum releases. The penalty cost (Ct), which is determined by the relationship between the volumes delivered and the demand, is as follows:

$$\mathbf{C_t = [1-(R_t / D)]^{\tau}} \tag{6.6}$$

Where, D = Demand or target release, τ = penalty cost exponent (τ = 2 Academic purpose). Backward recursive equation (Faber and Stedinger 2001) is given by Eq. (6.7).

$$\boldsymbol{f_t(S_t, Q_t)} = \min_{R_t} \left\{ \boldsymbol{C_t(S_t,\ Q_t, R_t)} + \underset{\boldsymbol{Q_{t+1}|Q_t}}{\boldsymbol{E}} [\boldsymbol{f_{t+1}(S_{t+1}, Q_{t+1})}] \right\}$$
$$\forall \boldsymbol{S_t}, \boldsymbol{Q_t} \textbf{ and } \boldsymbol{t} \in \{\mathbf{1}, \ldots\ldots, \boldsymbol{T}\} \tag{6.7}$$

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 **(**R) represents the probability of no failure. It is classified into time based and volumetric reliabilities. The expression for for reliability is as follows:

$$R= 1-\left(\frac{\sum_{i=1}^{N} D_i - D'_i}{\sum_{1=1}^{N} D_i}\right) \quad (6.8)$$

where $\boldsymbol{Di}$= Target demand during ith period; $\boldsymbol{D'i}$' = Actual volume supplied during the ith period; N = Number of time intervals in the simulation. **Resilience** ($\boldsymbol{\varphi}$) is the conditional probability of a recovery from the failure set in single time step which is expressed as follows:

$$\boldsymbol{\varphi}=\frac{f_s}{f_d} \quad (6.9)$$

Where, $\boldsymbol{f_s}$ = Number of individual continuous sequences of failure periods; $\boldsymbol{f_d}$= Total duration of all the failures. **Vulnerability (ή)** is the measure of likely damage in a failure event, which corresponds to the probable failure magnitude. It is expressed as follows:

$$ή= \Sigma(\mathbf{max}\boldsymbol{sj})\boldsymbol{fsj}=\mathbf{1}\boldsymbol{fs} \quad (6.10)$$

where, sj= Volumetric deficit during jth continuous failure sequence; $\boldsymbol{fs}$ = Number of persistent failure occurrences.

6.4 Development of Adaptation Strategies Using SDP

The ensemble climate model data of RCP 4.5 scenario (CORDEX) is used to simulate the streamflow in the reservoir and for developing adaptation strategies. Climate change impact on irrigation systems and its performance criteria (reliability with respect to volume, resilience and vulnerability) are evaluated using the r package "reservoir". The performance criteria obtained are studied initially with the SOP. The performance indices projected with the SOP for future scenario show decrease in reliability and resilience, while the vulnerability is likely to increase because of climate change. Hence, SDP is employed to optimize the tank releases. The irrigation demand outputs obtained from CROPWAT model are used target release vector in the SDP. The tank inflows obtained from SWAT model are given for inflow vector. The other inputs for SDP include tank surface area, initial capacity of the tank, and maximum depth of the tank. The following three demand-side adaptation strategies are applied:

- Change in cropping pattern to Mixed Cropping(MC),
- Delaying the Planting date (DP),
- Increasing the Irrigation Efficiency (IIE).

It is observed that the total irrigation demand is less when mixed cropping pattern considered when compared to the 100% rice cultivation scenario. Hence, mixed cropping pattern in both Rabi and Kharif seasons is selected as first adaptation strategy. From the rainfall analysis, it can be observed that there is a shift in monsoon period from the month of August to September, which in turn is causing irrigation water deficit at the start of both Kharif and Rabi seasons. So, in order to mitigate this effect, delayed plantation is suggested. For the study, the plantation is delayed by 7, 14, 28 days and the irrigation tank performance is measured respectively. A delay of 28 days in planting date gave better performance, hence it is chosen as second adaptation strategy. Increasing the irrigation efficiency by 10% i.e making the overall irrigation efficiency as 80% is considered as third adaptation strategy. In order to achieve this, the future irrigation demands are calculated in CROPWAT by changing the irrigation efficiency from 70% to 80%. The tank performance indices under SOP, SDP with and without adaptation are measured in order to obtain the best fit strategy. The summary performance indices for each of the strategy are depicted in figure 6.6. The optimum fit adaptation method is fixed based on the high reliability and resilience with low vulnerability values. The combination of 2 adaptation strategies i.e. mixed cropping and delayed plantation gives better reservoir performance, with 0.95, 0.73 and 0.19 reliability, reliance and vulnerability values respectively (Table 6.2). Even though the combination of mixed cropping and increase in irrigation efficiency give highest reliability with 0.97, the resilience of the system is low with a value of 0.32. Hence combination of MC and delayed plantation is chosen to the best fit strategy as the optimal performance indices are achieved when using this combined adaptation.

Table 6.2. Summary of Performance Indices

Inflow	**Operation Policy**	**Reliability**	**Resilience**	**Vulnerability**
Historic	SOP	0.59	0.42	0.85
Future (RCP 4.5)	SOP	0.57	0.34	0.88
Future (RCP 4.5)	SDP(without any adaptation)	0.66	0.38	0.82
Future (RCP 4.5)	SDP (MC)	0.80	0.14	0.3
Future (RCP 4.5)	SDP (MC and IIE)	0.97	0.32	0.15
Future (RCP 4.5)	SDP (MC and DP)	0.95	0.73	0.19

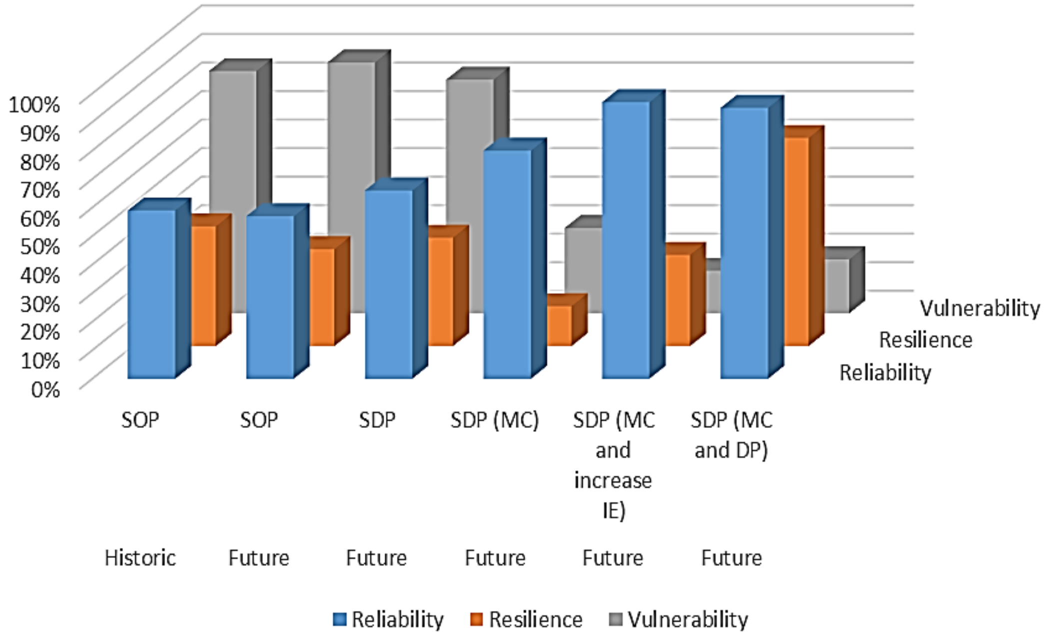


Figure 6.6. Summary of the performance indices for the tank system with adaptation.

6.4 Closure

To address the issues of both the present and future climate change, it is vital to develop adaptation mechanisms for water resource management policies and practices. The adaptation strategies which can bridge the gap between the water availability and demand are crucial to achieve water resilience at a particular region. Therefore, in the present chapter, estimates of future irrigation needs are made for the Pakhal study area, under eight distinct altering climate and cropping scenarios. The future climatic parameters from CORDEX and NEXGDDP ensemble model is used as an input for the CROPWAT model. The results show a significant increase in irrigation demand under CORDEX RCP 4.5 scenario. Performance indices of the irrigation tank projected with the SOP for future scenarios show a decrease in reliability, while the vulnerability as well as resilience are likely to increase because of changing climate. Irrigation tank optimization is performed using SDP. The findings from the research work can be used by the government and decision makers of the Pakhal tank to comprehend the effects of climate change and to modify tank management policy to deal with the concerns of fluctuations in tank water supply and future irrigation demand as well.

Chapter 7

Summary and Conclusions

7.1 Summary

The thesis work is focused on developing adaptation strategies for the management of water resources in an irrigation tank system in a semi-arid region under changing climate. Initially, the climate variability and trends are analyzed for the Telangana region in order to identify the areas that are most vulnerable to climate change. The present study uses gridded rainfall and temperature data of 63 years i.e. from 1951 to 2013 acquired from the IMD to evaluate the observed climatic trends. Using the regional climate model data retrieved from CORDEX under RCP 4.5 and RCP 8.5 for 31 years, the possible climate scenarios for Telangana are evaluated (2020–2050). The Coefficient of Variation (CV), which is stated in percentages, is used to calculate the variability of the climate. At each grid point, both parametric (Linear Regression) and nonparametric (Mann-Kendall and Sen's slope) approaches are used to identify potential trends in the climate variables.

The spatial plots show that the average annual rainfall is going to reduce in the future suggesting that there is a need to conserve the water resources of the Telangana region. Results of parametric and non-parametric tests on observed IMD data demonstrate a significant upward trend in daily maximum and minimum temperatures. Whereas daily precipitation shows no discernible trend, indicating precipitation uncertainty. Maximum and minimum temperatures have risen significantly, influencing precipitation patterns. The RCP 4.5 ensemble data showed an increasing trend for PCP and TMAX, but no significant trend for TMIN in NTZ and sections of CTZ, and a decreasing trend for STZ. RCP 8.5 ensemble results for future scenarios predicted less rain and higher daily maximum and minimum temperatures. CTZ is most vulnerable to climate change.

The climate change impacts on the Pakhal tank irrigation catchment are assessed for historic and future periods. Pakhal Lake is located in the CTZ over the tributary of Krishna River and serves the agricultural water needs of the local farmers. SWAT model is used for the hydrological modeling of the catchment water balance components and to study tank inflows variations. Because there is no of a gauge station at Phakal Lake, IMD data from the years 1985 to 2005 for the Konduru watershed, which is located downstream of the area of study, were utilized to run the SWAT model. The SUFI-2 technique in SWAT-CUP was used to calibrate and validate the SWAT model for the Konduru catchment. From the geospatial data of both the Phakal and Konduru watersheds, it can be observed that they have a physical similarity. Hence, the fitted model parameters transfer is done from Konduru to the Pakhal watershed using the regionalization approach. For the gauged watershed, the results from SWAT model's calibration and validation are satisifactory.

Two sets of data are used i.e. CORDEX and NEXGDDP under both RCP 4.5 and RCP 8.5 scenarios for future climate projections. The climate models are bias-corrected using a nonparametric quantile mapping method. The bias-corrected RCM data is incorporated in the SWAT model developed for the study area 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. The hydrologic components of the Phakal Watershed were simulated for the Baseline (1986–2018), Future-1 (2020–2050), Future-2 (2051–2080), and Future-3 (2081–2099) periods using the SWAT model, after its calibration and validation. For simulating the future hydrologic conditions, four CORDEX-RCM outputs under RCP 4.5 and RCP 8.5 scenarios were used. It has been noted that the predictions from the various climate models differ from one another. In order to make accurate estimates for the future, it is advised to take into account a variety of climate models.

The hydrologic components of the Phakal Watershed were simulated using the calibrated and validated SWAT model for Baseline (1986–2018), Future-1 (2020–2050), using REA ensemble of 21 NEX-GDDP models. For the analysis of climate change, the simulated hydrologic conditions are compared with the observed data. The NEX-GDDP models are at a higher spatial resolution than the CORDEX models with a resolution of 0.25^{o}. The CORDEX model results exhibited a significant change in hydroclimatic variables in Future-1 when compared to other future time periods. Hence, future-1 is considered for simulation using NEX-GDDP data for comparison between the two data sets.

The results of the climate change analysis reveal that surface runoff amounts quantities will be significantly impacted by the changing climate. The future tank inflow simulation results also exhibit a significant decrease. Future-1(2020-2051) is the most vulnerable as it experiences the highest decrease in tank inflow. The findings suggest that tank inflows could decline by as much as 59% between the historic and future time periods. The rainfall and lake inflow indicate a significant decreasing trend in the Phakal Watershed. The outcomes of both future climate scenarios for NEX-GDDP data are different. A decrease in streamflow is observed in RCP 4.5 which can be attributed to decreased precipitation and enhanced potential evapotranspiration (PET). Increased streamflow is predicted in RCP 8.5. Even though NEX-GDDP model data is at high resolution when compared to CORDEX, its correlation with observation data is less. The CORDEX model is a more suitable dataset for the climate change analysis of the study area.

The effect of climate change on water availability in Pakhal Lake is assessed by predicting future water level changes. SVR coupled with SWAT outputs is employed for predicting lake water levels under current and future climate change scenarios. The outputs of potential PET from SWAT (from the HRU consisting the lake) were used as a proxy for evaporation from the surface area of lake. The RBF kernel was used in the application of the v-SVR approach. PET and tank inflows from SWAT along with precipitation, outflow volume, were given as inputs for the ν-SVR model. The results indicate a significant decrease in lake water levels from October-March. (Rabi Season). This method can be an effective way of estimating water levels, since the changes in future lake area information are unavailable and also when the direct estimation of surface evaporation from the lake is not possible. The linking of SWAT outputs with the SVR model proved effective in predicting lake water levels because the performance metrics are satisfactory.

The irrigation water demand during historic and future periods is estimated using CROPWAT 8.0. The results demonstrate a 9% spike in irrigation demand under CORDEX RCP 4.5 scenario when mixed cropping is considered. The irrigation tank performance indices projected with the SOP for future scenarios show a decrease in reliability, while the vulnerability and resilience are likely to increase because of climate change. Irrigation tank optimization is performed using SDP. Three adaptation strategies are applied and reservoir optimization is performed. The best fit strategy is fixed based on the high reliability and resilience with low vulnerability values. The combination of two adaptation strategies i.e. mixed cropping and delayed plantation gives better reservoir performance.

7.2 Conclusions

The significant findings from the present research work are stated below:

- The results of both trend tests indicated a substantial increasing trend in daily maximum and minimum temperatures in Telangana. Whereas daily precipitation shows no discernible trend, indicating precipitation uncertainty.
- Maximum and minimum temperatures have risen significantly, influencing precipitation patterns.
- RCP8.5 ensemble results for future scenarios predicted less rain and higher daily maximum and minimum temperatures. CTZ is most vulnerable to climate change.
- With NSE and R2 values of 0.66 and 0.71 during calibration and 0.65 and 0.68 during validation, the SWAT model's calibration and validation show promising results for the gauged watershed.
- Among the four models under CORDEX data, the CCSM model is a better predictor of precipitation and streamflow.
- The average streamflow predicted by all the models is decreased by 21% under the RCP 4.5 and 41% under the RCP8.5 scenario.
- According to analyses of yearly and monthly streamflow changes, the RCP 4.5 scenario results in lower streamflow values under conditions of decreasing precipitation and raised temperatures.
- The REA model precipitation has a good correlation with the observed data with R^2 values of 0.89 for CORDEX and 0.74 for NEXGDDP.
- During the future time period (2021-2050), the precipitation projection with CORDEX data is reduced by 26% and 21% under RCP 4.5 and RCP 8.5.
- Under RCP 4.5 and RCP 8.5, respectively, the streamflow is reduced by 59% and 52%.
- The precipitation projection with NEXGDDP data indicates an increase in precipitation by 10% and streamflow is increased by 20% under RCP 8.5.

- The peaks in precipitation and streamflow for observed data are found during the month of July, however in the future scenarios, these peak months are August and September.

- Reduced values of surface runoff and base flow are produced by a rise in the temperature and a decline in precipitation, while an increase in evapotranspiration is produced.

- In calibration and validation, the SVR model developed to forecast water levels produced results that were satisfactory with R2 values of 0.79 and 0.74, respectively.

- The future irrigation demands obtained from CROPWAT showed an increase of 9% under the RCP 4.5 future scenario and a similar pattern during the rest of the scenarios. The peak irrigation demands are observed during July and November.

- The combination of two adaptation strategies i.e. Mixed cropping and delayed plantation gives better reservoir performance with reliability of 0.95, resilience of 0.73, and vulnerability of 0.13.

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 for the selected study region. The REA data exhibit a stronger association with the data on the observed climate.
- The SWAT model is set up for the Phakal tank irrigation system with is an ungauged catchment using a regionalization approach.
- SVR model is linked with SWAT outputs for the prediction of lake water levels.
- CROPWAT model is used for estimating the changes in future agricultural water demand.
- Adaptation policies are developed for optimal reservoir operations with respect to changing water demand.

7.4 Limitations of the study

The following are the constraints of this research work:

- The selected study area has limited observational data.
- In the study, only demand-side adaptation policies are proposed.
- The study is based on a single-tank system. Considering cascade tank system may be more effective in the study area.

7.5 Future Scope

As was already mentioned, the current study is focused on the availability of water in a tank irrigation system as well as estimates for rainfall and surface water. However, there are still a significant number of issues in the hydrology domain due to climate change. Hence, the scope for further study related to this work is as follows:

- Multiple ensemble scenarios, other than REA can be used for impact studies.
- Regionalization methods other than the proximity method can be explored for streamflow prediction in ungauged basins.
- Development of adaptation strategies in order to increase crop yield can be explored.
- Development of supply-side adaptation strategies can be explored for sustainable agriculture in the command area.

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Appendix-A

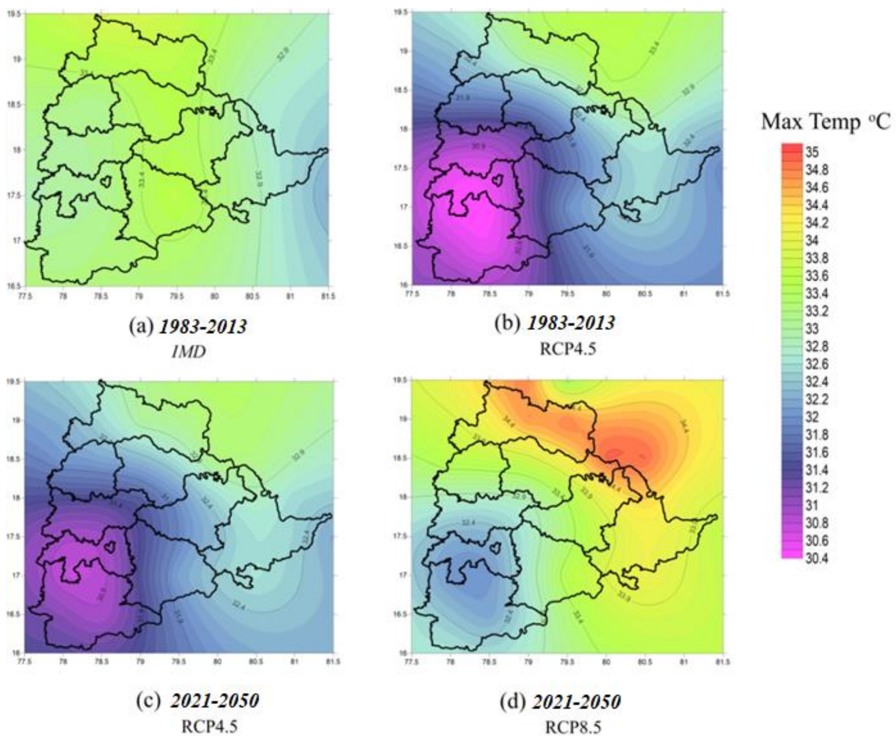

Figure A1. Mean Annual Precipitation for IMD, historic and future CORDEX scenarios

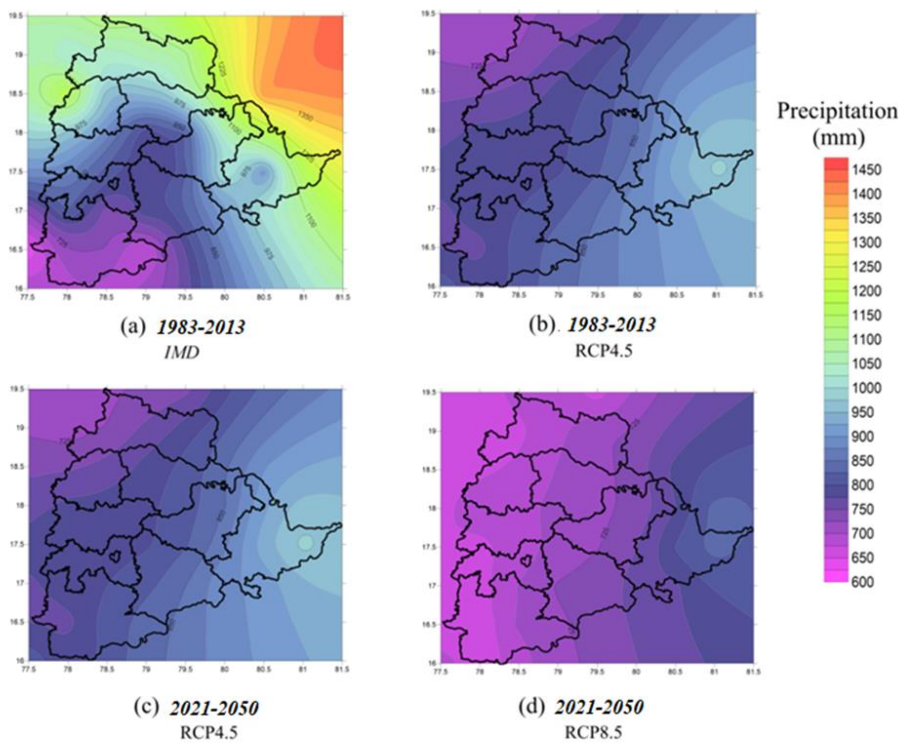

Figure A2. Mean of the daily maximum temperatures for IMD, historic and future CORDEX scenarios

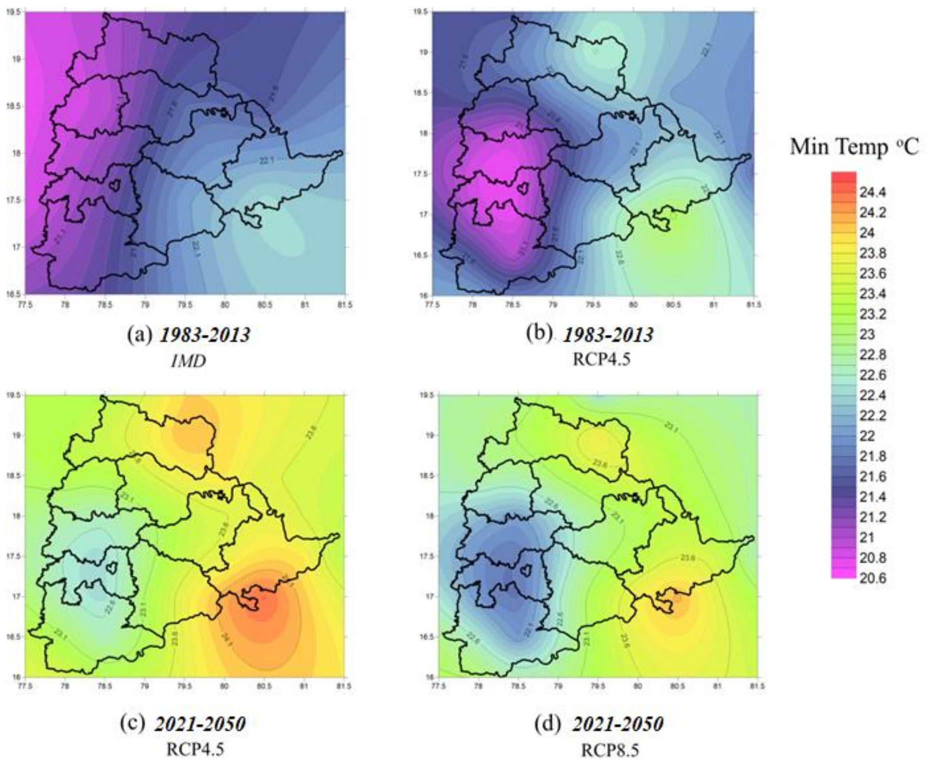

Figure A3. Mean of the daily minimum temperatures for IMD, historic and future CORDEX scenarios

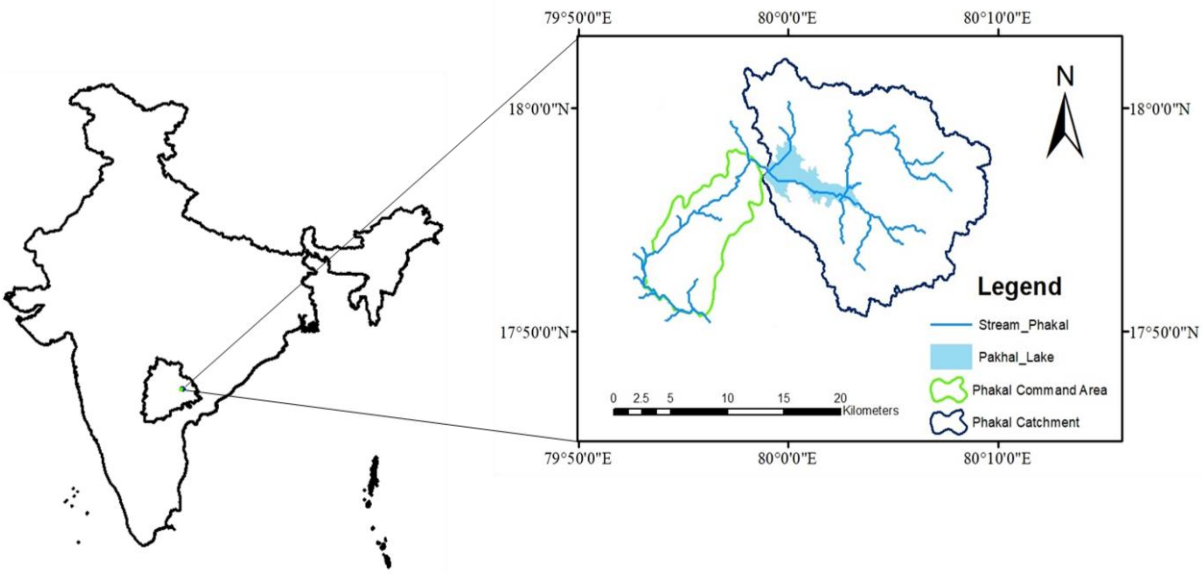

Figure A4. Location map of Pakhal Lake and its catchment and command area

Figure A5. Field Visit Photographs of Study Area

List of Publications

Journals

- Sri Lakshmi Sesha Vani Jayanthi & Venkata Reddy Keesara, Climate change impact on water resources of medium irrigation tank, *ISH Journal of Hydraulic Engineering*, (2019) DOI: 10.1080/09715010.2019.1649605. **(SCOPUS, 3.2)**

- Sri Lakshmi Sesha Vani Jayanthi & Venkata Reddy Keesara, Observed and simulated climate variability and trends in a semi- arid region. *Spatial Information Research*, **28,** 129–138 (2020) https://doi.org/10.1007/s41324-019-00278-w. **(ESCI)**

- Sri Lakshmi Sesha Vani Jayanthi, Keesara, Venkata Reddy and Venkataramana Sridhar, Prediction of Future Lake Water Availability Using SWAT and Support Vector Regression (SVR), Sustainability, 14(12), p. 1-17.(2022) **(SCI, I.F 3.88)**

Conferences

- Sri Lakshmi Sesha Vani Jayanthi., Venkata Reddy ,K., "Water Resilience through Tank Rejuvenation in Semi Arid Regions –A Climate Change Perspective", Conference On Next Frontiers In Civil Engineering Sustainable And Resilient Infrastructure, 30th Nov- 1st Dec, 2018- Mumbai, India

- Sri Lakshmi Sesha Vani Jayanthi., Venkata Reddy ,K., " Climate Change Impact on Water Resources of Phakal Lake using SWAT model", *2018 India SWAT Conference* , January 8-12, 2018 - Chennai, India.

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