

Change in Snow Cover Area and Flow Scenario of the Brahmaputra and Subansiri Basins Due to Climate Change

Thesis

submitted in partial fulfillment of the requirements

of the Degree of

DOCTOR OF PHILOSOPHY

by

Swapnali Barman



Department of Civil Engineering

Indian Institute of Technology Guwahati

Guwahati-781039

NOVEMBER, 2016



**Change in Snow Cover Area and Flow Scenario of the
Brahmaputra and Subansiri Basins Due to Climate Change**

Thesis

submitted in partial fulfillment of the requirements

of the Degree of

DOCTOR OF PHILOSOPHY

By

Swapnali Barman

(Roll No.10610426)

Under the Guidance of

Dr. R.K. Bhattacharjya

Professor

Civil Engineering Department

IIT Guwahati



Department of Civil Engineering

Indian Institute of Technology Guwahati

Guwahati-781039

NOVEMBER, 2016





भारतीय प्रौद्योगिकी संस्थान गुवाहाटी

Indian Institute of Technology Guwahati

Guwahati – 781 039

Assam, INDIA

Phones: 0361-2582428 (O)

0361-2584428 (R)

Fax: 0361-2582440

E-mail: rkbc@iitg.ernet.in

rajibkbc@gmail.com

DEPARTMENT OF CIVIL
ENGINEERING

Dr. Rajib Kumar Bhattacharjya
Professor

Date: 18 Nov 2016

CERTIFICATE

This is to certify that the work contained in the thesis entitled “**Change in Snow Cover Area and Flow Scenario of the Brahmaputra and Subansiri Basins Due to Climate Change**” submitted by **Swapnali Barman** to the Department of Civil Engineering, Indian Institute of Technology Guwahati, for the award of the degree of Doctor of Philosophy in Civil Engineering is a record of bonafide research work carried out by her under my supervision and guidance. This thesis work, in my opinion, has reached the requisite standard fulfilling the requirements for the degree of Doctor of Philosophy.

The research work contained in this thesis have not been submitted in part or full to any other University or Institute for award of any degree or diploma.

(Rajib Kumar Bhattacharjya)

Place: Guwahati



STATEMENT

I do hereby declare that the matter embodied in the thesis entitled “**Change in Snow Cover Area and Flow Scenario of the Brahmaputra and Subansiri Basins Due to Climate Change**” is the result of analytical work carried out by me in the Department of Civil Engineering, Indian Institute of Technology Guwahati, Assam, India.

In keeping with the general practice of reporting scientific evaluation, due acknowledgement have been made whenever the work described is based on the findings of literature review.

Date:

Swapnali Barman

Place: Guwahati



DEDICATION

This thesis is dedicated to God Almighty and my beloved parents Dr. T.S. Barman and Mrs. S.R. Barman who have loved me unconditionally and whose affection and prayers have created my edifice of success. I will always be indebted towards their overwhelming support and eternal love.



ACKNOWLEDGEMENT

I would like to express my deep sense of gratitude, indebtedness and sincere thanks to my research supervisor **Professor Dr. R.K. Bhattacharjya**, Department of Civil Engineering, Indian Institute of Technology Guwahati for his constant encouragement and invaluable guidance towards the successful completion of this work. His guidance helped me in all the time of research and writing of this thesis. I would like to appreciate the keen interest he showed in the project and the time spent by him on the discussion and also in editing this thesis. It was a great privilege and honor to work and study under his guidance. I am extending my heartfelt thanks to his family for their acceptance and patience during the discussion I had with him on research work and thesis preparation.

Besides my advisor, I would like to thank the rest of my committee members **Prof. Arup Kumar Sarma**, **Prof. Anjan Dutta**, and **Dr. Archana M. Nair** for their insightful comments and encouragement that helped me to widen my research from various perspectives. I thank them for their contribution and their good-natured support. Over the years, each has given me superb scientific guidance, many insightful suggestions and demonstrated a sincere interest in my work.

I extend my gratitude to my M.Tech. supervisors **Dr. S.P. Aggarwal**, Head, Water Resources Division, Indian Institute of Remote Sensing, Dehradun and **Dr. M.K. Dutta**, Assistant Professor, Civil Engineering Department, Jorhat Engineering College, Jorhat, Assam for their encouragement towards the fulfillment of the research work.

I wish to record my deep gratitude to **Dr. Bipul Talukdar**, Associate Professor, Department of Civil Engineering, Assam Engineering College, for his invaluable advice and feedback on my research.

I am equally thankful to **Dr. Triptimoni Borah**, Associate Professor, Civil Engineering Department, Assam Engineering College, who offered unflagging support and wise advice.

I am grateful to the **Water Resources Department, Govt. of Assam**, for providing me the necessary data required to carry out the project work.

My heartfelt thanks to the senior officers of the Water Resources Department, Govt. of Assam for their support to carry out my research work successfully. In particular I would like to show my gratitude to **Er. Ratul Sarma**, **Er. Pradipta Pran Changkakati**, **Er. Rajendra**

Prasad Das, Er. Dilip Sarma, Er. Rudreswar Sarma, Er. Mohan Ch. Medhi, Er. Kamal Bezbaruah, Er. Achinta Kr. Roy and Er. Samiran Deka for their encouragement during my Ph.D. tannure.

I would like to thank my friend **Mr. Saalim Mohammed** who helped in solving some difficult problems during the initial stages of my Ph.D.

My sincere thanks to **Ms. Sophia Laichombam, Mr. Bhrigumoni Sarma, Ms. Dipsikha Devi, Mr. Rajeev Gandhi and Mr. Manti Patel** of Civil Engineering Department, IIT Guwahati, who helped me in different ways during various stages of my Ph.D.

I wish to express my sincere thanks to the non-teaching staff of the Civil Engineering Department of IIT Guwahati for their help and support.

I express my deep love for IIT Guwahati and record my gratefulness to all the faculties who imparted me each and every bit of their valuable knowledge.

I warmly thank and appreciate my best friends **Barnali Deka** and **Protisha Borpuzari** for helping me get through the difficult times, and for all the emotional support, entertainment and caring they provided.

I am thankful to **Mrs. Dolly Sarmah, Ms. Jonali Saikia, Ms. Jayashree Sarma, Ms. Prativa Borah, Mrs. R. Saikia, Ms. Runti Choudhury and Mr. Bazal Hoque** for their help and encouragement during the project work.

I would like to express huge, warm thanks to my friends **Swati Bhave, Thiyam Tamphasana Devi, Harinder Thakan, Mahesh Patel, Fouzia Shaheen, Jumi Kalita, Swati Uniyal, Neha Mallick, Chhaya Minz, Rashmi Bante, Priyanka Goyal and Neetu Gill** whose friendship, hospitality, knowledge, and wisdom have supported, enlightened, and entertained me over the many years of our friendship.

Last but not the least I owe a lot to my parents **Dr. T.S. Barman** and **Mrs. Smriti Rekha Barman**, my elder sister **Barnali Barman**, brother-in-law **Mr. Indrajit Boiragi** and my nephew **Prayag Boiragi** for their love, inspiration and moral support during the entire period of work.

Swapnali Barman

ABSTRACT

Snow, a sensitive indicator of climate, is a crucial hydrological parameter in the global water cycle and also an important ingredient of the cryosphere. A large extent of the mountainous area of the Brahmaputra River basin is covered by Himalayan snow, which starts ablating in the spring due to rise in temperature. Apart from this snowmelt water, many small and large tributaries also contribute towards the discharge of the river Brahmaputra. The river Subansiri is one of the major north bank tributaries of the Brahmaputra and thus has major contribution towards its discharge. A part of the upper catchment of the Subansiri basin is also covered by snow. In this study, the impact of the change in temperature on the snow cover area of both the Brahmaputra and the Subansiri River basins has been analyzed from 2002 to 2015 for the months of January, April, July and October. The MOD09A1.5, MODIS data of 500m resolution have been used to prepare the snow maps using the Normalized Difference Snow Index Method. Cloud-free Landsat satellite data (Landsat 4-5 TM) of 30m resolution has been used to validate the snow map prepared from the MODIS image. The gridded temperature data of HadCM3 GCM of A2 scenario having a spatial resolution of $2.5^{\circ} \times 3.75^{\circ}$ (latitude by longitude) were used to get the average temperature of the basins. It has been found that the snow cover area showed decreasing trends with respect to the increasing trends of temperature for the months of April, July, and October. While, for the month of January, the snow cover area showed an increasing trend with respect to the decreasing trend of temperature. The effect of changes in snow cover area on the discharges of the river Brahmaputra and the Subansiri have also been studied and it has been found that w.r.t. the decreasing trends of snow cover area, the discharge showed increasing trends depicting the fact that snowmelt water influences on the discharge of the rivers at the downstream.

Land use/land cover (LULC) change detection of an area is essential as it is an indicator of climate change. In this study, LULC change detections have been carried out for both the Brahmaputra and the Subansiri basins using supervised classification method and maximum likelihood classifier algorithm. The MODIS data of 500m resolution have been used to prepare the LULC maps from 2002 to 2012 for January, April, and October. Five different LULC classes have been considered for the study. These are bare soil, surface water bodies, dense vegetation, light vegetation and snow cover area. It has been found that dense vegetation and snow cover area decreased during this period, while light vegetation and bare soil showed significant increase.

The future rainfall pattern over the Subansiri River basin has been studied by multiple linear and non-linear regression based statistical downscaling techniques and by Artificial Neural Network based model. APHRODITE's gridded rainfall data have been taken as the predictand and the HadCM3 GCM climatic parameters as the predictors. It has been found that multiple non-linear regression based statistical downscaling technique outperformed the other techniques. Using this method, the future rainfall pattern of the Subansiri basin has been analyzed up to the year 2099 for four different time periods, viz., 2020-39, 2040-59, 2060-79, and 2080-99. The spatial change in rainfall pattern showed a potential decrease of rainfall in the wet months and months with moderate rainfall. Further, it has been observed that the future rainfall during dry months may be increased.

The future flow scenario of the river Subansiri has been analyzed up to the year 2099 for the four different time steps. Two different rainfall-runoff models have been developed, the ANN-based rainfall-runoff model, and ANN-SCS based hybrid model. The evaluation of results showed that the performance of the hybrid model was better than the other model. Three different LULC scenarios have been created to study its impact on the future flow scenario of the river. No change in LULC from the present condition up to the year 2099 have been assumed in the first scenario, while various changes in the LULC categories have been incorporated in the other two scenarios. Decreasing trends of future runoff have been observed for the first scenario, while the future runoffs showed increasing trends for the other changed scenarios.

Several hydropower projects have been planned on the Subansiri River. One of them, the Subansiri Lower Hydroelectric Project (SLHEP), is under construction and in the advanced stage of completion. As such, it is necessary to evaluate the impact of climate change and change in LULC on the power potential of the river. To study the impact on the future power potential of the SLHEP, a reservoir simulation model has been developed. The runoff calculated for the different LULC scenarios by the ANN-SCS based hybrid model have been used as the inflow to the reservoir. For all the scenarios, lower power potentials have been observed compared to the power potential of the SLHEP during the historical period (1990-2014). It has also been observed that for a constant LULC scenario in the future, the power potential of the SLHEP showed decreasing trends for the four different time periods. However, for the changed scenarios, the future power potential of the project showed increasing trends for the different time periods.

Contents

Acknowledgement	III
Abstract	V
List of Figures	XIII
List of Tables	XIX
Symbols	XXIII
Abbreviations	XXV
Chapter 1: Introduction.....	1-8
1.1 General.....	1
1.2 Objectives of the thesis.....	5
1.3 Research queries.....	7
1.4 Organization of the thesis.....	7
Chapter 2: Review of Literature.....	9-52
2.1General.....	9
2.2Climate change and its significance.....	10
2.3 Snow and its study using remote sensing.....	11
2.3.1Snow properties in the electromagnetic spectrum.....	12
2.3.2 Mapping of snow extent from remotely sensed data.....	13
2.3.3MODIS data and its application in snow cover mapping.....	15
2.3.4Himalayan glaciers and its study using remote sensing and GIS.....	17
2.4Climate change and its impact on snow/glacier.....	19
2.4.1 Impact of climate change on Himalayan glaciers.....	21
2.5Impact of change in snow cover area on discharge of rivers.....	22
2.6Land use/land cover change detection study.....	23
2.6.1Application of remote sensing and GIS on land use/land cover study.....	24
2.6.2Impact of change in land use/land cover on hydrology.....	28
2.6.3Application of hydrologic models to study the impact of change in land use/land cover.....	29
2.7Rainfall-runoff modeling.....	30
2.7.1SCS-CN model and its application on runoff estimation.....	32
2.7.2Application of Artificial Neural Network model to estimate runoff.....	34
2.7.3Scenario-based simulation of hydrological response in a catchment.....	36
2.8General Circulation Models/Global Climatic Models.....	37

2.8.1 Approaches for downscaling of GCMs.....	38
2.8.1.1 Dynamic downscaling.....	38
2.8.1.2 Statistical downscaling.....	39
2.8.1.3 Downscaling by Artificial Neural Network (ANN) model.....	40
2.9 Reservoir operation study.....	42
2.9.1 Linear Programming (LP) model.....	43
2.9.2 Non-linear Programming (NLP) model.....	45
2.9.3 Dynamic Programming (DP) model.....	46
2.9.4 Simulation model.....	48
2.9.5 Models used as combination of two or more methods.....	48
2.9.6 Artificial Neural Network Models.....	49
2.9.7 Fuzzy rule based modeling.....	49
2.9.8 Genetic Algorithm (GA) model.....	50
2.10 Conclusions.....	52
Chapter 3: Snow cover area variation study of the Brahmaputra River Basin and its impact on the discharge in the river Brahmaputra.....	53-77
3.1 Introduction.....	53
3.2 Materials and Method.....	56
3.2.1 Data used.....	56
3.2.2 Normalized Difference Snow Index (NDSI).....	59
3.2.3 Preparation of snow map.....	59
3.2.4 Comparison of the snow maps with Landsat data.....	62
3.3 Results and Discussions.....	64
3.3.1 Variation of snow cover area with respect to temperature.....	64
3.3.2 Effect of change in snow cover area on discharge of the River Brahmaputra.....	72
3.4 Conclusions.....	76
Chapter 4: Status of snow cover of Subansiri basin and its impact on the discharge in the river.....	79-96
4.1 Introduction.....	79
4.2 Materials used.....	79
4.2.1 SRTM data.....	79
4.2.2 MODIS satellite data.....	81
4.2.2 Temperature data.....	81
4.2.3 Discharge data.....	81

4.3Methodology.....	81
4.3.1Watershed delineation.....	81
4.3.2Snow cover area study of the Subansiri River Basin.....	84
4.3.3Effect of change in snow cover area on discharge of the river Subansiri.....	85
4.4Results and Discussions.....	85
4.4.1Geomorphologic parameters of the Subansiri River and its Basin.....	85
4.4.2Variation of snow cover area with respect to change in temperature.....	85
4.4.3Effect of change in snow cover area on discharge of the River Subansiri.....	93
4.5Conclusions.....	96
Chapter 5: Land use/land cover change detection study of the Brahmaputra and the Subansiri River Basins.....	97-135
5.1Introduction.....	97
5.1.1Methods of LULC change detection study.....	97
5.1.2Image classification.....	98
5.1.2.1Deterministic Classification.....	98
5.1.2.1.1Manual Classification.....	98
5.1.2.1.2Automated Supervised Classification.....	99
5.1.2.1.3Unsupervised Classification.....	102
5.1.2.2Knowledge Base Classification.....	103
5.1.2.3Fuzzy/Soft Classification.....	104
5.2Materials and Methods.....	104
5.2.1Data used.....	104
5.2.2Database preparation.....	104
5.2.3Land use/land cover change detection and analysis.....	104
5.3Results and Discussions.....	105
5.3.1LULC change detection analysis for the Brahmaputra River Basin.....	105
5.3.1.1Change detection analysis for the month of January.....	105
5.3.1.2Change detection analysis for the month of April.....	110
5.3.1.3Change detection analysis for the month of October.....	115
5.3.2LULC change detection analysis for the Subansiri River Basin.....	120
5.3.2.1Change detection analysis for the month of January.....	120

5.3.2.2	Change detection analysis for the month of April.....	125
5.3.2.3	Change detection analysis for the month of October.....	129
5.3.3	General Analysis.....	134
5.4	Conclusions.....	135
Chapter 6: Prediction of Rainfall over Subansiri River Basin using Statistical Downscaling Technique.....		137-173
6.1	Introduction.....	137
6.1.1	General Circulation Models and their downscaling.....	137
6.2	Materials and Methods.....	139
6.2.1	Data and software used.....	139
6.2.2	Downscaling of rainfall.....	141
6.2.2.1	Selection of predictors.....	141
6.2.2.2	Model calibration and validation for regression analysis.....	143
6.2.2.3	Multiple Linear Regression Model.....	144
6.2.2.4	Multiple Non-linear Regression Model.....	144
6.2.2.5	Downscaling using Artificial Neural Network.....	145
6.2.3	Prediction of rainfall.....	147
6.3	Results and Discussions.....	147
6.3.1	Determination of correlation coefficient and selection of predictors.....	147
6.3.2	Comparison of regression based statistical downscaling method and downscaling using Artificial Neural Network Model.....	155
6.3.3	Prediction of future rainfall.....	163
6.3.3.1	Future rainfall analysis at all the APHRODITE rainfall points.....	163
6.3.3.2	Future average rainfall analysis over the Subansiri Basin.....	165
6.3.3.3	Spatial variation of rainfall over the Subansiri Basin.....	166
6.3.3.4	Future Rainfall Analysis at the APHRODITE points on the basis of wet months, dry months and months with moderate rainfall.....	167
6.3.3.4.1	Spatial variation of rainfall for the wet months.....	167
6.3.3.4.2	Spatial variation of rainfall for the months with moderate rainfall.....	169
6.3.3.4.3	Spatial variation of rainfall for the dry months.....	171
6.4	Conclusions.....	172

Chapter 7: Runoff Simulation of The Subansiri River using Ann Model and Ann-SCS Based Hybrid Model.....	175-211
7.1Introduction.....	175
7.2Materials and Method.....	176
7.2.1Data used.....	176
7.2.2 Runoff simulation of Subansiri.....	178
7.2.2.1Development of the Artificial Neural Network based rainfall-runoff model.....	179
7.2.2.3Development of an ANN-SCS based Hybrid Model.....	181
7.2.2.3.1Soil Conservation Service Curve Number Model.....	182
7.2.2.3.1.1Theory of SCS Model.....	182
7.2.2.3.2Calculation of Curve Numbers.....	185
7.2.2.3.3Creation of different land use/land cover scenarios.....	186
7.3Results and Discussions.....	189
7.3.1Sub-catchment wise rainfall analysis for each time step.....	189
7.3.2Runoff analysis for ANN based rainfall-runoff model.....	194
7.3.3Runoff analysis for ANN-SCS based hybrid model.....	196
7.3.3.1Curve numbers for different sub-catchments.....	196
7.3.3.3Performance of ANN-SCS based hybrid model and future runoff prediction.....	202
7.3.4Comparison of ANN based rainfall-runoff model and ANN-SCS based Hybrid model.....	210
7.4Conclusions.....	211
Chapter 8: Determination of Future Power Potential of the Subansiri Lower Hydro Electric Project.....	213-231
8.1Introduction.....	213
8.1.1Hydroelectric Power Plant.....	213
8.1.2 Downstream impact of reservoir operation.....	214
8.1.3Subansiri Lower Hydroelectric Project.....	217
8.1.3.1Principal features of Subansiri Lower Hydroelectric Project.....	218
8.2Materials and Methods.....	219
8.2.1Reservoir simulation model.....	219
8.2.2Data used.....	220
8.2.3Methodology.....	220
8.2.3.1Capacity-Area-Elevation relationship for the reservoir.....	220
8.2.3.2Problem formulation.....	221

8.2.3.2.1 Hydropower generation.....	221
8.2.3.2.2 Constraints.....	222
8.3 Results and Discussions.....	223
8.4 Conclusions.....	231
Chapter 9: Summary and Conclusions.....	233-237
9.1 General.....	233
9.2 Conclusions.....	234
9.3 Recommendations for future work.....	237
References.....	239-280

Annexures

- Annexure 1: Calibration and Validation graphs for multiple linear regression, performed by taking climatic parameters of one HadCM3 GCM point
- Annexure 2: Calibration and Validation graphs for multiple non-linear regression analysis performed by taking the climatic parameters of one HadCM3 GCM point
- Annexure 3: Calibration and validation graphs for multiple linear regression analysis performed by taking the weighted average of the climatic parameters of four HadCM3 GCM points
- Annexure 4: Calibration and Validation graphs for multiple non-linear regression analysis performed by taking the weighted average of the climatic parameters of the four HadCM3 GCM points
- Annexure 5: Regression plots for downscaling by ANN at different APHRODITE points
- Annexure 6: Graphs showing the future rainfall of Subansiri basin at 24 different APHRODITE's rainfall points

List of Figures

Fig. No.	Description	Page No.
Fig. 3.1	Map showing the HadCM3 points in and around the upper Brahmaputra basin taken to evaluate average temperature.....	58
Fig. 3.2	Flowchart for preparation of NDSI map in Erdas Imagine.....	60
Fig. 3.3	Flowchart for NDVI mask prepared in Erdas Imagine.....	62
Fig.3.4(a)	Comparison of Snow Cover Area of MODIS(LHS) and Landsat (RHS) data for the first portion.....	63
Fig.3.4(b)	Comparison of Snow Cover Area of MODIS(LHS) and Landsat (RHS) data the second portion.....	63
Fig.3.5	Final map showing Snow Cover Area of Brahmaputra River Basin.....	64
Fig.3.6	Snow Cover Maps of the Brahmaputra basin for January from 2002 to 2015.....	66
Fig.3.7	Snow Cover Maps of the Brahmaputra basin for April from 2002 to 2015.....	66
Fig.3.8	Snow Cover Maps of the Brahmaputra basin for July from 2002 to 2015.....	67
Fig.3.9	Snow Cover Maps of the Brahmaputra basin for October from 2002 to 2015.....	68
Fig.3.10	Trend showing Variation of Snow Cover Area w.r.t temperature for the month of (a) January,(b) April, (c)July and (d) October from 2002 to 2015.....	70
Fig.3.11	Percent change in snow cover area from 2003 to 2015w.r.t. snow cover area in 2002 for (a) January, (b) April, (c) July and (d) October for the Brahmaputra river basin.....	70
Fig.3.12	Percentage change in average Snow Cover Areas from 2003 to 2015 for the Brahmaputra River basin.....	71
Fig.3.13	Trend showing variation of discharge w.r.t. snow cover area for the month (a) January, (b) April, (c) July and (d) October.....	74
Fig.4.1	Digital Elevation Model, SRTM data.....	80
Fig.4.2	Methodology of ILWIS model.....	82
Fig.4.3	Some intermediate results obtained from ILWIS model.....	83
Fig.4.4	Subansiri Catchment showing the Flow direction and the longest flow path.....	84
Fig.4.5	Locations of four HadCM3 GCM points considered for Subansiri basin.....	84
Fig.4.6	Snow Cover Maps of the Subansiri basin for January from 2002 to 2015.....	87
Fig.4.7	Snow Cover Maps of the Subansiri basin for April from 2002 to 2015.....	88

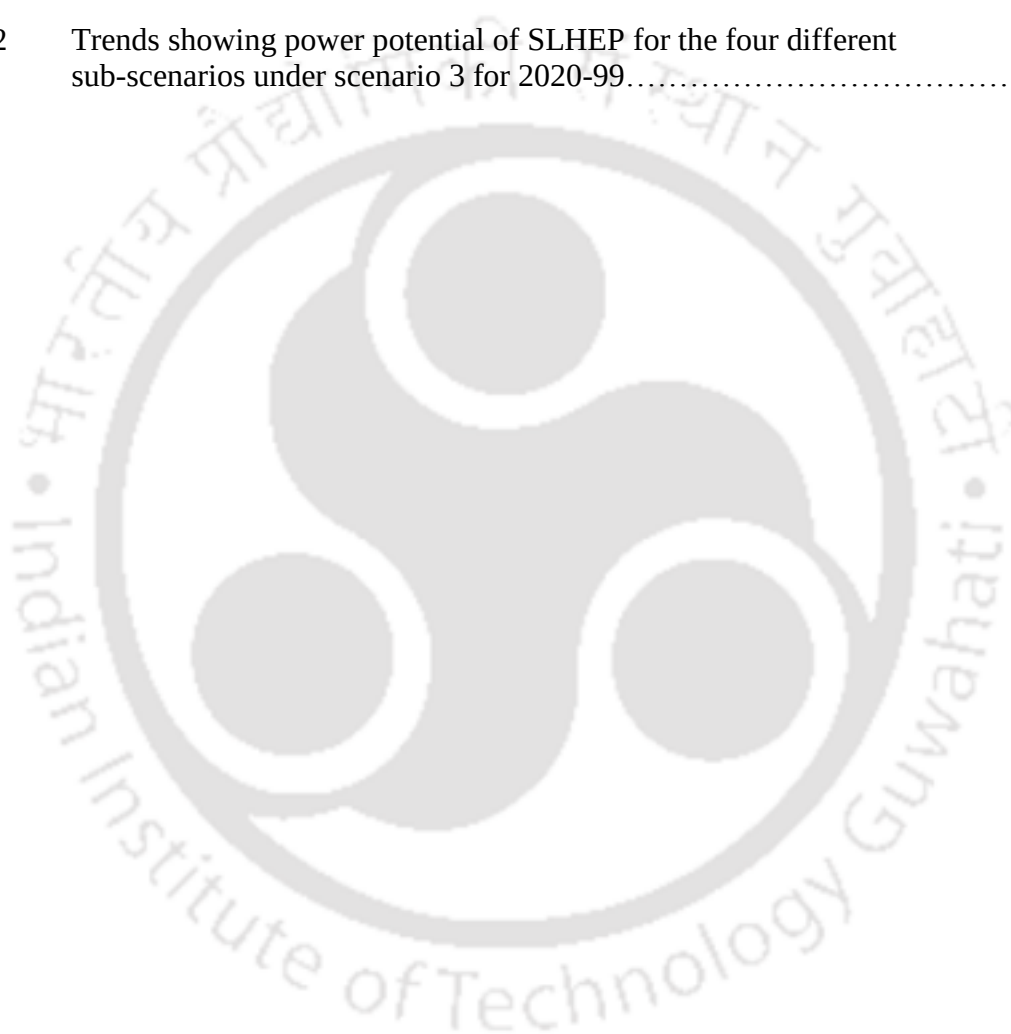
Fig.4.8	Snow Cover Maps of the Subansiri basin for July from 2002 to 2015.....	88
Fig.4.9	Snow Cover Maps of the Subansiri basin for October from 2002 to 2015.....	89
Fig.4.10	Trend showing Variation of Snow Cover Area w.r.t temperature for the month of (a)January, (b) April (c) July and (d) October from 2002 to 2015 in Subansiri River basin.....	91
Fig.4.11	Percent change in snow cover area from 2003 to 2015 w.r.t. snow cover area in 2002 for (a) January, (b) April, (c) July and (d) October for the Subansiri River basin.....	91
Fig.4.12	Percentage change in average snow cover area from 2003 to 2015 for Subansiri River basin.....	93
Fig.4.13	Trend showing variation of discharge w.r.t snow cover area for the month (a) January, (b) April, (c) July and (d) October.....	94
Fig.5.1	Parallelepiped Classification.....	100
Fig.5.2	Minimum distance to mean classification.....	101
Fig.5.3	Maximum likelihood classification.....	102
Fig.5.4	Pie diagrams showing percent of total area covered by different LULC classes in the Brahmaputra River basin from 2002 to 2012 for the month of January.....	106
Fig.5.5	Trends showing percent of total area covered by different LULC classes for the Brahmaputra River basin from 2002 to 2012 for the month of January.....	107
Fig.5.6	LULC maps of the Brahmaputra River basin for the month of January from 2002 to 2012.....	108
Fig.5.7	LULC change in the Brahmaputra River basin during 2002to 2012 for January.....	110
Fig.5.8	Pie diagrams showing percent of total area covered by different LULC classes in the Brahmaputra River basin from 2002 to 2012 for the month of April.....	111
Fig.5.9	Trends showing percent of total area covered by different LULC classes for the Brahmaputra River basin from 2002 to2012 for the month of April.....	112
Fig.5.10	LULC maps of the Brahmaputra River basin for the month of April from 2002 to 2012.....	113
Fig.5.11	LULC change in the Brahmaputra River basin during 2002 to 2012 for April.....	115
Fig.5.12	Pie diagrams showing percent of total area covered by different LULC classes in the Brahmaputra River basin from 2002 to 2012 for the month of October.....	116
Fig.5.13	Trends showing percent of total area covered by different LULC classes for the Brahmaputra River basin from	

	2002 to 2012 for the month of October.....	117
Fig.5.14	LULC maps of the Brahmaputra River basin for the month of October from 2002 to 2012.....	118
Fig.5.15	LULC change in the Brahmaputra River basin during 2002 to 2012 for October.....	119
Fig.5.16	Pie diagrams showing percent of total area covered by different LULC classes in the Subansiri River basin from 2002 to 2012 for the month of January.....	121
Fig.5.17	Trends showing percent of total area covered by different LULC classes for the Subansiri River basin from 2002 to 2012 for the month of January.....	122
Fig.5.18	LULC maps of the Subansiri River basin for the month of January from 2002 to 2012.....	123
Fig.5.19	LULC change in the Subansiri River basin during 2002 to 2012 for January.....	124
Fig.5.20	Pie diagrams showing percent of total area covered by different LULC classes in the Subansiri River basin from 2002 to 2012 for the month of April.....	126
Fig.5.21	Trends showing percent of total area covered by different LULC classes for the Subansiri River basin from 2002 to 2012 for the month of April.....	127
Fig.5.22	LULC maps of the Subansiri River basin for the month of April from 2002 to 2012.....	127
Fig.5.23	LULC change in the Subansiri River basin during 2002 to 2012 for April.....	129
Fig.5.24	Pie diagrams showing percent of total area covered by different LULC classes in the Subansiri River basin from 2002 to 2012 for the month of October.....	130
Fig.5.25	Trends showing percent of total area covered by different LULC classes for the Subansiri River basin from 2002 to 2012 for the month of October.....	131
Fig.5.26	LULC maps of the Subansiri River basin for the month of October from 2002 to 2012.....	132
Fig.5.27	LULC change in the Subansiri River basin during 2002 to 2012 for October.....	134
Fig.6.1	Map showing the APHRODITE's points over the Subansiri catchment taken for the study.....	140
Fig.6.2	Artificial neuron showing its functions.....	145

Fig.6.3	ANN structure for downscaling of rainfall.....	147
Fig.6.4	Calibration and validation graphs for (a) multiple linear regression and(b) multiple non-linear regression at the APHRODITE point 91.875°E; 28.625°N for the GCM that falls inside the study area.....	155
Fig.6.5	Calibration and Validation graphs for (a) multiple linear regression and (b) multiple non linear regression at the APHRODITE point 91.875°E; 28.625°N for the weighted average of all the GCMs.....	156
Fig.6.6	Regression plots for (a)Training, Validation and Testing for the ANN model at the APHRODITE point 91.875°E; 28.625°N.....	157
Fig.6.7	Historical and future rainfall at four different APHRODITE points.....	165
Fig.6.8	Trends showing change in average rainfall over the Subansiri catchment for different time steps.....	165
Fig.6.9	Spatial variation of total rainfall for different time steps over the Subansiri basin.....	166
Fig.6.10	Spatial variation of rainfall over the Subansiri basin during the wet months for different time steps.....	168
Fig.6.11	Spatial variation of rainfall over the Subansiri basin during the months with moderate rainfall for different time steps.....	170
Fig.6.12	Spatial variation of rainfall over the Subansiri basin during the dry months for different time steps.....	171
Fig.7.1	Soil map for the Subansiri River basin.....	177
Fig.7.2	The eleven sub-catchments of the Subansiri basin delineated in ILWIS software.....	178
Fig.7.3	ANN structure for rainfall-runoff model (open loop).....	180
Fig.7.4	NARX neural network (closed loop).....	181
Fig.7.5	Methodology for surface runoff estimation (SCS Model).....	185
Fig.7.6	Flowchart showing the methodology adopted to simulate future runoff.....	189
Fig.7.7	Sub-catchment wise changes in rainfall trends for the period 2020-39.....	190
Fig.7.8	Sub-catchment wise changes in rainfall trends for the period 2040-59.....	191
Fig.7.9	Sub-catchment wise changes in rainfall trends for the period 2060-79.....	192
Fig.7.10	Sub-catchment wise changes in rainfall trends for the period 2080-99.....	192
Fig.7.11	Trends showing future rainfall from 2020-99 at different sub-catchments of the Subansiri basin.....	193
Fig.7.12	Regression plot for ANN based rainfall-runoff model.....	194
Fig.7.13	Bar diagrams representing the runoff of Subansiri river for different time steps as obtained from ANN based rainfall-runoff model.....	195

Fig.7.14	Trends showing future runoff simulated by ANN based rainfall-runoff model for different time periods.....	196
Fig.7.15	Curve number maps of Subansiri Basin from 2002 to 2012.....	197
Fig.7.16	Curve number maps of eleven sub-catchments of the Subansiri Basin for the year 2005.....	199
Fig.7.17	Regression plot for ANN-SCS based hybrid model.....	202
Fig.7.18	Future runoff obtained from Scenario1.....	203
Fig.7.19	Future trends of runoff of the Subansiri River generated under scenario 1 for different time steps.....	204
Fig.7.20	Future runoff obtained from Scenario2.....	205
Fig.7.21	Future trends of runoff of the Subansiri River generated under scenario 2 for different time steps.....	205
Fig.7.22	Future runoff obtained from four different sub-scenarios under the Scenario3.....	207
Fig.7.23	Future runoff trend analysis of the Subansiri River for the period 2020-39 under four different sub-scenarios.....	207
Fig.7.24	Future runoff trend analysis of the Subansiri River for the period 2040-59 under four different sub-scenarios.....	208
Fig.7.25	Future runoff trend analysis of the Subansiri River for the period 2020-39 under four different sub-scenarios.....	208
Fig.7.26	Future runoff trend analysis of the Subansiri River for the period 2080-99 under four different sub-scenarios.....	209
Fig.7.27	Future runoff trend analysis of the Subansiri River for the period 2020-99 under four different sub-scenarios.....	209
Fig.8.1	Capacity-Area-Elevation curves:(a) elevation vs. capacity, (b) elevation vs. area and (c) area vs. capacity.....	221
Fig.8.2	Future power obtained at different time steps for the SLHEP under the Scenario 1.....	224
Fig.8.3	Trend analysis of future power potential of SLHEP under the Scenario 1.....	224
Fig.8.4	Future power obtained at different time steps for the SLHEP under the Scenario 2.....	225
Fig.8.5	Trend analysis of future power potential of SLHEP under the Scenario 2.....	226
Fig.8.6	Future power obtained at different time steps for the SLHEP under the Scenario 3.....	227
Fig.8.7	Future power obtained for SLHEP for each time period under the four sub-scenarios.....	

		228
Fig.8.8	Trends showing power potential of SLHEP for the four different sub-scenarios under Scenario 3 for 2020-39.....	229
Fig.8.9	Trends showing power potential of SLHEP for the four different sub-scenarios under scenario 3 for 2040-59.....	229
Fig.8.10	Trends showing power potential of SLHEP for the four different sub-scenarios under scenario 3 for 2060-79.....	230
Fig.8.11	Trends showing power potential of SLHEP for the four different sub-scenarios under scenario 3 for 2080-99.....	230
Fig.8.12	Trends showing power potential of SLHEP for the four different sub-scenarios under scenario 3 for 2020-99.....	231



List of Tables

Table No.	Title	Page No.
Table 3.1	Geographic coordinates of HadCm3 GCM points that fall in and around the upper portion of the Brahmaputra catchment.....	58
Table 3.2	Snow Cover Area and temperature for different months.....	65
Table 3.3	Snow Cover Area and discharge for different months.....	73
Table 4.1	Spatial extent of the SRTM DEM datasets used to delineate Subansiri basin.....	80
Table 4.2	Geographic coordinates of the GCM points.....	81
Table 4.3	Snow Cover Area and temperature for different months for Subansiri River basin.....	86
Table 4.4	Snow Cover Area and discharge for different months for Subansiri.....	93
Table 5.1	Area covered by different LULC classes in Brahmaputra basin for the month of January from 2002 to 2012.....	105
Table 5.2	Year wise Changes in Brahmaputra basin for different LULC classes from 2002 to 2012 for the month of January.....	108
Table 5.3	Area and amount of change in different LULC categories in the Brahmaputra basin during 2002 to 2012 for the month of January.....	109
Table 5.4	Area covered by different LULC classes in Brahmaputra basin for the month of April from 2002 to 2012.....	111
Table 5.5	Year wise Changes in Brahmaputra basin for different LULC classes from 2002 to 2012 for the month of April.....	113
Table 5.6	Area and amount of change in different LULC categories in the Brahmaputra basin during 2002 to 2012 for the month of April.....	114
Table 5.7	Area covered by different LULC classes in Brahmaputra basin for the month of October from 2002 to 2012.....	116
Table 5.8	Year wise Changes in Brahmaputra basin for different LULC classes from 2002 to 2012 for the month of October.....	118
Table 5.9	Area and amount of change in different LULC categories in the Brahmaputra basin during 2002 to 2012 for the month of October.....	119
Table 5.10	Area covered by different LULC classes in Subansiri basin for the month of January from 2002 to 2012.....	120
Table 5.11	Year wise Changes in Subansiri basin for different LULC Classes from 2002 to 2012 for the month of January.....	123
Table 5.12	Area and amount of change in different LULC categories in the Subansiri basin during 2002 to 2012	

	for the month of January.....	124
Table 5.13	Area covered by different LULC classes in Subansiri basin for the month of April from 2002 to 2012.....	125
Table 5.14	Year wise Changes in Subansiri basin for different LULC Classes from 2002 to 2012 for the month of April.....	128
Table 5.15	Area and amount of change in different LULC categories in the Subansiri basin during 2002 to 2012 for the month of April.....	128
Table 5.16	Area covered by different LULC classes in Subansiri basin for the month of October from 2002 to 2012.....	130
Table 5.17	Year wise Changes in Subansiri basin for different LULC classes from 2002 to 2012 for the month of October.....	133
Table 5.18	Area and amount of change in different LULC categories in the Subansiri basin during 2002 to 2012 for the month of October.....	133
Table 6.1	Geographical coordinates of the 24 APHRODITE's points.....	139
Table 6.2	Distance in km from rainfall points to the GCM points.....	142
Table 6.3	Weights calculated for APHRODITE's and GCM points.....	143
Table 6.4(a)	Correlation coefficient values between predictors and predictand when climatic parameters of one GCM point are taken (from Sl. No. 1 to 12 APHRODITE's points).....	149
Table 6.4(b)	Correlation coefficient values between predictors and predictand when climatic parameters of one GCM point are taken (from Sl. No. 13 to 24 APHRODITE's points).....	150
Table 6.5	Predictors selected for the APHRODITE's points.....	151
Table 6.6(a)	Correlation coefficient calculated by taking weighted average of the four GCM points for APHRODITE's points 1-12.....	152
Table 6.6(b)	Correlation coefficient calculated by taking weighted average of the four GCM points for APHRODITE's points 13-24.....	153
Table 6.7	Predictors selected for the APHRODITE's points.....	154
Table 6.8	R^2 values determined for regression and ANN methods.....	158
Table 6.9	MAE for each APHRODITE's point for linear regression, non-linear regression and ANN.....	159
Table 6.10	MSE for each APHRODITE's point for linear regression, non-linear regression and ANN.....	160
Table 6.11	RMSE for each APHRODITE point for linear regression, non-linear regression and ANN.....	161
Table 6.12	Average values of MSE, MAE and RMSE.....	162

Table 7.1	Soil types as per USDA NRCS and their description.....	177
Table 7.2	Division of soil types according to Hydrologic Soil Group.....	177
Table 7.3	Properties of the eleven sub-catchments of the Subansiri Basin.....	179
Table 7.4	Classification of Antecedent Moisture Conditions.....	184
Table 7.5	Hydrologic Soil Group.....	184
Table 7.6	Different land use/land cover scenarios created.....	188
Table 7.7(a)	CNI values for each sub-catchment for the Scenario1.....	200
Table 7.7(b)	CNII values for each sub-catchment for the Scenario1.....	200
Table 7.7(c)	CNIII values for each sub-catchment for the Scenario1.....	201
Table 7.8	CN values for each sub-catchment for each of the sub-scenarios under the Scenario2.....	201
Table 7.9	R values for the two different runoff simulation models.....	210
Table 8.1	Power in MW obtained for different scenarios.....	223



Symbols

$x_1, x_2, \dots, x_n$	Predictors
$\beta_1, \beta_2, \dots, \beta_n$	Regression parameters
A_t	Reservoir area in Mm^2
Q_t	Reservoir inflow during the period t
R_m	Minimum downstream release
$R_{t\ max}$	Maximum release in time t
R_t	release required in the period t to generate the specified power corresponding to the net head
S_d	Storage capacity of the reservoir at MDDL
S_{max}	Storage capacity of the reservoir at FRL
S_t	Storage in Mm^3 at the beginning of the period t
S_{t+1}	Storage in Mm^3 at the end of the time period t or beginning of time period t+1
Δw_{ij}	Change in weights
CNI, CNII, CNIII	Curve Number I, Curve Number II, Curve Number III
d	Number of delays
F	cumulative infiltration after runoff begins (mm)
H_t	Net head in m in period t
I_a	Initial abstraction before runoff (mm)
m	Momentum coefficient
P	Total precipitation (mm)
P	Power in MW
$p_1, p_2, \dots, p_n$	Model parameters
Q	Direct runoff (mm)
$q_1, q_2, \dots, q_n$	Model parameters
R	Coefficient of correlation
$r_1, r_2, \dots, r_n$	Model parameters
R^2	Coefficient of determination
R_t	Release to penstock in Mm^3 in period t
S	Potential maximum retention (mm)
x(t)	Inputs
Y	The independent variable, precipitation
y(t)	Series to be predicted (runoff)
η	Plant efficiency
λ	Initial abstraction (ratio) coefficient.
ε	Error



Abbreviations

µm	Micrometer
a.s.l.	Above Sea Level
AAR	Accumulation Area Ratio
AMC	Antecedent Moisture Content
ANFIS	Adaptive Neural Fuzzy Inference System
ANN	Artificial Neural Network
AOGCM	Atmosphere-Ocean General Circulation Model
APHRODITE	Asian Precipitation Highly Resolved Observational Data
AR3	Third Assessment Report
AR4	Fourth Assessment Report
ACRU	Agricultural Catchments Research Unit
ARX	Linear Autoregressive
ASTER	Advanced Spaceborne Thermal Emission and Reflection
ASVT	Application systems verification and transfer
AVCS	Advanced Vidicon Camera System
AVHRR	Advanced Very High Resolution Radiometer
BatNN	Bat Neural Network
BP	Back propagation
BS	Bare soil
CGCM2	Coupled Global Climate Model Version 2
CGCM3	Coupled Global Climate Model Version 3
CN	Curve Number
CO ₂	Carbon dioxide
CRCM	Canadian regional Climate Model
CVP	Cost Volume Profit
DEM	Digital Elevation Model
DHSVM	Distributed Hydrology-Soil Vegetation Model
DP	Dynamic Programming
DPFRB	Dynamic Programming Fuzzy Rule-Based
DV	Dense vegetation
dwsf	Downward short-wave flux
E	East
ECHAM	European Centre-Hamburg
ELA	Equilibrium Line Altitude
EOS	Earth Observing System

ESSA	Environmental Science Service administration
ETM	Enhanced Thematic Mapper
FCC	False Color Composite
FFLP	Fully Fuzzy Linear Programming
Fig.	Figure
FRB	Fuzzy Rule-Based
FRL	Full Reservoir Level
GCM	General Circulation Models
GIS	Geographical Information System
GLOFs	Glacier lake outburst floods
Govt.	Government
GP	Genetic Programming
GROS	General Reservoir Operation System
HadCM3	Hadley center Coupled Model version 3
HadRM3	U.K. Met Office Hadley Centre's Regional Climate Model
hdf	Hierarchical Data Format
HIRLAM	High resolution Limited Area Model
HKH	Himalaya Karakoram Hindu-Kush
HRU	Hydrologic Response Unit
HSG	Hydrologic Soil Group
HSPF	Hydrological Simulation Program-Fortran
Hur850	Relative humidity at 850 hPa
hurs	Near surface relative humidity
IHACRES	Identification of Unit Hydrographs and Component Flows
ILWIS	Integrated Land and Water Information System
img	Image file
IPCC	Intergovernmental Panel on Climate Change
IRS	Indian Remote Sensing
ISODATA	Iterative Self-Organizing Data Analysis Technique
JULES	Joint UK Land Environment Simulator
KBC	Knowledge Base Classification
km	Kilometer
LAC	Land Absorption Coefficient
LCR	Land Consumption Rate
LHS	Left hand side
LISEM	Limburg Soil Erosion Model
LISS	Linear Imaging Self Scanning Sensor
LM-FFNN	Levenberge- Marquardt algorithm based feed forward neural networks

LP	Linear Programming
LPJmL	Lund-Postdam-Jena managed Land
LSVI	Land Surface Vegetation Index
LULC	Land use/land cover
LV	Light vegetation
m	Meter
MAD	Multivariate Alteration Detection
MAE	Mean Absolute Error
MARMA	Multivariate Auto Regressive Moving Average
MCM	Million cubic meter
MDDL	Maximum Draw Down Level
MILP	Mixed Linear Programming
MLC	Maximum Likelihood Classifier
MLP	Multilayer Perception
mm	Millimeter
MNDWI	Modified Normalized Difference Water Index
MODIS	Moderate Resolution Imaging Spectroradiometer
MOEA	Multi-objective Evolutionary Algorithm
MOGA	Multi-objective Genetic Algorithm
MRI/JMA	Japan Meteorological Agency
MSE	Mean Square Error
mslp	Air pressure at sea level
MSS	Multispectral Scanner
MW	Mega Watt
MWL	Maximum Water Level
N	North
NARX	Non-linear autoregressive with External (Exogenous) Input
NASA	National Aeronautics and Space Administration
NCAR	National Centre for Atmospheric Research
NCEP	National Centre for Environmental Prediction
NCVP	Northern California Central Valley Project
NDSI	Normalized Difference Snow Index
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index (NDWI)
NE	Northeast
NEH	National Engineering Handbook
NIR	Near Infrared
NLP	Non-linear Programming

NLPM	Non-linear Perturbation Model
NOAA	National Oceanographic and Atmospheric Administration
NOHRSC	National Operational Hydrologic Remote Sensing Center
NRCS	National Resource Conservation Service
NRSA	National Remote Sensing Agency
NSE	Nash–Sutcliffe efficiency
NSIDC	National Snow and Ice Data Center
NW	Northwest
PAN	Panchromatic
RACMO	Dutch Regional Atmospheric Climate Model
RCM	Regional Climate Model
RegCM3	U.S. Regional Climate Model Version 3
REMO	German Regional Climate Model
RHS	Right hand side
RIHN	Institute for Humanity and Nature
RMSE	Root Mean Square Error
RS	Remote Sensing
S	South
S ₂₁ , S ₂₂ , S ₂₃ , S ₂₄	Sub-scenario 1, 2, 3 and 4 under scenario 2
S ₃₁ , S ₃₂ , S ₃₃ , S ₃₄	Sub-scenario 1,2,3 and 4 under scenario 3
SAC-SMA	Sacramento Soil Moisture Accounting Model
SAR	Synthetic Aperture Radar
SCA	Snow Cover Area
SCS-CN	Soil Conservation Service Curve Number
SDP	Stochastic Dynamic Programming
SDSM	Statistical Downscaling Model
SE	Southeast
SLHEP	Subansiri Lower Hydroelectric Project
SMMR	Scanning Multispectral Microwave Radiometer
SNOWMOD	Snowmelt Model
SOI	Survey of India
SOP	Standard Operation Policy
SPOT	Satellite Pour l'Observation de la Terre
SRES	Special Report of Emission Scenario
SRI	Shuttle Imaging Radar
SRTM	Shuttle Radar Topography Mission
SSA	Singular Spectrum Analysis
SSM/I	Special Sensor Microwave/Imager

SSVM	Smooth Support Vector Machine
STS	Simple Time Series
SVM	Support Vector Machine
SW	Southwest
SWAT	Soil and Water Assessment Tool
SWB	Surface water bodies
SWIR	Shortwave infrared
ta500	Air temperature at 500 hPa
tansig	Tan-sigmoid transfer function
THR	Trans Himalayan Region
TIROS	Television Infrared Observation Satellite
TM	Thematic Mapper
USDA	United States Department of Agriculture
VCC	Vegetative Cover Conversion
VHRR	Very High Resolution Radiometer
VIC	Variable Infiltration Capacity
W	West
WGS	World Geodetic System
XAJ	Xinjiang
zg200	Geopotential height at 200 hPa
zg500	Geopotential height at 500 hPa



CHAPTER 1

INTRODUCTION

1.1 General

With an average annual discharge of $19,830 \text{ m}^3/\text{s}$, River Brahmaputra ranks fourth among the large rivers of the world (Goswami, 1998). The river is a trans-Himalayan river as it rises in south Tibet from the glaciers of Mount Kailash at an elevation of about 5150m above sea level (a.s.l) at $30^{\circ}31' \text{N}$ and $82^{\circ}10' \text{E}$ (Burred et al., 1934; Dhar and Nandargi, 2000). The Brahmaputra River basin with an approximate area of 651,334 sq.km., covers four countries: China (50.5%), India (33.6%), Bangladesh (8.1%) and Bhutan (7.8%) (IUCN, 2014). Its basin in India is shared by Arunachal Pradesh (41.88%), Assam (36.33%), Nagaland (5.57%), Meghalaya (6.10%), Sikim (3.75%) and West Bengal (6.47%) (Singh et al., 2004). The basin lies between 23°N to 32°N latitude and 82°E to $97^{\circ}5' \text{E}$ longitude. The Brahmaputra basin is highly influenced by monsoon rainfall (Mirza, 2002). Most part of the runoff of the Brahmaputra river is because of the heavy rainfall of 510 cm-640 cm in the Abor and Mishmi hills in Arunachal Pradesh and 250-510 cm in the Brahmaputra plains (Murthy, 1981).

The rivers originating from the Himalayas experience two high-water seasons, one in early summer caused by snowmelt in the mountains, and one in late summer caused by runoff from monsoon rains. Thus, apart from heavy rainfall, the streamflow of the Brahmaputra River is also strongly influenced by the snow and ice melting in the upstream parts of the basin. The Brahmaputra River receives a substantial amount of snowmelt runoff into its annual streamflow (Singh et al., 1994a, 1997a). Eastern Himalaya ranges are the main source of glaciers that contribute to the discharge of Brahmaputra River. The elevation of the Tibetan plateau that falls under Brahmaputra basin varies between 3000-5000m a.s.l. with numerous glaciers covering the plateau (Singh et al., 2004). According to Immerzeel et al., (2008), Tibetan Plateau alone covers 44.4% of the total basin area, thus contributing more to the snowmelt runoff of the river. The snow and glacier melt contribution compared to total runoff has been estimated to be about 27% for Brahmaputra River (Immerzeel et al., 2010).

Global climate change has substantially increased the atmospheric concentration of carbon dioxide and other trace gases over the last century. It is expected that the concentration of carbon dioxide will be double by the middle or latter part of the next century (NAs, 1979;

Pearman, 1980; IPCC, 1995; Houghton et al., 2001; Kamga, 2001). It is obvious that, global warming caused by increased atmospheric concentration of carbon dioxide and other trace gases will alter the radiation balance of the atmosphere. This in turn will cause increases in temperature and changes in precipitation pattern and other climatic variables (Changchun et al., 2008). Higher greenhouse gas concentrations have trapped more thermal radiation and consequently warmed the planet (IPCC, 2007). In its Fifth Assessment Report, the Intergovernmental Panel on Climate Change reported that averaged combined land and sea surface temperature warmed between 0.65°C and 1.06°C from 1880 to 2012 (IPCC, 2013). As reported by the NASA Goddard Institute for Space Studies in January 2013, 2012 was the ninth-warmest year since 1880, and except for 1988, the nine warmest years in the 132-year record have all been since the year 2000. The year 2005 was the hottest year on record (GISS, 2013). Again, the precipitation is expected to increase under global warming at high latitudes and in the vicinity of the equator, but decreases in the subtropics (Watterson and Whetton, 2011). The GCMs can be used to simulate the present day and projected future climate conditions under different scenarios. However, the GCMs perform reasonably well at large spatial scales and perform poorly at the smaller space and time scales relevant to local and regional impact analyses. Various downscaling techniques have been developed to overcome this limitation of the GCMs. These are dynamic downscaling, statistical downscaling and downscaling using Artificial Neural Network. The statistical downscaling technique has been used extensively because of its less computational time.

Snow cover which is a crucial hydrological parameter in global water cycle and an important ingredient of the cryosphere, is considered as an active and multivariate part of the climate system. Snow is a sensitive indicator of climate (Foster et al., 1982; Namias, 1985; Gleick, 1987) and hence, seasonal snow is considered as an important part of Earth's climate system. In terms of area, snow cover is the single largest component of the cryosphere, covering an average of 46 million sq.km. of the Earth's surface each year and out of this, about 98 percent of the Earth's snow cover is located in the Northern Hemisphere (Brodzic and Armstrong, 2013). Because snow is highly reflective in nature, a vast amount of sunlight that hits the snow is reflected back into space instead of warming the planet. About 80-90% of incoming solar energy is reflected by snow cover whereas only 10-20% of solar energy is reflected by snow-free surfaces such as soil or vegetation. Without snow, the ground absorbs more sun's energy adding heat to the system, thereby causing even more snow to melt. Thus, surface temperature is highly dependent on the presence or absence of snow cover, and temperature

trends have been linked to changes in snow cover (Groisman et al., 1994). Studies on snow cover area indicated that in some regions, the snow cover area has been decreasing since 1980's (Groisman et al., 1994; Frei and Robinson, 1999) with rising temperature, whereas in some other regions snow cover area has been increasing with increasing temperature (Ke and Li, 1998) which gives an idea of existence of regional disparity.

Climate change is likely to lead to an intensification of the global hydrological cycle and to have a major impact on regional water resources (Arnell, 1999). Among the major river systems, the impact of climate change on the hydrological behavior of the Ganges-Brahmaputra Basin is expected to be particularly strong. As the Brahmaputra Basin is highly influenced by the monsoon rainfall, the climate change that results in variation in intensity of the monsoon, will affect both high and low flows leading to increased flooding and variability of available water both in space and time (Postel et al., 1996) in the basin. Himalayas are called the reservoirs of snow and glaciers. The ice mass over this region is the third-largest on the earth, after the Arctic/Greenland and Antarctic regions (Immerzeel, 2007). Bernett et al., (2005) indicated that Himalaya is perhaps the most critical area, where melting of snow and glaciers will negatively affect water supply in the next few decades, because of the region's high population. In this region, the increase in temperature will accelerate snow and glacial melt which in turn will increase water availability. According to Frauenfelder and Kaab (2009), total glacier area in the upper Brahmaputra River basin has been decreasing by 7% to 10% per decade from 1970/80 to 2000. Another study carried out by Bolch et al., (2010) for five glaciers in the south-eastern centre of the Tibetan Plateau, which feeds into the Tsangpo-Brahmaputra River revealed that glaciers in this area had been retreating at a rate of around 10m/year for the period 1976 to 2009. The increased rates of snow and glacial melt will increase summer flows in the river for a few decades, followed by a reduction in flow as the glaciers disappear and snowfall diminishes (Immerzeel, 2008). Brahmaputra River is most susceptible to reductions of flow, threatening the food security of an estimated 26 million people (Immerzeel et al., 2010).

During its course, the river Brahmaputra is joined by important tributaries from the Himalayan ranges of Arunachhal Pradesh and Bhutan in the north viz., Subansiri, Kameng, Dhansiri and Manas and from the south by Dihing, Disang, Dikhou and Kopili (Dhar and Nandargi, 2000). Out of these tributaries, the river Subansiri is considered as the major north bank tributary of the river Brahmaputra which contributes around 10% of the total annual discharge of Brahmaputra. Subansiri River flows through Tibet for 170 km, 250 km through

Arunachal Pradesh after which it enters Assam at Dulangmukh in Dhemaji district and flows for another 130 km through the plains of Assam before it joins the River Brahmaputra near Jamugurighat in Assam. During the long journey, Subansiri receives the discharges of numerous mountainous streams. The number of its tributaries is more in Siwalik foothills than in other zones. The total length of known and well-defined tributaries of Subansiri is 1,960 km (Sarkar, 2015). Subansiri basin is the largest river system of Arunachal Pradesh which covers more than 19,000 sq.km. in the central part of the State. The catchment area of Subansiri River is spread out further than the grand Himalayan mountain ranges, covering Tsona Dzong till the Great Loop of the Tsang Po River in Tibetan Territory. The entire Subansiri basin can be divided into four parts (Sarkar, 2015). These are, (i) the distant Tibetan mountains beyond the international border, (ii) the reach lying between the international boundary and Miri hills of Arunachal Pradesh, (iii) the Arunachal Pradesh portion between the outskirt of Miri hills and the inter-state boundary of Assam and Arunachal Pradesh and (iv) the plains of Assam. Out of these four parts, the first two belong to the great Himalayan range, the third belongs to the Sub-Himalayan and the fourth belongs to the fertile plains of Assam. It is evident from these categories that the upper part of Subansiri basin falls in the Himalayas and hence is covered with Himalayan snow and glaciers. Due to global warming this snow cover area of the basin changes which leads to the change in runoff of Subansiri River in its downstream. The heavy precipitation also strongly influences the discharge of the river. Subansiri basin extends from tropical to temperate zones and hence exhibits a great diversity in rainfall characteristics. In the Northern and Central Himalayan tracts, precipitation is scarce on account of high altitudes. On the other hand, Southeast part of the Subansiri basin comprising the sub-Himalayan and the plain tract in Arunachal Pradesh and Assam, lies in the tropics. Due to Northeast as well as Southwest monsoon, precipitation occurs in this region in abundant quantities. Particularly, Southwest monsoon causes very heavy precipitation in the entire Subansiri basin during May to October. July and August are the high flood months (Sarkar, 2015).

Not only the effect of snowmelt and rainfall, the change in land use/land cover that is taking place in the Subansiri basin also influences the change in runoff of the river. Fohrer et al., (2001) mentioned that surface runoff is highly affected by land use/land cover changes over a watershed. Researchers have investigated the relationship between climate, land use and hydrological processes and their studies showed that stream flow generation capacity is also dependent on vegetation type (Dwarakish and Ganasri, 2015). The rapid growth in population

has led to change in land use in terms of deforestation for improving the agricultural production (Lorup et al., 1998). This leads to decrease in infiltration rate and increase in surface runoff. However, Ozturk et al., (2013) reported that influence of climate variability is more significant on surface hydrology than the land use change.

The Subansiri river system has its practical importance as it holds high water resources as well as hydropower potential for the country. The change in runoff of the river due to change in climate and land use/land cover will have impact on the performance of the Subansiri Lower Hydroelectric Project (SLHEP). It is one of the largest under construction hydropower projects in India with an installed capacity of 2000MW. As such, there is a need to study the impact of climate change on power potential of this hydropower project. There is a possibility that rapid accumulation of water in the glacial lakes in the upstream of the Brahmaputra basin can lead to a sudden breaching of the unstable dams behind which they have formed reservoirs. The resultant discharge of huge amounts of water would have catastrophic effects on people, both upstream and downstream. This will affect the discharge of the river Subansiri and thus the power potential of the Subansiri Lower Hydroelectric Project will be changed.

There are various hydrologic models ranging from lumped conceptual model to physically based distributed models which are in use worldwide, for flow forecasting of rivers based on meteorological data and catchment characteristics (Lorup et al., 1998). The physically based models take into consideration the physical characteristics of a watershed whereas the semi-distributed and fully-distributed models are capable of representing the spatial heterogeneity of the watershed (Dwarakish and Ganasri, 2015). Integration of land use models with the rainfall-runoff models provides quantitative information about the land use changes on hydrological output. Also, different land uses in different sub-watersheds yield different hydrological outputs (Lin et al., 2009).

1.2 Objectives of the thesis

Due to the trans-boundary nature, inaccessible upper basins and inadequate network of gauging stations, not many scientific studies on climate change and its impact on hydrology have been made in the rivers of eastern Himalayan region. No study has been found that considers the entire Brahmaputra River Basin to determine the snow cover area and its sensitivity to warming. Studies on Subansiri River Basin are also very limited. A realistic estimation of runoff due to snowmelt, rainfall, land use/land cover changes as well as due to

the global climate change is important for flood forecasting, reservoir operation, watershed management, water supply and design of hydrologic and hydraulic structures. The planning of the multipurpose projects in the Himalayan region further emphasizes the need for reliable estimates of runoff from precipitation, snow and glaciers.

Again, many researchers have evaluated the impact of land use change on runoff of different rivers by considering single climatic condition of the catchments. However, it is of much importance to analyze the flow scenario of a river under different land use characteristics and climatic conditions.

Keeping these factors in mind, the present study has been taken up with the following objectives:

- Study of snow cover area variation in the Brahmaputra and the Subansiri River Basins from 2002 to 2015 for four different months viz. January, April, July and October using Remote Sensing and GIS techniques.
- Impact of change in snow cover area on the discharges of the rivers Brahmaputra and Subansiri from 2002 to 2015 for the months of January, April, July and October.
- Land use/land cover change detection study of the Brahmaputra and the Subansiri River Basins from 2002 to 2012 for January, April and October using Remote Sensing and GIS techniques.
- Downscaling of rainfall in Subansiri River Basin at different locations using regression based statistical downscaling technique and Artificial Neural Network Model.
- Prediction of rainfall over the Subansiri Basin up to the year 2099 and its analysis for four different future time periods (2020-39, 2040-59, 2060-79 and 2080-99).
- Development of an ANN based rainfall-runoff model to study the impact of change in rainfall on the future flow scenario of the river Subansiri up to 2099.
- Development of an ANN-SCS based hybrid model by considering different land use/land cover scenarios to determine the future flow scenario of Subansiri River up to 2099.
- Impact of change in land use/land cover of the basin on the flow scenario of the river.
- Determination of future power potential of the Subansiri Lower Hydroelectric Project under different flow scenarios of Subansiri River.

1.3 Research Queries

- What is the impact of increase in global temperature on the change in snow cover/ glacial cover in the Brahmaputra and Subansiri basins?
- What is the impact of change in snow cover/ glacial cover on the flow scenarios of the rivers Brahmaputra and Subansiri?
- What is the impact of climate change on the snow cover variations in the Brahmaputra and Subansiri River Basins?
- How the change in climate is effecting the change in land use/land cover of the basins under study?
- What is the future rainfall pattern of the Subansiri Basin and how it will impact on the future flow scenario of the River Subansiri?
- How the change in land use land cover will affect the future flow scenario of Subansiri River?

1.4 Organization of the thesis

There are nine chapters in the thesis including the introductory chapter 1. In Chapter 2, works relevant to the present study, carried out by various researchers around the world, have been described in detail. These include, study on climate change and its effect on snow cover area, application of remote sensing and GIS on snow cover mapping and land use land cover change detection study, use of different hydrologic models to assess the impact of change in climate and land use on runoff of a river, GCMs and different approaches to downscale the GCM data and studies related to the reservoir operation by different models.

In Chapter 3, the snow cover area of the Brahmaputra River Basin has been determined by the Normalized Difference Snow Index (NDSI) method using MOD09A1.5 (MODIS/Terra Surface Reflectance 8-Day L3 Global 500m SIN Grid) MODIS data of 500m resolution from 2002 to 2015 in the months of January, April, July and October. The change in temperature over this basin has been analyzed using the HadCM3 GCM temperature data. A relation has been established between the change in snow cover area and change in temperature of the basin for the different months. The impact of change in snow cover area on the discharge of the river Brahmaputra has also been analyzed.

In chapter 4, different geomorphologic parameters of Subansiri River and its catchment have been determined in the ILWIS GIS software. With the same NDSI method used for the

Brahmaputra Basin, the snow cover area of the Subansiri Basin has been determined and the change in snow cover area with respect to the change in temperature has been analyzed. The change in discharge of the river Subansiri due to the change in the snow cover area has also been analyzed.

In Chapter 5, the land use/land cover change detection has been performed for both the Brahmaputra and the Subansiri River Basins using supervised classification technique and maximum likelihood classifier algorithm. The yearly variations as well as the decadal variations in land use/land cover have been analyzed for the basins starting from 2002 to 2012 for three different months viz. January, April and October.

In Chapter 6, the downscaling of rainfall has been performed for the Subansiri River Basin at 24 different APHRODITE rainfall points using both multiple linear and non-linear regression based statistical downscaling techniques and by Artificial Neural Network Model. Different HadCM3 GCM climatic parameters have been used as the predictors for the study. The best downscaling technique has been determined on the basis of mean absolute error, mean square error, root mean square error and coefficient of determination. Using the best method, the future rainfall over the Subansiri basin at all the 24 points have been determined and forecast accordingly for four different future time steps viz. 2020-39, 2040-59, 2060-79 and 2080-99.

In chapter 7, two ANN based models have been developed to study the future flow scenario of the river Subansiri. One, an ANN based rainfall-runoff model considering the rainfall as the input and the other, an ANN-SCS hybrid model where different land use/land cover scenarios are considered to study the impact of change in land use/land cover on the runoff of the Subansiri River. The simulated runoffs from both the models were then forecast for future four time periods, 2020-39, 2040-59, 2060-79 and 2080-99. These two models have then been compared for the better simulation of the runoff of the river.

Chapter 8 contains the future power potential study of the Subansiri Lower Hydroelectric Project. Considering the runoffs as simulated in Chapter 7 as the inflow to the reservoir, the power potential of SLHEP has been computed using reservoir simulation model. The power potential has been analyzed up to 2099 for the four different time steps and for different land use/land cover scenarios.

The summary, conclusions and the recommendations for future study are presented in Chapter 9.

CHAPTER 2

REVIEW OF LITERATURE

2.1 General

In recent years, numerous studies have investigated the impact of climate change on hydrology and water resources in many regions (Dunne et al., 2008). In the context of India, the three major river systems, the Indus, the Ganges and the Brahmaputra have their origins in the Himalayas and flow throughout the year though their flow significantly reduce during summer. The flows of these river systems are supplemented by Himalayan snow and glacier melts. The Himalayan region has shown consistent warming trends over the past 100 years (Yao et al., 2006). Global warming is accelerating the melting of glaciers in the Himalayas, which are melting faster than the global average (Dyurgerov and Meier, 2005). Because of this, the snow and glacier area in the region is gradually decreasing which contributes to the increase in discharge of the rivers at downstream. Along with the snowmelt water, the heavy precipitation over this region also contributes to the flow regime of the rivers. For the Brahmaputra river basin, the precipitation varies from a few 100 mm on the Tibetan plateau to more than 5000 mm in places along the southern Himalayan slopes in Arunachal Pradesh and Bhutan. Changes in glacier regimes and runoff from snow and ice, combined with changes in precipitation timing and intensity will most likely increase human vulnerability in many areas.

Watershed hydrology is also affected by vegetation types, soil properties, geology, terrain, climate, land use practices and spatial patterns of interactions of these factors. Several analyses show that increasing precipitation alone is not sufficient to explain increasing discharge trends in a watershed (Schilling and Libra, 2003; Raymond et al., 2008). Changes in land use that have accompanied climate change also affect changes in discharge. Both climate and land use changes are important drivers of changes in watershed hydrology and hence, distinguishing effects of land use changes and concurrent climate variability poses a particular challenge (Lioubimtseva et al., 2005; Tollan, 2002).

The studies related to the impacts of climate change on the runoff of a river, may be classified broadly into two categories: (i) Studies using GCMs directly to predict impact of climate

change scenarios (Sausen et al., 1994; Loaiciga et al., 1996), and (ii) studies using hydrological models with assumed plausible hypothetical climatic inputs (Chiew et al., 1995; Singh et al., 1997a). Although GCMs are considered as invaluable tools for identifying climatic sensitivities and changes in global climate characteristics, their application for studying the impact of climate change on the hydrological response on the basin scale is limited due to their poor spatial resolution. Usually, the output of GCMs is given for much larger scale than the scale of even a large watershed. Various downscaling techniques are available to overcome the spatial resolution limitation of the GCMs (Bardossy and Van Mierlo, 2000) and the two major techniques are the dynamic downscaling and statistical downscaling. Application of hydrological models on the other hand is a suitable approach for assessing the expected changes in the hydrological response due to changes in temperature and precipitation and other climatic variables as well as land use changes on the basin scale. The input variables to the hydrological models can be either hypothetical climate scenarios or the output of GCMs. The ability of hydrologic models to incorporate projected variations in climatic variables makes them attractive for climatic change impact studies related to water resources.

The streamflow of the Himalayan Rivers consists of contributions from melting of snow and ice, and rainfall-induced runoff. Data on precipitation, temperature and river flow are scarce because of inadequate hydro-meteorological network in the high altitude regions with rugged terrain and poor accessibility. A hydrological model, which can handle both snowmelt and rainfall runoff efficiently, using limited data, is considered most suited for the simulation of streamflow generated from the Himalayan basins.

2.2 Climate change and its significance

Accelerated change in climate is expected to have major impact on the future sustainability of the earth (Stern, 2006; McMullen and Jabbour, 2009). The main driving force is the increase in earth's temperature as a result of human activities which include greenhouse gas emissions. Increase in anthropogenic emissions of gases (e.g., carbon dioxide, methane) into the atmosphere, and an enhanced greenhouse effect are the major driving forces behind the accelerated global warming that has taken place over the last century (IPCC, 2007a,b). According to Intergovernmental Panel on Climate Change (IPCC), there is a possibility of temperature increase of 1.1°C to 6.4°C by 2100, due to which storms and floods will get affected and lead to rise in sea level because of the thermal expansion of the oceans and the

melting of ice sheets and glaciers (IPCC, 2007a). Vermer and Rahmstorf (2009) estimated a global sea level rise of between 50 cm and 190 cm from 1990 to 2100. The main factors responsible for climate change as given by McMullen and Jabbour (2009) includes the following:

- Variation of radiation emitted from the sun
- Cyclical behavior of the Earth's orbit and axis
- Change in the gas composition of the atmosphere
- Volcanism, uplifting and wearing away of land surfaces
- Shifting distribution of land masses caused by plate tectonics and
- Change in characteristics of the earth's land surface

Amongst the various impacts of climate change, the followings can be listed as the major ones:

- There will be a change in global moisture content and atmospheric water balance due to changes in the thermal properties of the Earth's atmosphere (McMullan and Jabbour, 2009).
- The intensity of storms will increase as the change to the global distribution of heat flows and atmospheric circulation patterns will influence the air flow systems and ocean currents (McCabe et al., 2001; Wang et al., 2008).
- Change in climate will lead to melting of glaciers and warming of ocean waters. The melting of ice will change the volume, temperature and salinity of the oceans (Arctic Climate Impact Assessment, 2005). Estimation has been made by IPCC (2007c) and it was found that, since 1993, melting of ice caps and glaciers contributed about 28% to sea level rise.
- Climate change will lead to the land movement and land subsidence (Peltier, 2004; Leys, 2009).

2.3 Remote sensing of snow

Snow is defined as the mixture of ice crystals, liquid water and air (Rees, 2006). The distribution and extent of snow in space and time is considered as an important parameter as it provides information on amount of water expected from snowmelt available for runoff and water supply (Salomonson and Appel, 2004). Snow cover area is a key element of hydrological and climatological studies. Measuring ongoing glacier decrease is a first step

towards the prediction of future water resources and thus, has important social and economical impacts (Barnett et al., 2005). Adverse impacts of snow include, death of livestock in deep snow, flooding caused by rapid snowmelt and crop failure due to soil temperature fluctuations (Zhang et al., 2010). Hence, snow cover monitoring is becoming very important in current earth observation studies. Before, the application of satellite remote sensing, the monitoring of snow cover was not an easy task for the researchers. Since the 1970s, snow cover monitoring from space has become a routine operation using satellite optical imagery (Matson et al., 1986).

2.3.1 Snow properties in the electromagnetic spectrum

The important regions of the electromagnetic spectrum used to study snow are, Visible, Near Infrared, Thermal Infrared and Microwave. The behavior of snow in these regions is briefly explained below:

➤ Visible and Near Infrared

The human eye is sensitive to the range of wavelengths from 0.4 to 0.65 μm and snow is highly reflective with little variation over this range (Rees, 2006). The reflectivity of snow depends upon its age in both the visible and infrared region of the spectrum *i.e.* the snow reflectivity decreases as it ages; however, the decrease is more pronounced in the infrared region. Typically, new snow will have an albedo of 90% or more and the older snow that has been weathered and accumulated snow and litter can have an albedo as low as 40% (Foster et al., 1987). Various snow characteristics like shape and size of snow crystals, liquid water content, impurities in the snow, depth of snow, surface roughness etc. influence the reflectivity of snow. Apart from these, the influence of solar elevation on spectral reflectance of snow is also very significant (Hall and Martinec, 1985). Decreasing reflectivity in the visible region can be attributed to the contaminants such as dust, pollen and aerosols. An advantage of using visible and near infrared data is the easy interpretation of the image.

➤ Thermal Infrared

The use of thermal data has been less than other remote sensing data for measurement of snow characteristics. In order to determine the snowpack temperature, the spectral emissivity of the snow must be known. This in turn requires the knowledge of liquid water content and the grain size as well as other factors. According to Rezaei (2004), thermal data are of great use to recognize the boundary between snowy zones and non snowy zones. Similar to visible and near infrared images, the usability of thermal infrared images is also limited by the cloud

cover. If there are clouds, temperature above them will be measured (Tekeli, 2005). The emissivity of snow approaches that of a black body at the 10.5-12.5 μm atmospheric window. Griggs (1968) has shown that melting snow can have an emissivity as high as 99%, whereas the emissivity of no-snow areas is typically 95% or less.

➤ Microwave

Microwave satellite imagery is also an important source for getting snow cover information. The main advantage is that, microwave radiation can penetrate clouds and most precipitation. Thus, it helps in providing all-weather observational capability (Schanda et al., 1983). In large catchments, microwave images have been used to analyze snow cover and depth. However, because of low spatial resolution, it prevents their usability in mountainous basins (Tekel, 2005). Unlike optical sensors, the microwave sensors can penetrate into snow and can obtain information about it. The passive microwave data are not limited by solar illumination or cloud cover and offer a higher resolution.

2.3.2 Mapping of snow extent from remotely sensed data

Due to difficult accessibility and hostile climatic conditions in the remote and mountainous areas, snow cover measurements are difficult and estimates are neither reliable nor cheap in such areas. Mapping of the extent of snow cover has been the principal operational use of remote sensing of snow properties. Snow by virtue of the high reflectivity is one of the objects on surface of the earth which is readily detected or identified on any visible or near IR remotely sensed image. The albedo of snow is higher in the visible region of the electromagnetic spectrum compared to most other natural surface cover. This is the reason for which snow cover area mapping was one of the first remote sensing applications (Tarble, 1963; Martinec, 1972). The aerial extent of snow can be determined through various remote sensing techniques. For example, Leaf (1969) used aerial photographs to establish a relationship between snow cover and accumulated runoff for few Colorado watersheds. Sequential photographs showing snow cover depletion were used to estimate the timing and magnitude of snowmelt peak. The launch of the Environmental Science Service administration (ESSA-3) satellite which carried the Advanced Vidicon Camera System (AVCS) and operated in the spectral range of 0.5-0.75 μm with a spatial resolution of 3.7 km helped in successful mapping of snow in the mid-1960s. Since 1966, the National Oceanographic and Atmospheric Administration (NOAA) have measured snow cover on weekly basis in the Northern Hemisphere using various sensors, including the Scanning Radiometer, Very High Resolution Radiometer (VHRR) and the Advanced Very High

Resolution Radiometer (AVHRR) (Matson et al., 1986; Matson, 1991). Development of sub-pixel analysis techniques (Gomes-Landesha, 1997) has allowed snow cover mapping on basins as small as 10 km² using the AVHRR data. The NOAA product is a daily snow cover product (Ramsay, 1998). The NOAA visible satellite based snow cover analysis since 1972 (Robinson, et al., 1993), Scanning Multispectral Microwave Radiometer (SMMR) and Special Sensor Microwave/Imager (SSM/I) data from 1978 can be used to derive information about extent of snow (Chang et al., 1987), depth (Foster et al., 1984) and snow water equivalence (Chang et al., 1991).

The major problem with NOAA-AVHRR data is that the spatial resolution of 1km is not sufficient for snow cover mapping of small basins. The spatial resolution of remotely sensed data is necessary to get accurate results from snow cover mapping (Rango et al., 1983). The NOAA dataset has also limitations in areas with persistent cloud cover, low solar illumination, dense forest, patchy snow and mountainous regions (Robinson et al., 1993). However, the relatively stable analysis methodology for over 25 years is one of the important characteristics of NOAA dataset for studying snow cover variability (Basist et al., 1996). Shafer and Leaf (1979) used Landsat imagery to determine snow cover areas for six basins in Colorado, USA, for the period 1973 to 1978. They found that Landsat satellite imagery was of sufficient quality to monitor snow cover area accurately. Brown et al., (1979) combined aircraft and landsat snow cover data to form a long-term database for predicting runoff from basins of California. Their results indicated a potential improvement in forecast accuracy by using snow cover area. NASA, in cooperation with several federal and state water resources agencies in the USA, conducted an application systems verification and transfer (ASVT) study on the effectiveness of satellite derived snow cover data for operational forecasting (Rango, 1980). Three years of testing in three California basins resulted in the reduction in the forecast errors of between 10 and 15%. Ostrem et al., (1981) developed a method for using NOAA and TIROS data for measuring the remaining snow and to predict the corresponding snowmelt runoff volume for a number of Norwegian high mountain basins. But, this method is applicable only when the area is vegetation-free and when roughly 20% of the basin is snow-free. As the capabilities for remote sensing of snow cover extent are more advanced and simpler, the remote sensing of snow depth and water equivalent has a very high potential.

2.3.3 MODIS data and its application in snow cover mapping

The MODIS (Moderate Resolution Imaging Spectroradiometer) is a 36- channel visible to thermal-infrared sensor that was first launched as part of the Earth Observing System (EOS) Terra payload on 18 December, 1999. A second MODIS was launched as part of the payload on the Aqua satellite on May 4, 2002. The MODIS products are available at a variety of spatial and temporal resolutions. Two channels in the visible and near-infrared spectral bands are available at 250m resolution, five channels in the visible, near-infrared and shortwave-infrared bands are available at 500 m resolution and the remaining 29 MODIS channels have a spatial resolution of 1 km. Most of the products are archived at the National Snow and Ice Data Center (NSIDC) in Boulder, CO.

The freely available MODIS snow products (Hall et al., 2002), with 500m spatial and daily temporal resolution can provide a basis for regional snow cover mapping and monitoring (Liang et al., 2008). Many researchers in different parts of the world tested the accuracy of MODIS snow products under clear sky conditions and shows a very higher agreement (overall agreement>93%) and they found overall accuracy of MODIS data to be between 85 and 99% (Hall and Riggs, 2007; Maurer et al., 2003). The main advantages of MODIS over AVHRR are,

- MODIS has onboard visible/near-infrared calibrators which enables some of the MODIS sensors to derive radiances of snow. AVHRR does not have such calibrators.
- At least one of the MODIS channels does not saturate over snow while, AVHRR and TM sensors experience significant saturation over snow and ice targets in visible channels.
- Obscuring of the ground by cloud cover and obscuring of snow cover by vegetation canopies are the two main difficulties in estimating snow cover area from AVHRR images. MODIS on the other hand gives better estimation of snow cover area due to better spectral resolution (36 MODIS bands compared to 5 on AVHRR) and higher spatial resolution of the daily gridded snow cover products (Hall et al.,1998).

Several studies have been conducted to determine the ability of MODIS to detect snow cover area. Prior to the launch of MODIS, Hall et al., (1998) and Klein et al., (1998), used a prototype of the MODIS SCA classification algorithm (SNOWMAP) to estimate the expected performance of the MODIS SCA product (Hall et al., 2000a). They used Landsat thematic mapper of 30m resolution data with the SNOWMAP algorithm to derive prototype SCA images. These prototype SCA images were then compared with NOHRSC (National

Operational Hydrologic Remote Sensing Center) snow maps and coarser scale SCA maps derived from the operational Special Sensor Microwave Imager (SSM/I) sensor. Their results showed that, the SNOWMAP algorithm applied to Landsat data provided a better overall representation of the total snow cover over four regions than did the NOHRSC and SSM/I snow maps. Maurer et al., (2000) identified significant improvement in SCA determination using MODIS product in the forested and topographically complex portions of the Columbia River basin. For this, they used ground observations of snow depth to evaluate differences between the MODIS SCA product and the operational NOHRSC images for few specific days during March to May, 2000.

Apart from the advantages, the main shortcoming in the MODIS SCA data is the high cloud obscuration which prevents its use in many applications. However, researchers have developed several methods to reduce the cloud cover pixels from the MODIS products. Such methods include, (i) combining Terra and Aqua MODIS data, (ii) Spatial filtering, (iii) Temporal filtering, (iv) eight days' maximum snow cover extent and (v) time series of thresholds of snow accumulation and melt. Most studies implemented the combination of both Terra and Aqua MODIS products to reduce cloud cover by considering the local crossing time difference between these two satellites (Gofurov and Bardossy, 2009; Parajka and Blöschl, 2008; Wang et al., 2008). By doing this, it is possible to have different cloud coverage within a difference of three hours (as local equatorial crossing time of Terra is 10:30 a.m. in a descending node and of Aqua is 1:30 p.m. in an ascending node).

Another procedure of reducing cloud cover pixels is the spatial filtering based on 4 or 8 neighboring pixels (Xie et al., 2009). However, in this process, there is a possibility of sacrificing some of the spatial resolution by replacing cloud pixels with the majority class of neighboring pixels (Gao et al., 2010). But, better spatial resolution can be maintained by using spatial filtering based on only orthogonal neighboring pixels (Gafurov and Bardossy, 2009). Snow cover products produced by compositing the daily images is used as a temporal approach to maximize the number of snow pixels and to minimize the number of cloud pixels (Gao et al., 2010; Liang et al., 2008; Riggs et al., 2006). Another approach used to reduce cloud pixels is the temporal filtering (Zhao and Fernandes, 2009) where the cloud pixel is replaced by the most recent preceding non-cloud observation at the same pixel.

Various researchers across the globe used MODIS data to study snow and glacier. Khosbayan et al., (2008) determined the yearly areal extent of glacier and snow coverage in Western part of Mongolia for June-August, 2006 using MODIS data MOD10A2 and MODIS's snow

product of 8-day temporal resolution. They used Normalized Difference Snow Index with K-means classification method to determine the snow cover area. They established the fact that MODIS snow products are easy to use and suitable for seasonal period of many year snow cover.

Anderson (2008), studied on a small section of ocean off shore of the United Kingdom and France using MODIS 250m cloud mask to determine the probability of glaciation. They found that for thicker clouds, temperature is a more important factor defining the glaciation level. They also found that thicker clouds reach glaciation at higher temperatures than thin clouds.

Chu et al., (2009) explored whether temporal variations in ice-sheet surface hydrology can be linked to the development of a downstream sediment plume in Kangerlussuaq Fjord by comparing (1) plume area and suspended sediment concentration from MODIS imagery and field data; (2) ice-sheet melt extent from Special Sensor Microwave/Imager (SSM/I) passive microwave data; and (3) supraglacial lake drainage events from MODIS. Their results confirmed that the origin of the sediment plume is meltwater release from the ice-sheet. They also concluded that remote sensing of sediment plume behavior offers a novel tool for detecting the presence, timing and inter-annual variability of meltwater release from the ice-sheet.

2.3.4 Himalayan glaciers and its study using remote sensing

Glaciers constitute an important component of the Himalaya which covers over 33,000 km² of area (Dyrgerov and Meier, 2005; Kaul, 1999). Melting of these huge glaciers may significantly contribute to the ongoing sea level rise and because of this, monitoring of glaciers has become very important (Kaser et al., 2006). Also, runoff generated by the melting of these glaciers is an important source of water for the people living in the Himalayan Valleys (WWF, 2005). In regions where the climate change signal is not clear, the change in glacier length, areal extent and mass balance can be used as climate indicators (Roy and Balling, 2005; Yadav et al., 2004). Due to size and remoteness of glaciers in Himalaya, satellite imagery is a suitable means to obtain comprehensive and more frequent sampling of their evolution (Bishop et al., 2000). Remote sensing studies in this region mainly aim at establishing digital glacier inventories to track the changes in glacier surface when compared to older map-based inventories (Kargel et al., 2005; Kaul, 1999). Rango et al., (1977) used simple photo interpretation techniques to map snow cover areas in the Indus and Kabul river basins in Pakistan. Kargel et al., (2005) and Wessels et al., (2002) used multispectral (in

particular ASTER) images to detect the growth of supra-glacial and moraine dammed lakes in the central and eastern Himalaya. Also, Ageta et al., (2000) studied the variations of such lakes in Bhutan using satellite imageries, photographs and maps.

SPOT images have been used to observe the surface features of Khumbu glacier, Nepal Himalaya (Seko et al., 1998) and Batura glacier in Pakistan (Bishop et al., 1995).

The advantage of the use of combination of ASTER and SRTM data to produce a synthetic digital elevation model (DEM) has been given by Kaab (2005). He used this synthetic DEM to map the dynamic behavior of glaciers in the northern and southern flanks of the main mountain ridge in Bhutan (East Himalaya) and the results were quite satisfactory.

Immerzeel et al., (2008) used various remote sensing products to identify the spatial and temporal trends in snow cover in river basins originating in the Himalayas and adjacent Tibetan-Qinghai plateau. Their study also proved that remote sensing allows detection of spatial-temporal patterns of snow cover across large areas in inaccessible terrain. Their results showed large variation in snow cover between years while an increasing trend from west to east was observed.

Glacier mapping from satellite multispectral image data is hampered by debris cover on glacier surfaces. To map the supra-glacial debris, Paul et al., (2004) developed a method by combining the advantages of automated multispectral classification for clean glacier ice and vegetation with slope information derived from ASTER DEM. They compared it to an ANN classification of debris using only multispectral data. They found that the combination with an ASTER-derived DEM revealed promising results compared to the ANN classification that was done without DEM data.

Considering the widespread retreating trend of the Himalayan glaciers, an attempt has been made by Phillip and Sah (2004) to employ high resolution Indian Remote Sensing satellite (IRS) data to (a) map distinct glacier landforms belonging to the Shaune Garang glacier, (b) comprehend different phases of glacial advance and retreat and (c) evaluate the utility of high resolution satellite data in glacier studies. High resolution IRS-1C/1D-LISS-III and Panchromatic (PAN) data had appeared to be useful to delineate glacier landforms that are indicative of glacier recession and advance in inaccessible terrain like the Himalaya.

Luckman et al., (2007) compared two techniques to measure flow rates in the Everest region glaciers. Using the examples of the Khumbu glacier flowing south into Nepal and the Kangshung glacier flowing east into China, they compared SRI and SAR feature tracking in ERS images. They examined the potential to monitor flow rates across the region. The

techniques were found to be highly complementary and appropriate for monitoring flow rates in this region, suggesting that routine monitoring of Himalayan glacier is possible.

Paudel and Anderson (2011) proposed a five successive steps approach- combining Terra and Aqua MODIS satellite data; adjacent temporal deduction; spatial filtering based on orthogonal neighboring pixels; spatial filtering based on a zonal snowline approach; and temporal filtering based on a zonal snow cycle to remove cloud obscuration from MODIS snow products as well as to examine the spatial and temporal variability of snow cover in Trans Himalayan region (THR) of Nepal. The proposed five-step method was found to be efficient in cloud reduction with average accuracy of > 91%. The results showed very high inter-annual and intra-seasonal variability of average snow cover, maximum snow extent and snow cover duration over the last decade.

Only few remote sensing studies addressed the crucial question of glacier mass balance till now. Kulkarni (1992) established a relationship between the specific mass balance and the accumulation area ratio (AAR) of the equilibrium line altitude for two glaciers (Gara and Gor-Gorang) in Himachal Pradesh. Assuming that the snow line at the end of the melting season indicates the ELA, Kulkarni et al., (2004) proposed to estimate the mass balance of these two glaciers using Landsat images. However, this relationship is different from one glacier to another. Berthier et al., (2007) used remote sensing data to monitor glacier elevation changes and mass balance in the Spiti/Lahaul region, Himachal Pradesh, Western Himalaya. They compared a 2004 DEM which was derived from two SPOT5 satellite optical images to the 2000 SRTM topography. Between 1999 and 2004, they obtained an overall specific mass balance of -0.7 to -0.85 m/a (water equivalent). The rate of ice loss was twice higher than the long-term (1977 to 1999) mass balance record for Himalaya indicating an increase in pace of glacier wastage. They concluded that future studies using a similar methodology could determine whether similar ice losses have occurred in other parts of the Himalaya and may allow evaluation of the contribution of this mountain range to ongoing sea level rise.

2.4 Climate change and its impact on snow/glacier

Mountain glaciers play an important role to detect and monitor climate change in regions not typically monitored by instrumentation (Haeberli et al., 2007). The rate of warming in lower troposphere increases with altitude *i.e.* temperature increases more in high mountains than at low altitudes (Bradley et al., 2004). Again, mountain areas exhibit a large spatial variation in climate zones due to large differences in altitude over small horizontal distances. These

conditions make mountain areas more vulnerable to climate change (Beniston et al., 1997). The change in climate and its impact on the extent of global snow covered and glacierized areas have been studied by many researchers around the world. Walcher (1773) was one of the first to propose the fact that glacier fluctuations are the result of variations in climatic conditions. Angstrom (1933) stressed on the importance of temperature, radiation and wind as agents for snow and glacier melting. Ahlmann (1935; 1948) derived the first empirical formula for the computation of ablation from known values of climatic parameters such as incident radiation, air temperature and wind velocity.

IPCC (2001a) reported that extent of snow cover has decreased by 10% since late 1960s. Long-term records on glacier fluctuation indicating retreat of mountain glaciers support the change in climate in the past century (Letreguilly and Reynaud, 1990). In contrast to this, some glaciers like Nigardsbreen (Norway) and Franz Josef Glacier (New Zealand) are in advancing trend (Oerlemans et al., 1998). However, an overall retreat of mountain glaciers has been observed in non-polar regions during the 20th century. According to Haeberli and Beniston (1998), the retreat extent of glacierization in the European Alps is reduced to 30-40%, whereas the volume of ice has been reduced by 50% since the middle of the past century. Dyurgerov (2002) reported that melting of glaciers will accelerate in continental regions, North America, South America, Central Asia, sub-polar glaciers and will contribute to sea level rise.

If glaciers continue to retreat this way, many small mountain glaciers will disappear within the 21st century (Nesje et al., 2008). However, within a region, small and large glaciers retreat/advance at different rates (Granshaw and Fountain, 2006; Fountain et al., 2009) and past retreat and advances of a glacier may not indicate how that glacier will change in the future. In addition, because of the fact that climate change within a region is not typically spatially uniform, similar glaciers in different basins within the same region may not experience identical changes (Shindell and Faluvegi, 2009).

In a western Canadian mountain range, De Beer and Sharp (2009) found that 75 out of 86 small glaciers did not show noticeable size change during a similar time period. The lack of change implies that either this mountain region experienced no late 20th century warming or that the small glaciers did not respond to any warming. The authors stated that the lack of glacier change was due to small size and sheltered locations of glaciers which allowed them to be roughly in balance with late 20th century climate conditions. The interpretation of

climate change based on the behavior of small cirque glaciers is not always straightforward or unique (Bolch et al., 2010).

Brown et al., (2010) considered 11 different warming scenarios for Sperry glacier, Glacier National Park, Montana to study future change of glaciers under these warming scenarios. The scenarios varied from no warming to warming at a linear rate of 10°C/century. They assumed constant precipitation and considered only the change invoked by warming. They derived a relationship between magnitude of temperature change and the sensitivity of the glacier to the change in temperature. Their result showed that under large magnitude warming, the glacier undergoes rapid area and volume reductions that are insensitive to minor variations to the warming rate. They concluded that a small change in climate would produce varying responses for glaciers throughout the region, whereas the glacier response to a large change in climate would likely to be very similar over the entire region.

2.4.1 Impact of climate change on Himalayan glaciers

Brahmaputra, Ganges and Indus are the three major river systems of Indian subcontinent which originate in the Himalayas and are expected to be much vulnerable to climate change because of substantial contribution from snow and glaciers (Singh et al., 1997a; Singh and Jain, 2002). During winter, a large extent of mountainous area of Himalayan river basins is covered by snow which starts ablating during summer causing huge discharge at the downstream of these rivers.

The snow cover in the Himalayas can be categorized as, temporary snow cover, seasonal snow cover and permanent snowfields or glaciers. Snow cover that stays for a few days and then melts away is termed as 'temporary snow cover'. Such snow usually occurs at lower altitude during winter and sometimes at higher altitude during summer. Snow cover that is formed over weeks or months by consecutive snowfalls and then melts away during the following summer is termed as 'seasonal snow cover'. The snow cover above a certain altitude that is carried over to the next winter season without melting during summer is termed as 'permanent snowfields or glaciers'. The seasonal snowpack is more important in that it contributes to the water resources during lean summer months.

The Himalaya-Karakoram-Hindu Kush (HKH) along with the adjoining Tibetan Plateau and central Asian mountain ranges such as Tien Shan and Kunlun ranges of western China, have the most highly glaciated area and largest body of ice outside the polar region (Kulkarni et al., 2007). The glaciers and snowfields of the HKH mountain belts and Tibetan Plateau are

amongst the fastest receding glacial and snow cover in the world (Dyurgerov and Meier, 2005). According to Kulkarni et al., (2007) and Raina (2009), widespread fragmentation of glaciers has also degraded the total areal coverage of perennial snow and ice in this region.

Jain (2001) used SNOWMOD model to study the impact of warmer climate on melt and evaporation in the Satluj basin. They adopted three future temperature scenarios (T+1, T+2 and T+3°C). They found that under a warmer climate, melt was reduced from snowfed basins, but increased from glacierfed basins. For T+2°C scenario, annual melt was reduced by 18% for snowfed basin, while it increased by 33% for the glacierfed basin.

Afzal et al., (2014) used MODIS 8 day composite data to identify spatial-temporal trends in snow cover in the upper Indus basin from 2001 to 2005. For the same period, they analyzed the temperature data for upper Indus basin. They found that the snow cover of Indus basin showed an increasing trend from west to east. They also concluded that regional warming is affecting the hydrology of upper Indus basin due to accelerated glacial melting.

2.5 Impact of change in snow cover area on discharge of rivers

Mountains are considered as the important source of water supply to the downstream areas. More than one sixth of the global population depends on water supplied by mountains and hence changes in hydrology and water availability are expected to be large in mountain basins (Barnett et al., 2005; Viviroli et al., 2007). Snow and ice are considered as the natural store of water in the mountainous regions. Due to global warming and other climatic factors, the snow cover areas are gradually decreasing and this diminishing role of snow and ice will have a tremendous impact in the downstream (Afzal et al., 2014). The degradation of snow cover area will have influence on stream water availability in the river basins where snow and glacier melt constitute the main component of stream flow in summer. On the contrary, advancing glacier may store solid-precipitation, reducing summer stream flow and can cause local hazards (Bochhiola et al., 2011).

The Himalaya-Karakoram-Hindu Kush region is referred to as the 'Water Tower of Asia' and is the source of ten largest rivers in Asia namely, Ganga, Brahmaputra, Indus, Tarim, Mekong, Irrawady, Amu Darya, Salween, Yangtze Kiang and Huang Ho (Yellow River). Snow, ice and glacial melts constitute a significant component of the river flows in all the Himalayan river basins. However, the percentage contribution of melt water from snow and ice on the discharge varies considerably from one river to another (Singh and Bengtsson, 2004; Barnett et al., 2005; Xu et al., 2009).

Hakeem et al., (2014) examined the annual snow and glacier cover variations in the Shigar river basin of the Indus River and its impact on discharge of the river. For this study they used the MODIS snow products. Their analysis showed that Shigar river discharge is mainly influenced by seasonal and annual snow cover area variation.

Siderius et al., (2013) used four hydrological models, VIC, JULES, LPJmL and SWAT to estimate snowmelt contribution to flow at seasonal and annual timescale for Ganges River. They found that snowmelt contribution is between 1-5% of overall basin runoff.

Sarkar, A.(2015) used the SNOWMOD model to study the behavior of total streamflow as well as snowmelt runoff under changing climatic conditions for the Subansiri sub-basin of the Brahmaputra River basin. They found that the total streamflow as well as snowmelt runoff for this basin increase with temperature. Snowmelt runoff was found to increase by 5% and 12% for the increase of 1°C and 2°C in temperature respectively. However, not much change in snowmelt runoff was observed with changed precipitation scenarios.

2.6 Land use/land cover change detection study

Land is the most important natural resource, which embodies soil, water and associated flora and fauna involving the total ecosystem (Shamsudheen et al., 2005). Extra pressure on the available land has been brought by the growing pressure of population coupled with increasing demands made on land resources (Rao et al., 1996). Land use and land cover are two separate terminologies and are often used interchangeably (Dimyati et al., 1996). Land cover refers to the physical characteristics of the earth's surface such as vegetation, water, soil etc., while the way in which the land has been used by humans and their habitat is referred to as land use. Natural and socio-economic factors and their utilization by humans in time and space mainly affect the land use/land cover pattern of a region. Land use/land cover assessment is an important parameter for meaningful planning of land resource management (Rawat and Kumar, 2015). The change in the state of the biosphere and bio-geochemical cycles are driven by heterogeneous changes in land use and continuation of those uses (Turner et al., 1995). Agriculture planning, settlement surveys, environmental studies and operational planning based on agro-climatic zones are the various resource sectors where the importance of land use/land cover change detection is gradually increasing (Jayakumar and Arockiasamy, 2003). Land use/land cover changes are important elements of the global environmental change processes and its detection is very essential for better understanding of landscape dynamics during a known period of time (Jaisawal et al., 2001). The changes in

land use/land cover is a widespread and accelerating process which in turn impacts the natural ecosystem (Ruiz-Luna and Berlanga-Robles, 2003; Turner and Ruscher, 2004).

2.6.1 Application of remote sensing and GIS on land use/land cover study

Remote sensing and GIS plays an important role in detection of land use/land cover changes (Yuan et al., 2005; Brondizio et al., 1994). Remote sensing collects multi-spectral, multi-resolution, multi-temporal data, and turns them into useful information. Remote sensing and GIS techniques are widely used in the determination of spatial distribution of the catchment ecosystem characteristics and their impacts on catchment hydrology (Sharma et al., 2001; Zhan and Huang, 2004; Tsou and Zhan, 2004). Since the invention of remote sensing and GIS, scientists around the world have been using this technology to prepare land use land cover maps (Khoram and John, 1991). The conventional methods of land use mapping are both labor intensive and time consuming. With passage of time, such maps along with the technology have become outdated. According to Olorunfemi (1983), monitoring changes and time series analysis is quite difficult with traditional method of surveying. The rapid development of satellite remote sensing techniques helps in preparation of accurate land use/land cover maps which in turn helps in monitoring changes at regular intervals of time. The accurate mapping of a region is an efficient way to improve the selection of areas designed to agriculture, urban and/or industrial areas of a region (Selcuk et al., 2003). One advantage of remotely sensed data is that, it made possible to study the changes in land cover in less time, at low cost and with better accuracy (Kachhwala, 1985) in association with GIS that provides suitable platform for data analysis, update and retrieval (Chilar, 2000). As a result, the land use/land cover mapping has become one of the most important applications of remote sensing (Lo and Choi, 2004). Analysis of satellite data in conjunction with drainage, lithology and land use/land cover data, assist evaluation of geomorphological conditions and status of degraded land in a particular region. As GIS provide an excellent means of spatial data analysis and interpretation, the datasets in GIS would provide a powerful mechanism to monitor degraded lands and other environmental changes (Burrough, 1986; Reddy et al., 2002).

Land use/land cover studies have been carried out in an extensive way ever since the launch of the first remote sensing satellite (Landsat-1) in 1972. For instance, NRSA used 1980-82 Landsat multispectral scanner data for waste land mapping of India on 1:1 million scales. About 16.2% of waste lands were estimated based on the study.

Shoshany (1994) investigated the advantages of remote sensing techniques over field surveys providing a regional description of vegetation cover. The results of their research were then used to produce four vegetation cover maps that provided new information on spatial and temporal distribution of vegetation and also allowed quantitative assessment of vegetation cover.

Adeniyi and Omojola (1999), used aerial photographs, Landsat MSS, SPOT XS/Panchromatic images to study land use/land cover changes in two dams (Sokoto and Guronyo) between 1962 and 1986 in the Sokoto-Rima basin of North-Western Nigeria. Their work revealed that before the construction of the dams, the land use/land cover in the basin was unchanged and settlement alone covered most part of the area. However, during the post-dam era, land use/land cover classes changed but with settlement still remaining the largest.

Daniel et al., (2002) compared five different methods to study the land use/land cover changes. The methods they employed were, traditional post-classification cross tabulation, cross correlation analysis, neural networks, knowledge-based expert systems and image segmentation and object-oriented classification. Nine land use/land cover classes were selected for the analysis. They observed that there are merits to each of the five methods examined and that, at the point of their research, no single approach can solve the land use change detection problem.

Pandy and Nathawat (2006) carried out a study on land use/land cover mapping of Panchkula, Ambala and Yamunanger districts, Haryana state in India. They observed that the development of land use and land cover in these districts is mainly due to heterogeneous climate and physiographic conditions. By analysis of satellite data they also found that majority of areas in these three districts are used for agricultural purpose.

Bhagawat (2011) presented the change analysis based on the statistics extracted from four land use/land cover maps of the Kathmandu Metropolitan area using GIS. According to him, land use statistics and transition matrices are important information to analyze the changes of land use.

El-Asmar et al., (2013) applied two remote sensing indices, i.e., normalized difference water index (NDWI) and modified normalized difference water index (MNDWI) in the Burullus Lagoon, North of the Nile Delta, Egypt for quantifying the change in the water body area of the lagoon in 1973 and 2011.

Landsat-TM images represent valuable and continuous records of the earth's surface and are also a wealth of information for identifying and monitoring changes in manmade and physical environments (USGS, 2014; Chander et al., 2009; El Bastawesy, 2014). To map and monitor land cover changes in the seven-country Twin Cities of Metropolitan Area of Minnesota for 1986, 1991, 1998 and 2002, Yuan et al., (2005) developed a methodology using multi-temporal Landsat TM data. They found from the analysis that between 1986 and 2002 the amount of urban land increased from 23.7% to 32.8% of the total area, while agriculture, forest and wetland cover decreased from 69.6% to 60.5%. A post-classification method with maximum likelihood classifier algorithm was adopted by Adepoju et al., (2006) to examine the land use/land cover changes that have taken place in Lagos for the last two decades due to rapid urbanization. Nori et al., (2008) applied two different change detection techniques namely, comparison of classification and multivariate alteration detection(MAD) to assess land cover changes in El Rawshda forest, Sudan by using Landsat ETM+ and ASTER imageries. They found increase in area in both close forest and open forest and decrease in area covered by grasslands within the period 2003-2006.

The freely available MODIS data can also be used efficiently to study land use/land cover with greater thematic, spatial and temporal detail. Zhan et al., (2002) used the MODIS 250m Level 1B radiance data for five different cases viz., Idaho-Montana wildfires, the Cerro Grande prescribed fire in New Mexico, flood in Cambodia, Thailand-Laos flood retreat and deforestation in southern Brazil to test the Vegetative Cover Conversion (VCC) change detection algorithm for the year 2000. VCC product is designed to serve as a global alarm for land cover change caused by anthropogenic activities and extreme natural events. They found that four of the five change detection methods for the MODIS VCC product worked satisfactorily for the detection of flooded area, burned area and deforestation.

The MODIS 500m resolution data are particularly relevant for regional and continental applications. Giri and Jenkins (2005) prepared land cover database of Greater Mesoamerica using MODIS 500m resolution satellite data. These land cover data were an improvement over traditional AVHRR based land cover data in terms of both spatial and thematic detail. Their study revealed that MODIS 500 m data are quite useful for broad-scale land cover mapping.

Kaishan et al., (2011) used MODIS 250m Normalized Difference Vegetation Index (NDVI), Land Surface Vegetation Index (LSVI) and reflectance time series data for 2001 and 2007 to map land use/land cover in the Amur River basin. They found that MODIS 250m NDVI

datasets provide sufficient spatial, spectral and temporal resolution to detect major land cover types compared to the existing land use/land cover data as derived from Landsat TM data.

Hu and Zhang (2013) detected temporal and spatial changes of land use/land cover over the Pearl River Delta region, China from March 2008 to December 2009 using multi-temporal MODIS images. They used post-classification change detection method and maximum likelihood classifier algorithm to detect the changes in five classes (cropland, water, bare land, urban and woodland). The study provides an example of seasonal change detection of land use/land cover types using MODIS data in regions of rapid urbanization.

Usman et al., (2015) used MODIS data of 250m spatial resolution for preparation of land use maps of the Lower Chenab canal irrigated region of Pakistan from 2005 to 2012. They concluded that MODIS products are quite useful to discriminate different land use/land cover classes.

Like in other parts of the world, in India also, various scholars have done researches on land use/land cover analysis. Sarma and Kushwaha (2005) worked on the impact of coal mining on land use/land cover in Jaintia hills district of Meghalaya, India using Landsat data of 1975, 1987, 1999 and 2005. Visual interpretation technique has been used to prepare the land use/land cover maps. They concluded that there was fourfold increase in mining area from 1975 to 2005 accompanied by three fold decrease in forest area. Kuldeep and Kamlesh (2011) studied the land use/land cover change detection in the Dehradun valley, India between 2000 and 2009 using Landsat (ETM+, TM, MSS), LISSIII, SRTM and digital SOI topographic maps. They found that during this period, forest area has decreased by 3.75% and water has decreased by 9.5%. Also built up area during this period has remarkably increased by 112.4%. Pooja et al., (2012) studied the land use/land cover changes of Gagas watershed of Almora district over a period of 43 years using Survey of India toposheet of the year 1965 and LISS III satellite data for the year 2008. Amin et al., (2012) carried out a study on land use land cover mapping of Srinagar city in Kashmir valley. Significant changes have been observed in the city during 1990 to 2007 including loss of forest area, open spaces etc. Mehta et al., (2012) presented an integrated approach of remote sensing and GIS for land use/land cover study of arid environment of Kutch region in Gujarat from 1999 to 2009. Sharma et al., (2012) introduced land consumption rate (LCR) and land absorption coefficient (LAC) for quantitative assessment of changes in Bhagalpur city of Bihar, India between the years 1976 and 2008. Rawat et al., (2013a-d, 2014) carried out land use land cover of Ramnagar, Nainital, Bhimtal, Almora and Haldwani towns of Kumaun Himalaya in

Uttarakhand, India. Based on satellite data from 1990 to 2010 of land use/land cover change, they found that built up area has sharply increased due to the construction of new buildings in agricultural and vegetation lands. Singh et al., (2014) used Landsat-8 data to assess the land use pattern and their spatial variation in Orr watershed of Ashok Nagar district, Madhya Pradesh, India. Bora and Goswami (2016) used Survey of India toposheets for the year 1967-68 and Landsat (ETM+) for the year 2014 to study the changes in land use/land cover in the Kolong river basin of Assam, India. They found that agricultural land has decreased from 2216.96 km² to 1449.39 km² during the period from 1967-68 to 2014. The built up area has increased from 1069.05 km² to 1838.84 km² during the study period.

2.6.2 Impact of change in land use/land cover on hydrology

The change in land use/land cover has considerable impact on the runoff characteristics and related hydrological processes. For example, during urbanization trees and vegetations are removed which leads to decrease in evapotranspiration and interception and also shortens the time of concentration. Many researchers have investigated the relationship between land use change and hydrologic response in catchments (Isik et al., 2013; Ozturk et al., 2013). The hydrology of a watershed is affected by many factors such as vegetation types, soil properties, geology, terrain, climate, land use practices etc. Increasing precipitation alone is not sufficient to explain the increasing discharge in a watershed (Schilling and Libra, 2003; Raymond et al., 2008). Along with precipitation, streamflow of a river is also affected by the changes that occur in land use/land cover of the watershed. A study done on the Iowa's river by Schilling and Lutz (2004) proved that increasing base flow is related to increasing agricultural intensity. Zhang and Schilling (2006) stated that increasing streamflow in Mississippi River was mainly due to an increase in base flow resulting from land use changes. Both climate and land use change are important drivers of change in watershed hydrology (Raymond et al., 2008; Lioubimtseva et al., 2005). Land use change can result in change in flood frequency (Brath et al., 2006), base flow (Wang et al., 2006) and annual mean discharge (Costa et al., 2003), while change in climate has impact on change in flow routine time, peak flows and volume (Changon and Dimissie, 1996). Fohrer et al., (2001) showed the impact of land use change on the annual water balance and temporal discharge variability in a meso-scale catchment using Soil and Water Assessment Tool (SWAT) model. They found that surface runoff is the most sensitive variable affected by the considered change.

Liu et al., (2003) based on the simulated results of (SWAT) model concluded that climate variation decreased runoff by 109% and land use change increased runoff by 10% in a region of the Yellow River during 1980-1990. Hessel et al., (2003) used Limburg Soil Erosion Model (LISEM) to simulate the effect of land use and management strategies on runoff reduction and erosion rates in the Danangou catchment in the Loess Plateau. They reported significant decrease in discharge and soil loss if the land use pattern was changed according to the slope-steepness-based conservation strategies. Huang and Zhang (2004) found that mean annual surface runoff and base flow decreased by 32% during 1967-1989 due to the implementation of conservation practices in the Jialuhe River catchment after removing the contribution of precipitation variation. Mu (2007) statistically separated the impacts of precipitation and land use change in the He Long region of Yellow River from 1950s and reported 29% and 71% decreases in runoff due to changes in precipitation and land use respectively. Li et al., (2009) studied the impacts of land use change and climate variability on surface hydrology in the Heihe catchment in the Loess plateau using SWAT model. Their study showed that both land use change and climate variability decreased runoff by 9.6% and 95.8% respectively. Sharma et al., (2001) carried out a study to assess the impact of land use changes on hydrological response in Jasdan Taluka of Rajkot district in Gujarat, India, where they used Curve Number model to estimate runoff from the watershed. It was observed that the runoff yield decreased by 42.88% of the pre-conservation value of the watershed. Noorazuan et al., (2003) evaluated the impact of urban land use/land cover change on hydrological regime for the period 1983-1994 in Langat river basin, Malaysia. Their study revealed that due to the change in landscape diversity in Langat after 1980s, surface runoff increased from 20.35% in 1983-1988 to about 27-31.4% in 1988-1994. Evidence from the research suggested that urbanization and changes in urban related land use/land cover could affect the streamflow behavior.

2.6.3 Application of hydrologic models to study the impact of change in land use/land cover

The relationship between land use/land cover changes and the hydrological response of a watershed can be evaluated by lumped, distributed, conceptual, or physical models. Lorup et al., (1998) combined a statistical method with Nedbor-Afstromnings conceptual hydrological model to study the effect of climate variability and land use change on runoff from six semi-arid catchments. The model gave good performance and the difference between simulated and observed flow was considered to be a key test variable to assess the impact of land use

change on catchment runoff. Thanapakpawin et al., (2006) utilized a spatially explicit hydrological model named the Distributed Hydrology-Soil Vegetation Model (DHSVM) to simulate forest-crop expansion and crop to forest reverse expansion scenario based on land use change during the period 1989-2000. Their results showed that the expansion of highland crop fields led to slightly higher annual and wet season water yields compared to similar expansion in lowland-midland zones. Numerical data-driven models such as Regression, ANN, Fuzzy and GA are not capable of modeling the relationship between hydrologic response and physical characteristics of the basin. However, process-based distributed models have the potential to quantify and forecast the dynamics of water availability with land use and climate change (Haigen et al., 2015). One drawback of these models is that they are highly data intensive and are not applicable to catchments with sparse datasets (Elfert and Bormann, 2010; Lin et al., 2008). Onstad and Jamicson (1970) studied the effect of land use change on runoff using a hydrological model and experienced the lack of data to validate the results. In order to meet the data requirement of such models, Thanapakpawin et al., (2006) utilized the Diurnal interpolation scheme from Variable Infiltration Capacity (VIC) model wherein they sub divided the daily records into three-hourly temperature, radiation and relative humidity. Niehoff et al., (2002) studied the impact of land surface conditions on storm runoff generation at meso-scale in three catchments which represent different land use patterns. Warburton et al., (2012) used the conceptual and physical Agricultural Catchments Research Unit (ACRU) model to study the difference in hydrological response in three diverse and complex catchments in South Africa.

2.7 Rainfall-runoff modelling

Modelling of rainfall-runoff process is very complicated due to spatial and temporal variability of topographical characteristics, rainfall pattern and the number of parameters to be derived during the calibration (Nandakumar and Mein, 1997). Hydrologic models can be broadly classified into the following categories (Chow et al., 1988):

1. **Deterministic models:** In deterministic models, randomness is not considered and a given input always produces the same output. Deterministic models are further categorized as,
 - a. **Deterministic lumped model:** Such models are in general applied to a single point or a region (Niel et al., 2003). The parameters used in lumped model represent spatially averaged characteristics in the system.

- b. Deterministic semi-distributed model: Such models divide the whole catchment into Hydrologic Response Units (HRUs) based on land use/land cover, soil type and slope and simulate the various hydrological processes in each HRU.
 - c. Deterministic distributed model: It considers the hydrological processes taking place at each grid and defines the model variables as functions of the space dimensions (Beven et al., 1980; Feyen et al., 2000).
2. Stochastic models: The output of stochastic models is at least partially random and hence these models make statistical predictions. Stochastic models are classified as space independent or space correlated depending on whether the random variables in space influence each other.

Apart from these, the hydrological models can also be classified as conceptual, empirical and physical models. Many empirical models such as linear and non-linear regression, ANN etc. are used for rainfall-runoff modelling to predict runoff in different catchments (Chen et al., 2013; Halff et al., 1993; Shirke et al., 2012). Empirical models establish the relationship between rainfall and runoff based on the hydro-meteorological data and contain no physical transformation function to relate input to output (Sarkar and Kumar, 2012; Sudheer et al., 2002). Rainfall alone cannot explain the runoff variance efficiently which can be attributed to antecedent moisture content, rainfall intensity, and physical characteristics of the catchment such as geology, soil, slope and land use/land cover conditions (Costa et al., 2003). Thus, the main constraint of the empirical models is the non-consideration of physical processes such as sub-surface flow, surface runoff and infiltration in the catchment. Moreover, these numerical models are incapable of modelling the influence of change in vegetation on various hydrological components. Conceptual models are simplifications of the complex process of runoff generation in a catchment. Viviroli et al., (2009) introduced precipitation-runoff-evapotranspiration HRU model, a semi-distributed hydrological model that implements a conceptual process-oriented approach. The model was developed to suit mountainous environmental conditions. Valent et al., (2012) used lumped conceptual model, Hron rainfall-runoff model to predict runoff. The results suggested that the model has uncertainties with respect to conceptualization of complex runoff generation process. Parajka et al., (2006) also used a conceptual semi-distributed model to study the soil moisture dynamics which alter the hydrological processes by utilizing scatterometer data in the model. The physically based distributed models on the other hand are able to represent the spatial variability of land surface characteristics such as topographic elevation, slope, aspect, vegetation, soil and

climatic parameters like precipitation, temperature and evapotranspiration (Akbari and Singh, 2012; Grayson et al., 1992; Niehoff et al., 2002).

2.7.1 SCS-CN model and its application for runoff estimation

The Soil Conservation Service Curve Number (SCS-CN) (SCS, 1956) method is a rainfall-runoff modelling used efficiently and widely to determine direct runoff from a storm event. The CN is estimated based on the hydrologic soil group (HSG), land use/land cover and hydrologic conditions. Compared to the hydrological conditions, the soil properties and land use/land cover are of greater importance in controlling the values of CN (USDA, 1986). SCS-CN is an infiltration loss model and does not account for evaporation and evapotranspiration loss (Ponce and Hawkinsm, 1996). CN is not a constant and varies from event to event (Kannan et al., 2007). Many researchers have used SCS model using remote sensing and GIS to explain the effect of land use/land cover change on runoff. The land use/land cover is an important parameter input of the SCS-CN model (Pandey and Sahu, 2002). Nayak and Jaiswal (2003) pointed out that GIS is an efficient tool for the preparation of most of the input data required by the SCS-CN model. Zhan and Huang (2004) elucidated the application of ArcCNRunoff tool which is an extension of ArcGIS software. This tool can be applied to determine the CNs and calculate runoff for a storm event within a watershed. They also suggested that implementation of precipitation time series and consideration of antecedent moisture conditions would improve the prediction of the ArcCNRunoff tool.

Hong and Adler (2008) derived a global CN map by classifying hydrologic soil group (HSG) from digital soil maps and then estimating CN as a function of HSG, land cover classification and hydrologic conditions according to USDA (1986) and NEH-4 (1997) standard lookup tables. The application of this global CN map includes real time global flood assessment by incorporating an operational multi satellite precipitation estimation system.

Jabari et al., (2009) used SCS-CN method to estimate runoff from the WadiSu'd watershed in Dura area of the Herbon district, West Bank, Palestine. The rainfall and land use data were used along with experimental data of soil classification and infiltration rate for the estimation of runoff. Their results revealed that the average annual runoff depth for the study area is 36.3 mm and average volume of runoff from the same watershed is 67840.2 cubic meter per year.

Banasik (2010) determined runoff CN in a small lowland and agricultural watershed in Center of Poland using over sixty rainfall-runoff events collected during 1980-2008. The analysis showed that empirical CN computed for events of precipitation larger than 20 mm is very close to CN estimated on the basis of land use and soil types for the watershed.

Nayak et al., (2012) applied SCS-CN model in ILWIS GIS platform to estimate variations in runoff for two different periods *i.e.* 2001 and 2007 for the GoI river catchment of Narmada River basin in Central India. Remote sensing satellite data have been used to prepare the land use/land cover and soil maps. They found that the agricultural area has increased drastically and forest area has reduced considerably resulting in 20-40% increase in the surface runoff volume in 2007 compared to those in 2001 for similar rainfall events.

Williams et al., (2012) described the evolution of the continuous CN method and its recent developments. They presented the test results on the basis of the direct-link soil moisture approach and the revised soil-moisture index method. Their results indicated that the revised soil-moisture index method is robust and produces realistic runoff estimates over a wide range of soil properties.

Sahu et al., (2012) compared the performance of four modified SCS-CN methods in surface runoff computation in two catchments in Maharashtra, India. Their study mentioned that despite very large size of the watersheds, all the four modified SCS-CN based models performed reasonably well.

Fan et al., (2013) developed a simulation model based on the SCS-CN method to analyze the rainfall-runoff relationship in Guangzhou, China. They used remote sensing variables such as vegetation, impervious surface and soil to calculate CN. Their experiment showed that the proposed method can derive composite CN effectively.

Bansode and Patil (2014) estimated runoff for GP-3 watershed of Khuldabad Taluka in Aurangabad district in Maharashtra, India using modified SCS method for a period of 10 years from 2003-2012. They calculated the monthly and yearly runoff for this period and found that graph for the yearly runoff was best fitted than the monthly runoff.

Hejduk et al., (2015) computed the CN parameter for snowmelt-runoff events based on snowmelt and rainfall measurements in Zagozdzonka river catchment in Central Poland. They compared the CN received from 28 snowmelt-runoff events with the CN computed from rainfall-runoff events.

Ahmed et al., (2015) used SCS-CN method in remote sensing and GIS environment to estimate the runoff depth in the Sheonath River of upper sub-basin of Chattisgarh in India. Their study revealed that remote sensing and GIS based SCS-CN method can be used effectively to estimate runoff from river basins of similar geo-hydrological characteristics.

Viji et al., (2015) also generated a GIS based CN method to determine the average annual runoff depth in the Kundapallam watershed of Tamil Nadu, India. The average annual runoff depth for the average annual rainfall of 173.5 mm was found to be 72.5 mm. The obtained results were comparable to the measured runoff in the watershed.

Chavda et al., (2016) estimated runoff and water availability for two sites (Ozat-2 and Zanzesri) in the Ozat catchment situated in Junagadh, Gujarat, India using remote sensing and GIS based CN method. They concluded that SCS-CN method along with remote sensing and GIS can be used successfully in semi-arid region to estimate runoff.

2.7.2 Application of Artificial Neural Network Model to estimate runoff

Although the conceptual and physically based models account for the physical processes involved in the rainfall-runoff process, yet their use is limited because of the need of catchment specific parameters involved in the governing equations (Abulohom et al., 2001). Again the use of time series stochastic models is complicated because of non-linearity in the data (Guldala and Tongal, 2010). In such cases, Artificial Neural Network (ANN) acts as a powerful computing system for highly complex and non-linear systems. ANN can treat the non-linearity of the system to some extent due to their parallel architecture. The ANN model can identify the non-linear relationship between runoff and rainfall, even though it cannot represent the physical process of the catchment (Hsu et al., 1995). Kumar et al., (2005) and Mutlu et al., (2008) used different input variables to the ANN model for runoff simulation. They found that ANN model run with both rainfall and discharge as inputs gave better result than the ANN with only rainfall as the input. In contrast, few studies also reported poor performance of ANN compared to the conventional methods. For example, Gaume and Gosset (2003) compared feed forward ANN model with a linear model and a conceptual model. They found that the conceptual model outperformed the linear and the ANN model. Some other studies proved successful use of the ANN model in runoff simulation with high degree of accuracy (Agarwal and Singh, 2004). Maria et al., (2004) compared ANN and Box and Jenkins (Box and Jenkins, 1976) techniques and found that ANN is better than the Box and Jenkins model. Sohail et al., (2006) compared ANN with the Multivariate Auto Regressive Moving Average (MARMA) model in a small watershed of Tonoarea in Japan for wet and dry seasons. Their study also concluded that ANN gave better result than MARMA when the non-linearity of rainfall-runoff process is high. Thus, from the various studies, it is evident that ANN models provide better prediction compared to the conventional models. However, the accuracy and quantity of input data play important roles in ANN models. Much

of the works done using ANN to simulate rainfall-runoff process required good quality and highly reliable datasets. In addition, the quantity of data available is sufficient enough for the proper generalization of the ANN models. On the contrary, very few studies have reported the application of ANN in watersheds where the quality of collected dataset is poor and quantity wise the data is scarce (Sajikumar and Thandaveswara, 1999).

A few studies carried out by various scientists to simulate runoff using ANN model are briefly described below:

Reddy et al., (2008) modeled the rainfall-runoff process using simple time series (STS) and linear autoregressive (ARX) models and compared with ANNs. They used the monthly data of Sriramsagar, Mancheri and Polavaram gauging sites of Godavari basin in India. Their study revealed that the ANN models, because of their non-linear capability, outperformed the empirical approaches. They also found that the performance of ANN model in simulation and forecasting of monthly runoff can be improved by including the residuals derived from STS and ARX models as additional inputs together with rainfall.

Ghunman et al., (2011) compared the performance of an ANN based rainfall-runoff model with a mathematical conceptual model in a watershed in Pakistan. They found that ANN model is an important alternative to conceptual models and can be used when the range of collected dataset is short and is of low standard.

Song et al., (2012) proposed a hybrid rainfall-runoff model that integrates ANN with Xinanjiang (XAJ) model for Yanduhe watershed, the upper tributary of Yangtze River basin. ANN which is an effective tool in non-linear mapping was employed to explore non-linear transformations of the runoff generated from the individual sub-catchments into the total runoff at the entire watershed outlet. The results indicated that the approach of integrating ANN with XAJ model may achieve the promising results with acceptable accuracy for flood events simulation and forecast.

Lafdani et al., (2013) used Adaptive Neural Fuzzy Inference System (ANFIS) and ANN to predict rainfall based on historical data in Eskandari basin in Iran for a 10-year period (1999-2009). The runoff discharge produced by the predicted rainfall and observed rainfall were simulated by MIKE11/NAM model. They found that NAM model simulated the base flow more accurately than simulating the peak flow in the basin.

Amirhossien et al., (2015) evaluated the capability of two different types of models including Hydrological Simulation Program-Fortran (HSPF) as a process-based model and ANN as a data driven model in simulating runoff from the Balkhichai River watershed in northwest of

Iran. Results of runoff simulation indicated that the simulated runoff by ANN was closer to the observed values than that predicted by HSPF.

Wang et al., (2015) developed an SSA-ANN model by adopting singular spectrum analysis (SSA) as the data preprocessing technique. They compared SSA-ANN model with original ANN model without data preprocessing and a non-linear perturbation model (NLPM) based on ANN (NLPM-ANN). They found that the training ability of ANN models can be improved by SSA and NLPM techniques significantly, and the performance of SSA-ANN model is much better than the NLPM-ANN model with high forecasting accuracy.

Daliakopoulos and Tsanis (2016) compared a conceptual model with the ANN based Sacramento Soil Moisture Accounting Model (SAC-SMA) for Crete, Greece using monthly rainfall, streamflow and potential evapotranspiration as the inputs. They found that the ANN based SAC-SMA performed better and is superior to the conventional models.

Karamouz et al., (2012) developed two models viz., IHACRES (Identification of Unit Hydrographs and Component Flows from Rainfall, Evaporation and Streamflow data) and ANN model and were compared for runoff simulation for the south-eastern part of Iran. The results showed that the IHACRES model outperformed ANN in simulating runoff and its results were comparable to the observed values.

2.7.3 Scenario-based simulation of hydrological response in a catchment

It becomes necessary to study the impact of changes in climate variables and land use on runoff, one of the major components of hydrological cycle (Huang et al., 2015). Legesse et al., (2003) assessed the sensitivity of water resources to the change in climate and land use in a semi-arid to sub-humid basin using a physically based semi-distributed model. Their climate scenario study revealed that the hydrologic system was more reactive to an increase in rainfall than to a decrease in rainfall. Li et al., (2009) and Ozturk et al., (2013) stated that the influence of climatic variability is more significant on surface hydrology than the land use change. Huang et al., (2015) in their study simulated the runoff of the upstream of Minjiang River for nine climate change scenarios by varying precipitation, temperature and potential evapotranspiration. Their study revealed that precipitation variation had more influence on simulated runoff than the temperature variation.

Many researchers have developed various scenarios in order to study the effect of future land use/land cover on hydrological systems. Niu and Sivakumar (2013) and Wu and Johnson (2007) studied conversion of agricultural land to urban, forest and grassland to analyze its

impact on future hydrology. Scenario-based studies have shown that when a large part of a catchment is affected by extreme land use change, even a validated catchment model might not be able to simulate significant changes in water flows (Legesse et al., 2003). The proper land use/land cover change scenarios may promote reduction in natural hazards (He and Hogue, 2012; McColl and Aggett, 2007). Wijesekara et al., (2012) assessed the impact of land use changes over the next 20 years on the hydrologic process by combining Cellular Automata model and MIKE-SHE/MIKE11 hydrologic model. They found a reduction of net capacity of water retention on surface due to the expansion of built-up and agricultural area which has led to an increase in surface runoff caused by a reduction in infiltration.

2.8 General Circulation Model/ Global Climatic Model

To study the impact of climate change at regional scale, the General Circulation Models(GCMs) are the most adapted tools which describe the atmospheric process by mathematical equations. The fully coupled Atmospheric-Ocean GCMs (AOGCMs), along with transient methods of forcing the concentration of greenhouse gases, have brought considerable improvement in the climate model results. The main limitations in application of GCMs and hydrological modes as given by Fowler et al., (2007) are, (i) the spatial scales of GCM and hydrological models are not consistent and hence, the output of GCMs cannot be used directly as inputs to the hydrological models, and (ii) the accuracy of precipitation simulations from GCMs cannot meet the requirements of hydrological simulations. There exist three considerable types of errors in the assessment of climate change impacts, namely uncertainty of climate modeling, uncertainty of downscaling techniques and uncertainty of hydrological modeling. GCM provides output at nodes of grid boxes which are tens of thousands of square kilometers in size, whereas the scale of interest to the hydrologists is of the order of a few hundred square kilometers. In spite of these limitations that lead to uncertainties, GCMs provide a robust and unambiguous picture of the climate system (Carmen et al., 2013). GCM principles are based on well established fundamental laws of physics such as conservation of mass, energy and momentum (Pitman and Perkin, 2008). These models are also capable of simulating important aspects of the current and past climates as well as their changes (Randall et al., 2007). Multi-model climate predictions have demonstrated that combining a number of models generally increases the skill, reliability and consistency of model predictions (Thomson et al., 2006; Cantelaube, 2005).

Several downscaling methods have been developed to deal with this problem of mismatch of spatial resolutions between GCMs and hydrological models. Downscaling has wide application in simulation/prediction of (i) regional precipitation (Kim et al., 2004), (ii) low-frequency rainfall events (Wilby, 1998), (iii) mean, minimum and maximum air temperature (Kettle and Thompson, 2004), (iv) soil moisture (Georgakakos and Smith, 2001; Jasper et al., 2004), (v) runoff (Arnell et al., 2003) and streamflows (Cannon and Wheatfield, 2002), (vi) ground water level (Bouraoui et al., 1999), (vii) transpiration (Misson et al., 2002), wind speed (Faucher et al., 1999), potential evapotranspiration rates (Weisse and Oestreicher, 2001), (viii) soil erosion and crop yield (Zhang et al., 2004), (ix) landslide occurrence (Buma and Dehn, 2000) and (x) water quality (Hassan et al., 1998).

2.8.1 Approaches for downscaling of GCMs

The approaches, which have been proposed for downscaling GCMs, can be broadly classified into two categories: dynamic downscaling and statistical downscaling and are the most commonly used methods in the one-way coupling of GCM and hydrological models (Bergstrom et al., 2001; Fowler et al., 2007; Pinto et al., 2010).

2.8.1.1 Dynamic downscaling

In the dynamic downscaling approach, a Regional Climate Model (RCM) is embedded into GCM. The RCM is a numerical model in which GCMs are used to fix boundary conditions. Despite of having clear physical meanings, the major disadvantages of RCM are its complicated design and high computational cost. Another drawback associated with RCM is that expanding the region or moving to a slightly different region requires redoing of the entire experiment (Crane and Hewitson, 1998). Because of the fact that RCM is nested in a GCM, the overall quality of dynamically downscaled RCM output is tied to the accuracy of the large-scale forcing of the GCM and its biases (Seaby et al., 2013). The RCM outputs bear some systematic errors, despite the fact that it recovers important regional-scale features that are underestimated in coarse resolution GCMs. Hence, RCM outputs require bias correction as well as further downscaling to higher resolution. Moreover, the quality of RCM outputs depends on the driving GCM information. For example, if the GCM misplaces storm tracks, there will be errors in the RCM's precipitation climatology (Wilby et al., 2009). The grid-box size of an RCM is typically greater than 10 km, which is too coarse for hydrological impact studies (Benestad, 2009). To obtain higher resolution results, statistical methods are used in lieu of RCMs, or the RCM output is further downscaled via statistical means. The most

commonly used RCMs in downscaling studies are, U.S. Regional Climate Model Version 3(RegCM3), Canadian regional Climate Model (CRCM), U.K. Met Office Hadley Centre's Regional Climate Model Version 3(HadRM3), German Regional Climate Model (REMO), Dutch Regional Atmospheric Climate Model (RACMO) and German HIRHAM which combines the dynamics of the High resolution Limited Area Model (HIRLAM) and European Centre-Hamburg (ECHAM) models.

2.8.1.2 Statistical downscaling

Statistical downscaling involves deriving empirical relationships that transform large-scale features of the GCM (predictors) to regional-scale variables (predictands) such as precipitation, temperature and streamflow. Since it is based on statistical relationships between predictors and predictands, the statistical downscaling approach requires less computational time. Hewitson and Crane (1996) enumerated three main assumptions involved in statistical downscaling. These are, (i) the predictors are variables of relevance and are realistically modeled by the host GCM; (ii) the empirical relationship is valid also under altered climatic conditions and (iii) the predictors employed fully present the climate change signal.

As per Musau et al., (2013), the statistical downscaling methods are categorized into following three different categories:

- 1) Transfer functions: In this technique, linear and non-linear methods are used to infer the relationship between predictors and predictands (Hashmi et al., 2011; Guo et al., 2011). This predictor-predictand relationship then can be verified by using multiple linear regressions (Winkler et al., 1997), principal component analysis (Huth, 2004), canonical correlation analysis (WASA, 1998) on artificial neural network and singular value decomposition (Jeong et al., 2012).
- 2) Weather typing: This method is based on classification of the large scale atmospheric structure into 'weather types' and then associating local meteorological variables with each of these types (Cheng et al., 2011b). However, since this method does not assume continuous relationship between large-scale circulation and local climate, there is a chance of potential loss of information (Chen et al., 2012).
- 3) Weather generators: In this technique, parameter values are perturbed according to the changes projected by climate models (Zhang, 2007; Jones et al., 2009). This method is useful in evolution of synthetic series of unlimited length (Yang et al., 2005). Two

types of weather generators are Markov chain approach and spell-length approach (Karl et al., 1990).

Various researchers conducted various studies using various statistical downscaling techniques. Dibike and Coulibaly (2005) applied a stochastic based and a regression based statistical downscaling technique along with two hydrological models to simulate the future flow regime in a catchment. Prudhomme and Davies (2009) used a lumped conceptual rainfall-runoff model, three GCMs and two downscaling techniques to study the impact of climate change on river flows. Chiew et al., (2010) used SIMHYD rainfall-runoff model with daily rainfall which was downscaled from three GCMs using five downscaling models to simulate runoff. Segui et al., (2010) evaluated the uncertainty related to climate change impacts on water resources by applying a distributed hydrological model and three different downscaling techniques. Chen et al., (2011) used SSVM (Smooth Support Vector Machine) and SDSM (Statistical Downscaling Model) to compare the difference in water balance simulations in upper Hanjiang basin in China. The A2 emission scenarios from CGCM3 and HadCM3 were used as input to the statistical downscaling models. They found that for the same GCM, the simulated runoff varied greatly when rainfall provided by different downscaling techniques were used as the inputs to the hydrological models. Tripathi et al., (2006) proposed a Support Vector Machine (SVM) approach for statistical downscaling of precipitation at monthly time scale. The climatic parameters of Coupled Global Climate Model (CGCM2) have been used as predictors. They showed that SVMs provide a promising alternative to conventional ANN for statistical downscaling and are suitable for conducting climate impact studies. SVM has found wide applications in the field of pattern recognition and time series analysis (Vapnik, 1995, 1998). Hu et al., (2013) compared three statistical downscaling methods: SDSM, Generalized linear model for daily climate and Non-homogeneous Hidden Markov Model for downscaling summer precipitation from a network of 14 stations over the Yellow River region using National Centre for Environmental Prediction (NCEP) reanalysis data and GCMs CGCM3 and ECHAM5.

2.8.1.3 Downscaling by Artificial Neural Network (ANN) model

Artificial Neural Network (ANN) based downscaling techniques are widely used because of their ability to capture non-linear relationship between predictors and predictand (Solecki and Oliveri, 2004; Tatli et al., 2004).

Karamouz et al., (2009) conducted a study in the south-eastern part of Iran using field and GCM data with the Statistical Downscaling Model (SDSM) and the ANN model to predict rainfall. The results showed that SDSM outperformed the ANN model.

Mendes and Marengo (2010) compared ANN with an autocorrelation statistical downscaling model to downscale five coupled GCMs for a region in the Amazon Basin. Their results indicated that ANN model outperformed the other statistical models for downscaling of daily precipitation.

Chadwick et al., (2011) used an ANN approach for downscaling GCM temperature and precipitation and applied this approach to a nested RCM over Europe. They found that the ANN was able to recreate RCM output fields from GCM input data for both temperature and rainfall.

Hoai et al., (2011) used an empirical-statistical downscaling method for prediction of precipitation using feed-forward multilayer perception (MLP) neural network for the Bon River basin in Central Vietnam. The downscaled precipitation was then used as input to the runoff model for flood prediction. Their results revealed that the precipitation predicted by MLP outperformed the precipitation directly obtained from model outputs or that downscaled using multiple linear regression.

Samadi et al., (2012) conducted a study in Karkeh catchment, west Iran to determine the change in streamflow for the period 2040-2069 using a hybrid conceptual hydrological model in conjunction with model outcomes from HadCM3 GCM. They performed two downscaling techniques, Statistical Downscaling Model and ANN. The results suggested a significant decrease of streamflow in both downscaling projections, particularly in winter.

Chitra and Thampi (2013) applied an advanced non-linear bias correction method to ANN based downscaling models to obtain projections of monthly precipitation at two rain gauge stations, one in the Chaliyar river basin located in the humid tropics in Kerala, India and other located close to it. The predictors were extracted from National Centre for Environmental Prediction and National Centre for Atmospheric Research (NCEP/NCAR) and CGCM3 GCM models. The performance of the models was reasonably good except for a few extremes.

Okkan and Fistikoglu (2013) applied Levenberge- Marquardt algorithm based feed forward neural networks (LM-FFNN) to downscale GCM CGCM3 for present day and future climates for precipitation and temperature over the Thatali River basin in Turkey. They used parametric hydrological model GR2M to observe the impacts of temperature and

precipitation on runoff. Their findings indicated that the near future runoff was likely to decrease by 32% leading to a reduction in water supply.

Pour et al., (2014) proposed a genetic programming (GP) based logistic regression method for downscaling of rainfall over the east coast of Peninsular Malaysia. The results were compared with those obtained using ANN and SDSM. It was found that models derived using GP can predict both annual and seasonal rainfall more accurately compared to ANN and SDSM.

Vu et al., (2016) utilized ANN method to downscale climate models for rainy season at meteorological site locations in Bangkok, Thailand. The downscaled results showed good agreement against station precipitation with a correlation coefficient of 0.8 and Nash-Sutcliffe efficiency of 0.65. The final downscaled results showed an increasing trend of precipitation for rainy season over Bangkok by the end of the 21st century.

Kueh and Kuok (2016) proposed an ANN approach to forecast future precipitation through spatial downscaling for which the bat neural network (BatNN) was developed and benchmarked with the traditional Scaled Conjugate Gradient Neural Network (SCGNN). Their results revealed that BatNN outperformed its benchmark in terms of prediction accuracy.

2.9 Reservoir Operation Study

Reservoirs are usually constructed to serve multiple purposes, such as irrigation, hydropower generation, municipal and industrial water supply and flood control. Reservoir operation policies are developed to enable the operator to take appropriate decision. The reservoir operation policy indicates the amount of water to be released based on the state of the reservoir, demands and the likely inflow to the reservoir. The release from a single-purpose reservoir can be done with the objective of maximizing the benefits. For multi-purpose reservoir there is a need to optimally allocate the releases among the different purposes. The Standard Operation Policy (SOP) is the simplest of the reservoir operation policies. According to SOP, if the water available (storage +inflow) at a particular period is less than the demand, then all the available water is released. On the other hand, if the available water is more than the demand but less than demand plus storage capacity, then release is equal to the demand. If after releasing the demands, there is no space for extra water, then the excess water is also released.

Reservoir operation plays a vital role in maximizing beneficial use of the reservoir. A number of methods are available for reservoir operation. These include, linear programming (LP), dynamic programming (DP), non-linear programming (NLP) and simulation. The approach and technique employed varies from problem to problem as the configuration, state of development of the system and the nature and the stage of decision making differs from situation to situation.

The reservoir operation models developed were under deterministic or stochastic environment. The deterministic models use a specific sequence of stream flows, either historical or synthetically generated, while the stochastic models use a statistical description of the stream flow process instead of a specific stream flow sequence (Karamouz and Houck, 1982).

Loucks et al., (1981) developed the Yield model which is a general purpose stochastic LP model that incorporates several approximations to reduce the size of the constraints set needed to describe the reservoir system operation and to capture the desired reliability target releases. He also demonstrated that in several cases the Yield model provides a reasonable estimate of the distribution of reservoir capacity requirements obtained with the sequent peak algorithm.

Dahe and Srivastava (2000) made a study on Yield assessment for reservoir based on a specified reliability and the extent of availability of supply during failure years which can lead to effective management of irrigation reservoir systems.

Dahe and Srivastava (2002) developed the basic Yield model and presented a multiple Yield model for a multiple reservoir system consisting of single purpose and multipurpose reservoirs. The objective is to achieve pre specified reliabilities for irrigation and energy generation and to incorporate an allowable deficit in the annual irrigation target.

2.9.1 Linear Programming (LP) Models

Linear programming (LP) has been a valuable tool in the optimization of reservoir operations. LP can be used to solve a number of problems in relation to the planning and operations of multiple reservoir systems. The application of LP to water resources field is traced back to the early 1960s (Simonovic, 1982). The application of LP technique in reservoir system planning programme was initiated by Dorfman (1962). LP is considered as a useful tool for optimization of reservoir operation (Yeh, 1985). LP can be applied to a reservoir operation problem provided the objective function and constraints are linear in nature.

Meier and Beightler (1967) introduced a branch-compression technique for decomposing parallel reservoir systems, but their approach did not consider temporal allocations over seasons.

Parikh (1966) put forth the idea of spatial decomposition by applying dynamic programming to sub systems under an initial set of prices. Then, releases over time from all subsystems were allocated over space by using LP from which dual values were used to adjust the initial prices assigned to the subsystems. Roefs and Bodin (1970) suggested an extension of this methodology for decomposition over time, but substantial computational difficulties were encountered when it was applied to a system of three reservoirs.

Loucks (1968) developed a stochastic LP model for a single reservoir subject to random, serially correlated, net inflows. The net inflows for each time period were described by a first order Markov chain and transition probabilities of inflows were estimated from historical inflows. The stochastic LP model was applied to a simplified representation of the Finger Lakes within the Oswego river basin. He pointed out the dimensionality problem associated with the type of model in real situations, which may easily involve several thousand constraints.

Needham et al., (2000) used LP to study the reservoir operation of the Iowa/Des Moines system where linear functions were used to represent penalties for release, storage and flow parameters that diverge from desired conditions. He provided several recommendations for future work including reevaluation of penalty functions.

Deeprasertkul (2015) presented the optimization of reservoirs operation in Chao Phraya basin of Thailand using linear Programming to calculate the optimal volumes of water released and water storage of Bhumibol and Sirikit reservoirs. It helped to decrease the volume of downstream flood peak.

Heydari et al., (2015) developed a model based on mixed linear programming (MILP) technique for systematic operation of multi reservoirs (Laar, Lartian and Karaj dams) of the Tehran-Karaj plain. A comparison between the MLP developed model's results against the periodic data showed 21.7% less overflow, 11.6% more outflow and 15.9% more reservoir storage respectively. The outcome of the MLP-based modeling indicated superior performance to that of the historical period.

2.9.2 Nonlinear Programming (NLP) model

Nonlinear programming (NLP) has not received the popularity that LP and DP have in water resource systems analysis (Yeh, 1985). Yeh, 1985 explained that this is particularly due to the fact that the optimization process is usually slow and takes up large amounts of computer storage and time when compared with other methods. The mathematics involved in the nonlinear models is much more complicated than in the linear case, and NLP unlike DP cannot easily accommodate the stochastic nature of inflows to the system. NLP does offer, however, a more general mathematical formulation and may provide a foundation for analysis by other methods. NLP can effectively handle a non separable objective function and non-linear constraints which many programming techniques cannot. NLP includes quadratic programming, geometric programming, and separable programming as special cases which can be used iteratively as a master program or as a sub-program in large-scale system problems (Yeh, 1985).

Simonovic and Marino (1982) applied gradient projection method with a two dimensional Fibonacci search to solve a reliability programming problem for single reservoir management. They considered both random inflow and demand in their continuity equation, and both benefit and risk in their objective function for discrete determination of reliability concerning flood and drought.

Marino and Loaiciga (1985) developed a quadratic model for monthly release policies for Northern California Central Valley Project (NCVP). They compared the quadratic model with a simplified linear model and found that optimal release schedules are robust to the choice of the model, both yielding an increase of nearly 27% in the total annual energy production with respect to conventional operation procedures, although quadratic model is more flexible and of general applicability.

Peng and Buras (2000) developed the optimal operation policies for a multi-reservoir hydropower system in Maine, USA using the NLP technique and reported that the model allows the decision makers to adjust the operations for different alternative operation scenarios.

Devamane et al., (2006) developed a NLP model for a multi-reservoir system in upper Krishna basin for maximizing the irrigation, municipal and industrial releases and hydropower production. On comparing the results with the LP model, it was reported that the NLP model resulted in less irrigation deficit with more hydropower production.

A non-linear multi-objective optimization model was developed by Moosavian et al., (2008) to optimize the annual scheduling of power generation in serial or parallel hydropower plants for dry, medium and wet scenarios. The multiple objectives were converted to a single objective using weighted sum method. It was reported that the wet scenario resulted in increased amount of energy production due to high inflow.

Arunkumar and Jothiprakash (2012) optimized Koyna multi-purpose reservoir for maximizing the hydropower production subject to the condition of satisfying the irrigation demands using a non-linear programming model. The hydropower production from the reservoir was analyzed for three different dependable inflow conditions, representing wet, normal and dry years. It was observed that more hydropower can be generated for various dependable inflow conditions, if the restrictions on releases are slightly relaxed.

2.9.3 Dynamic Programming (DP) Models

Dynamic Programming (DP), a method first introduced by Bellman (1957), is an optimization procedure for solving a multistage decision process. The popularity and success of this technique can be attributed to the fact that the non-linear and stochastic features, which characterize a large number of water resources systems, can be translated into a DP formulation. In addition, it has the advantage of effectively decomposing highly complex problems with large number of variables into a series of sub problems, which are solved recursively. A major limitation in the use of dynamic programming is the well-known ‘curse of dimensionality’ (Bellman and Dreyfus, 1962). The computational requirement for DP increases exponentially with increase in state dimension.

Young (1967) was the first to apply deterministic dynamic programming algorithm in reservoir operation. He studied a finite horizon single reservoir operation problem. After Young (1967) a number of modified DP algorithms have been developed to alleviate the computational burden in DP when applied to multi-reservoir planning and operation problems.

Bellman and Dreyfus (1962) first developed discrete dynamic programming (Discrete DP). The Discrete DP requires that the control and state space be discretized by a finite set of vectors.

Young (1967) first applied this Discrete DP approach to find the optimal operating policy of a single reservoir. He used release for current period as decision variable and initial storage

for current period as state variable. He first proposed a means to obtain general operating rules from the results of the deterministic optimization model.

Hall et al., (1968) used the Discrete DP technique for optimizing operation of a multipurpose reservoir. The objective of their analysis was to determine for a given initial state of the system, price schedule and sequence of inflows, the set of decisions regarding release of water from the reservoir that will maximize the total return from the operation subject to physical and other constraints.

Hall et al., (1969) modified their earlier method (Hall et al., 1968) by incorporating additional factors like firm water and on-peak energy constraints, energy pricing, and flood control desiderata etc.

Roef and Bodlin (1970) made a critical analysis of reservoir operating rules using deterministic, implicit stochastic and explicit stochastic algorithm and extended the Discrete DP to a multi-reservoir case.

Karamouz and Houck (1982) developed general reservoir system operating rules by deterministic optimization. They constructed a dynamic programming regression based model. They used a hypothetical loss function, which involved only reservoir release.

Majumdar and Ramesh (1997) developed a real time reservoir operation model for irrigation of multiple crops using deterministic dynamic programming. The reservoir storage, soil moistures of individual crops, and a crop production measures constituted the stage space. The model was applied to the Malprabha reservoir in Karnataka (India).

Liu et al., (2012) applied stochastic dynamic programming to China's Three Gorges Reservoir. Based on the derived operating rules, the reservoir was simulated with the inflow from 1882 to 2005. It was shown that the SDP works well in the reservoir operation.

Zhao et al., (2012) derived a monotonic relationship between reservoir storage and optimal release decision under both deterministic and stochastic conditions, and proposed an algorithm to improve the computational efficiency of both deterministic dynamic programming (DP) and stochastic dynamic programming (SDP) for reservoir operation with concave objective functions. The results showed that the improved DP and SDP exhibit higher computational efficiency than conventional DP and SDP.

2.9.4 Simulation Models

Simulation is a modeling technique that approximates the behavior of system on the computer, representing all the characteristics of the system by mathematical relationship. It is an effective tool for studying the management of a complex water resources system, for it can incorporate the experience and judgment of the planner or designer into the model.

Jacoby and Loucks (1972) proposed the combined use of optimization and simulation model. Chaturvedi and Srivastava (1981) analyzed six major reservoirs of Narmada basin in India using deterministic LP with simulation model.

Palmer et al., (1982) developed simulation and LP models to determine the yield of a reservoir system when operated jointly with the Potomac River.

Srivastava and Patel (1992) used optimization (LP and DP) simulation models for the system analysis of the Karjan irrigation reservoir project in India.

Sharif et al., (2013), applied a simulation model for operation of Karangates reservoir in the Brantas Basin located in East Java, Indonesia. Simulation models runs have been carried out to estimate peak and off peak power that could be generated from the Karangates reservoir at different exceedence probabilities. A distinct practical advantage of the simulation model presented is that it can be used to simulate the operation of reservoirs under various user defined operating policies.

2.9.5 Models used as combination of two or more methods

In an attempt to utilize the advantages of different methods and to overcome the limitations of a particular method, researchers have also developed some hybrid optimization techniques, which are combinations of two or more algorithms.

Becker et al., (1976) used a monthly model and developed daily and hourly model for the CVP system. The monthly model output was used as an input to the daily model and output of the daily model was used as an input to the hourly model.

Chaturvedi and Srivastava (1981) analyzed six major reservoirs of Narmada basin in India using deterministic LP with simulation model.

Marino and Mohammadi (1983) developed a methodology for the monthly operation of a system of two parallel multipurpose reservoirs. The model employed LP nested in DP. At every stage of DP (i.e. months) a series of LP's are solved. The objective of LP was to minimize the total releases from the reservoir in each month. The objective of DP was to maximize the weighted sum of monthly water and power production.

2.9.6 Artificial Neural Network (ANN) model

ANN models have also been successfully applied in reservoir operation problems.

Raman and Chandramouli (1996) derived a general operating policy for a reservoir using ANN from the deterministic DP results. They used ANN for inferring optimal release rule conditioned on initial storage, inflows and demands. Operating rule derived by ANN model was compared with a stochastic dynamic programming model, standard operating policy and the operating policy produced by multiple linear regressions from the deterministic DP results. The performance of the ANN model was reported as better than those of the other models.

Cancelliere et. al. (2002) used a neural network approach for deriving irrigation reservoir operating rules. In their approach operating rules were determined as a two step process: first, a dynamic programming technique which determines the optimal releases with minimizing sum of squared deficit as objective function, subject to various constraints was applied. Then the resulting releases from the reservoir were expressed as a function of significant variables by neural networks. They reported improved performance of ANN approach.

Thair et al., (2015), applied ANN model for Mosul-Dam reservoir located on Tigris River. They concluded that ANN is an important Model for finding the missing data. Also, the ANN technique can accurately predict the monthly Outflow.

Ehsani et al., (2016) developed a new ANN based general reservoir operation system (GROS). Embedding GROS in a water balance model, they analyzed the hydrological impact of dam size as well as their distribution pattern within a drainage basin and concluded that for large-scale studies it is generally acceptable to aggregate the capacity of smaller dams, instead of model a hypothetical single larger dam with the same total storage capacity.

2.9.7 Fuzzy rule based modeling

The concept of fuzzy logic was first introduced by Zadeh (Zadeh, 1965). The fuzzy logic based modeling of a reservoir operation is a simple approach, which operates on an ‘if-then’ principle, where ‘if’ is a vector of fuzzy explanatory variables or premises such as the present reservoir pool elevation, the inflow, the demand, and time of the year. The ‘then’ is a fuzzy consequence such as release from the reservoir (Panigrahi and Majumdar, 2000). The fuzzy logic approach is more flexible and allows incorporation of expert opinions, which could make it more acceptable to operators (Russell and Campbell, 1996). Shrestha et al., (1996)

also confirmed that fuzzy logic is an appropriate tool to consider the impreciseness of variables like inflows, in reservoir operation modeling.

Panigrahi and Majumdar (2000) developed a fuzzy rule based model for operation of the single purpose Malaprabha irrigation reservoir in Karnataka, India. Reservoir storage, inflow, and demands were used as premises and the release as the consequence. They concluded that while a fuzzy rule based model is easy to develop and adopt for operation, it suffers from the curse of dimensionality, and therefore the applications of fuzzy logic to reservoir operation problems may remain limited to single reservoir systems.

Mousavi et al., (2005) presented a dynamic programming fuzzy rule-based (DPFRB) model for optimal operation of reservoir system. In the first step, a deterministic dynamic programming (DP) model was used to develop the optimal set of inflows, storage volumes, and reservoir releases. These optimal values were then used as inputs to a fuzzy rule-based (FRB) model to establish the general operating policies in the second step. The performance of DPFRB was compared to a model, which uses the multiple regression-based operating rules. The results indicated that DPFRB performs well in terms of satisfying the system target performance.

Kamodkar and Regulwar (2013) developed a Fully Fuzzy Linear Programming (FFLP) for the Jayakwadi reservoir stage-II, Maharashtra, India. The objective was to maximize the annual releases for irrigation and hydropower generation. The study demonstrated that use of FFLP in multipurpose reservoir system optimization presents a potential alternative to attain an optimal operating policy.

A Decision Support Model had been evolved by Umadevi et al., (2014) using fuzzy logic with different combinations of inputs for developing rules for the operation of a reservoir in South India under the prevalent varying conditions. The results of the analysis showed that fuzzy-logic can be effectively applied for evolving reservoir operation rules.

2.9.8 Genetic Algorithm (GA) model

Genetic algorithm (GA) derives its concept from Darwin's theory of survival of the fittest and was first envisaged in 1975 by John Holland (Holland, 1992). Genetic Algorithms use a population of solutions in each iteration instead of a single solution and hence they are called population-based approaches (Goldberg, 1989). This is the major difference between classical optimization methods and GAs. GAs use objective function information directly and do not require its derivatives or any other auxiliary information.

Oliveira and Loucks (1997) used a GA to evaluate operating rules for multi-reservoir systems demonstrating that GA can be used to identify effective operating policies. They used the real-valued chromosomes containing the coordinates of the points that define the piecewise linear operating rule functions. Their research suggests that GA may be a practical and robust way of evolving operating policies for complex reservoir systems.

Reddy and Kumar (2006) developed a Multi-objective Evolutionary Algorithm (MOEA) to derive a set of optimal operation policies for a multipurpose reservoir system, the Bhadra Reservoir system, in India. This study employs a population based search evolutionary algorithm namely Multi-objective Genetic Algorithm (MOGA). The results obtained using this algorithm were able to offer many alternative policies for the reservoir operator, giving flexibility to choose the best out of them.

Ahmed and Sarma (2005) developed a GA model for deriving the optimal operating policy and compared its performance with that of stochastic dynamic programming (SDP) for a multipurpose reservoir. The objective function of both GA and SDP was to minimize the squared deviation of irrigation release. They found that GA model releases nearer to the required demand and concluded that GA is advantageous over SDP in deriving optimal operating policies.

Jotiprakash and Shanthi (2006) developed a GA model for deriving the optimal operating policy for a multi-purpose reservoir. The objective function was to minimize the squared deviation of monthly irrigation demand deficit along with the deviation in the target storage. They found that the GA model is advantageous in deriving optimal operating policies.

Mathur and Nikam (2009) used GA to optimize the operation of an existing multipurpose reservoir in India namely, the Upper Wardha reservoir in Maharashtra and to derive reservoir operating rules for optimal reservoir operations. Results showed that, even during low flow condition the GA model can satisfy downstream irrigation demand.

Parmar et al., (2015) applied GA to Sukhi Reservoir project in Gujarat, India to develop a policy for optimizing the release of water for the purpose of irrigation. The fitness function used is to minimize the squared difference between the monthly reservoir release and irrigation demand along with squared deviation in mass balance equation. The results derived by using GA showed that the downstream irrigation demands can be fully satisfied and also considerable amount of water saved.

2.10 Conclusions

The detailed review of the literature indicates that due to climate change, the temperature is increasing gradually and there is a possibility of temperature increase of 1.1°C to 6.4°C by 2100. This global warming is accelerating the melting of glaciers in the Himalayas, which are melting faster than the global average. However, the studies of climate variability on both short and long time scales to establish climate changes over India have been found to be limited. Brahmaputra, one of the major river systems of the Indian sub-continent which originates in the Himalayas, is expected to be more vulnerable to climate change because of the substantial contribution from snow and glaciers into its runoff at downstream. But, only a little emphasis has been placed on studying the hydrological response of this Himalayan River. The impact of climate change on hydrology of a river can be studied by using General Circulation Models. Many researchers have found the suitability and efficiency of the statistical downscaling technique more acceptable than the dynamic downscaling technique which is computationally very expensive. Comparatively, the ANN model to downscale GCMs has got wide recognition due to its ability to establish non-linear relationship between predictors and predictands.

Various hydrological models have been developed around the world to study the impact of rainfall and change in land use/land cover on the discharge of a river. Different types of models have both advantages and disadvantages. However, it is seen that even though the ANN model cannot represent the physical process of the catchment, yet it can identify the non-linear relationship between runoff and rainfall efficiently.

CHAPTER3

SNOW COVER AREA VARIATION STUDY OF BRAHMAPUTRA RIVER BASIN AND ITS IMPACT ON DISCHARGE IN THE RIVER BRAHMAPUTRA

3.1 Introduction

River Brahmaputra, one of the major river systems of the Indian subcontinent, which originates in the Himalayas, is expected to be much vulnerable to climate change because of the substantial contribution from snow and glaciers (Singh et al., 1997a; Singh and Jain, 2002). Snow and Glaciers play essential roles on hydrological, geomorphic and ecological processes of high elevation catchments and are particularly sensitive to climate change (Beniston, 2003; Viviroli et al., 2011). Assessing the influence of ice and snow melt water on groundwater recharge, runoff and sediment transport dynamics is essential in order to provide conceptual models useful for correct management of water resources in mountain regions (Huss, 2011; Lebedeva and Semanova, 2011) and also for long-term projections of the potential hydrologic effects of climate change (Jost et al., 2012).

Snow cover area (SCA) has long been recognized as an important hydrologic variable for streamflow prediction (Martinec, 1985; Hall and Martinec, 1985). The presence of snow in a basin strongly affects moisture that is stored at the surface, and is available for future runoff. During winter, a large extent of the mountainous area of Himalayan river basins is covered by snow, which starts ablating in the spring due to rise in temperature. IPCC (2001a) has indicated that the average global surface air temperature has increased by $0.6 \pm 0.2^{\circ}\text{C}$ since the late 19th century and it is projected to increase by $1.4\text{--}5.8^{\circ}\text{C}$ over the period 1990–2100. Lal and Singh (2001) and Lal (2001) have reported that the average annual mean surface temperature over Indian sub-continent is likely to increase by about 2.7°C and 3.8°C during the decades of the 2050s and 2080s, respectively. Dyurgerov and Mier (2005) and Prasad et al., (2009) mentioned that in recent years, the glaciers and snowfields of the Himalaya-Karakoram-Hindu Kush (HKH) mountain belts and Tibetan plateau are found to be amongst the fastest receding glacial and snow covers in the world. Again, Kulkarni et al., (2007) and Raina (2009) inferred that simultaneous fragmentation of the glaciers along with glacial retreats has also degraded the total areal coverage of perennial snow and ice in the HKH

region. Covering over 33,000 km², glaciers constitute an important component of the Himalaya (Kaul, 1999). Monitoring their evolution is a key issue as the melting of all glaciers in central Asia may significantly contribute to ongoing sea level rise (Kaser et al., 2006). Changes in glacier length, areal extent or mass balance can also be used as climate indicators in a region where climatic series (temperature, precipitation) are rare and the climate change signal is not clear (Roy & Balling, 2005; Yadav et al., 2004). In addition, runoff generated by the melting of these glaciers is an important source of water for the people living in the Himalayan valleys. Measuring ongoing glacier wastage is a first step toward the prediction of future water resources in an area and has, thus, important social and economical impacts (Barnett et al., 2005).

There has been no long-term comprehensive in-situ monitoring of snow/glacial melt contributing to the knowledge of hydrology in the river basins of the Himalayan region. As a result, studies on snow melt/glacial melt that describe a basin's hydrology lack direct evidence and sometimes appear to be inconsistent (Armstrong, 2010; Kaser et al., 2010). Most of the upper parts of the Brahmaputra catchment is covered by Himalayan snow and have a major effect on the downstream flow characteristics of the river. Along with temperature, other climatic factors such as heavy precipitation, wind speed etc. also have impacts on melting of snow. The effect of wind is important for the melting process of snow or chipped ice (Hasebe and Kumekawa, 1994). According to the result of a laboratory experiment, performed by Hasebe and Kumekawa (1994), the relation between the ratio of volume of snowmelt water to air temperature and wind speed is nearly linear. They also found that peak discharge is sharp as the wind speed increases and Lag time from the beginning of snowmelt runoff to peak discharge is faster according to an increase in wind speed. Rainfall on existing snow cover frequently occurs in spring. At the onset of a rain storm, the snow cover often stores a portion of the rain and consequently attenuates runoff formation. However, if the rain persists and the snow cover becomes saturated, any additional melt water will increase runoff formation.

Many studies stated that the melting of glaciers is a clear indicator of climate change (Xu et al., 2009) and noted that glacier change is the most visible and obvious indicator of changing temperatures (Armstrong, 2010; Winkler et al., 2010). The rising temperature in the Himalayas would affect glacier melt (Barnett et al., 2005). In the present study, the temperature factor has been taken into consideration to study its impact on the change in snow cover area of the Brahmaputra river basin.

A widely cited estimate shows considerable variation in the contribution of melt-water across the river basins fed by the Himalayan glaciers (Eriksson et al., 2009; Xu et al., 2008) although this varies seasonally and spatially. The primary effect of climate warming on runoff is the increased streamflow caused due to larger glacier melt rates (Hock, 2005). The importance of melt-water contribution also varies from basin to basin. It is extremely important for Indus basin and it is important for Brahmaputra basin. But it plays modest roles for Ganges, Yangtze and Yellow Rivers (Immerzeel et al., 2010). By region, melt-water contributes 30 percent to the total water flow in the eastern Himalayas, 50 percent in the central and western Himalayas and 80 percent in Karakoram (Xu et al., 2009). Glacier retreat and the release of freshwater are expected to be a key element in projections of discharge from glacierised catchments over the next decades (Huss et al., 2010; Finger et al., 2012). Using climate model data as forcing, different studies indicate an increase in discharge in spring due to earlier onset of snowmelt, but a decline later in the year due to reduced glacier extent (Stahl et al., 2008; Huss et al., 2008). Glacial melt water can also have relevant impacts on the hydrological regime of larger watersheds further downstream. Keeping all these factors in mind, the effect of variation in snow cover area on the discharge of the river Brahmaputra has also been analyzed in this study.

Mountain glaciers are used to detect and monitor local climate change in regions not typically monitored by instrumentation, as they are considered to be sensitive indicators of climate (Haeberli et al., 2007). Due to the large extent and difficult accessibility of high mountainous terrain, remote-sensing techniques provide an efficient way to collect data in such regions. The satellites imageries are well suited for measuring the snow cover because the high albedo of snow gives better contrast with most of the other natural surfaces except clouds (Hall et al., 2002). The remote sensing-based measurements provide an opportunity to achieve large and possibly complete spatial coverage, even in very remote areas. Identification of snow cover using only the visible reflected light may be difficult because many things appear as white, such as clouds or even rocks. However, comparing the reflectance of other wavelength, such as infrared, it is possible to differentiate snow from clouds. Reflectance of snow is higher in the visible (0.5–0.7 μm) wavelengths and has a low reflectance in the shortwave infrared (1–4 μm) wavelengths (Nolin and Liang, 2000) which enables to distinguish snow from clouds and other non- snow-covered conditions. The ratio between short-wave infrared channel and visible channel was used by Kyle et al., (1978) and Bunting and d'Entremont (1982) for snow cover mapping. This band ratio method was later utilized by Dozier (1989) to map snow cover area in the Sierra Nevada Mountains. This method is known as Normalized Difference

Snow Index (NDSI) method and is one of the very potential methods to map snow cover of an area. This NDSI method is used in the present study to prepare snow maps of the Brahmaputra River basin.

3.2 Materials and Method

3.2.1 Data used

The variation of snow cover area in the Brahmaputra river basin has been studied starting from 2002 to 2015 for four different months viz. January, April, July and October using the MODIS (Moderate Resolution Imaging Spectroradiometer) image, MOD09A1.5 (MODIS/Terra Surface Reflectance 8-Day L3 Global 500m SIN Grid) of 500m resolution consisting of seven bands (band-1 to band-7). The freely available MODIS products, with 500 m spatial resolution can provide a basis for regional snow cover mapping, monitoring and hydrological modelling (Liang et al., 2008). MODIS imageries have successfully been applied in monitoring snow cover from space using the Normalized Difference Snow Index (NDSI). Relative to similar sensors such as the Advanced Very High Resolution Radiometer (AVHRR), the MODIS sensor offers some significant advantages. The two main difficulties in estimating SCA from AVHRR images are obscuring of the ground by cloud cover, and obscuring of snow cover by vegetation canopies (especially forests). The MODIS provides observations at a nominal spatial resolution of 500m versus the 1.1km spatial resolution of the AVHRR. MODIS's data are available continuously (spatially and temporally) and also has several spectral bands which facility is useful for distinguishing the extent of snow cover (Salomonson and Appel, 2004). Most of the MODIS accuracy assessments reported overall accuracy between 85 and 99% during clear sky conditions (Parajka and Blöschl, 2012).

The climate change scenario data used in this study are based on simulations carried out using General Circulation Models (GCMs) for the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC, 2007). The gridded temperature data of HadCM3 (Hadley center Coupled Model version 3) model of A2 scenario were used to get the average temperature of the upper portion of the Brahmaputra River basin. HadCM3 is a coupled atmosphere-ocean general circulation model (AOGCM) developed at the Hadley Centre in the United Kingdom (Gordon et al., 2000; Collins et al., 2001). In this model, spatial resolution is 2.5° X 3.75° (latitude by longitude) forming the global grid of 96×73 grid cells with 19 levels. In the oceans, this model has a resolution of 1.25° X 1.25° (latitude by

longitude) with 20 vertical levels. This model has been used by several researchers to study the impact of climate change. The model has also been used in IPCC third assessment report. A2 scenario which is based on IPCC SRES-A2 (Special Report of Emission Scenario A2) considers the effect of greenhouse gases and Sulphate aerosol. HadCM3 model was selected since it has the highest 'skill scores' for both precipitation and temperature of all the models used for the AR4 (Cai et al., 2009). This model does not require flux adjustment and has higher resolution compared to other models. The raw data were downloaded from the website of IPCC Data Distribution Centre (http://www.ipcc-data.org/ar4/gcm_data.html).

The area of Brahmaputra river basin is very large and getting the actual temperature data at the upper part of the catchment is quite troublesome. Hence, the average temperature values of the GCM points that fall in and around the upper catchment have been used to study the temperature variations at different time periods. It has been reported that the GCMs simulate temperature better than rainfall and therefore there is more confidence in predictions of temperature than rainfall (Masanganise et al., 2013). McMahon et al., (2014) in their study have found that the monthly pattern of temperature is generally well reproduced by the GCMs compared to the monthly pattern of precipitation. They calculated the Nash–Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970) to compare the GCM climate data and the observed data. They found that the median NSEs of all monthly temperature patterns are greater than 0.75, with 41% greater than 0.90. They also concluded that along with few other GCMs, HadCM3 is also a better performing GCM. Miao et al., (2012) assessed the performance of the AR4 GCMs in simulating precipitation and temperature in China from 1960 to 1999 by comparing with the observed data. They used system bias (B), root-mean-square error (RMSE), Pearson correlation coefficient (R) and Nash-Sutcliffe model efficiency (E) metrics to compare the GCM output. They observed that GCMs gave reasonably accurate predictions of the temperature, but were less successful at reproducing the precipitation. Again, Mavromatis and Jones (1999) evaluated precipitation and near surface air temperature in two successive versions of the Hadley Centre General Circulation Model (GCM). Their conclusion was positive towards the direct use of raw temperature data of HadCM2. Considering the accuracy of GCMs' temperature data, here in this study, the HadCM3 temperature data was used to study its impact on melting of snow in the Brahmaputra River basin. The HadCM3 GCM points falling on the upper Brahmaputra basin have been considered in this study. There were fifteen points that fall in and around the upper catchment of the Brahmaputra basin. Fig.3.1 shows the HadCM3 GCM points considered for

temperature evaluation. The geographic coordinates of these 15 HadCM3 GCM points are given in Table 3.1.

Table 3.1: Geographic coordinates of HadCM3 GCM points that fall in and around the upper portion of the Brahmaputra catchment

HadCM3 GCM points	Geographic Coordinates
1	82.50° E, 32.00°N
2	86.25°E, 32.00°N
3	90.00°E, 32.00°N
4	93.75°E, 32.00°N
5	97.50°E, 32.00°N
6	82.50°E, 30.00°N
7	86.25°E, 30.00°N
8	90.00°E, 30.00°N
9	93.75°E, 30.00°N
10	97.50°E, 30.00°N
11	82.50°E, 27.00°N
12	86.25°E, 27.00°N
13	90.00°E, 27.00°N
14	93.75°E, 27.00°N
15	97.50°E, 27.00°N

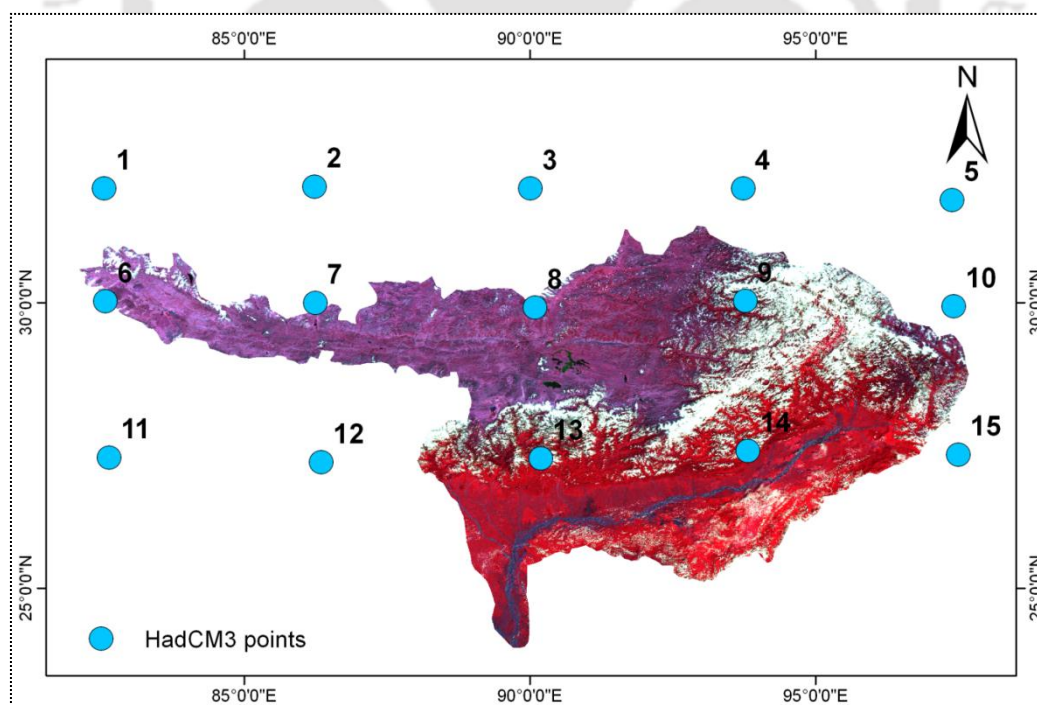


Fig.3.1: Map showing the HadCM3 points in and around the upper Brahmaputra basin taken to evaluate the average temperature

The daily discharge data from 2002 to 2015 at Pandu gauge site on the river Brahmaputra has been collected from the Water Resources Department, Govt. of Assam to study the variation of discharge of the river Brahmaputra with respect to the change in snow cover area.

3.2.2 Normalized Difference Snow Index (NDSI)

The NDSI method is generally used for snow cover mapping using satellite data (Hall et al., 1995, 2002, Kulkarni et al., 2002b, 2006; Negi et al., 2008). NDSI uses the high and low reflectance of snow in visible (Green) and shortwave infrared (SWIR) regions respectively. Additionally, the reflectance of clouds remains high in SWIR band, thus NDSI allows in discriminating snow and clouds. NDSI ranges from -1 to +1 and is defined by the following relation:

$$NDSI = \frac{Green - SWIR}{Green + SWIR}$$

Where, Green and SWIR are the reflectance of the green and shortwave infrared bands respectively. Snow has a high reflectance in band-4 (0.545-0.565 μ m, visible green) and a low reflectance in band-6 (1.628-1.652 μ m, shortwave near infrared) of the MODIS instrument. A threshold value of NDSI of 0.4 is defined for the pixels that are approximately 50% or greater covered by snow from imageries of different sensors (Xiao et al., 2001). However, identification of snow covered areas using NDSI is difficult if snow cover areas are mixed with vegetation (Hall et al., 1998). Distinguishing snow from other non-snow features such as water, or dense forests may be difficult because they have similar NDSI readings to snow. To overcome this difficulty *i.e.*, to distinguish these features from snow cover, it becomes necessary to examine other wavelengths. For this, reflectance in band-2 and band-4 are examined primarily to separate water bodies and forest respectively from snow. It is also important to examine the Normalized Difference Vegetation Index (NDVI) to see if a pixel is snow covered forest.

3.2.3 Preparation of snow map

The snow maps of the study area have been prepared in the Erdas Imagine remote sensing software. The various operations performed were: importing the original *.hdf* format of the raw satellite data to *.img* format, mosaicing of all the tiles that cover the whole Brahmaputra River basin, re-projection of image to geographic latitude longitude and WGS84, sub-setting of the mosaiced image as per the area of interest to get the shape of the Brahmaputra River basin and finally stacking operation was performed to get the image consisting of seven bands.

The high reflective nature of both snow and cloud tops in the visible part of the electromagnetic spectrum, makes cloud indistinguishable from snow. On the other hand, snow is highly absorptive in the short wave infra red part of the electromagnetic spectrum while cloud is highly reflective. NDSI is thus one method that can efficiently differentiate between snow and cloud cover of a satellite image. Pixels that are approximately 50% or greater covered by snow have NDSI values of 0.4 (Hall et al., 2002). Hence, a threshold value of 0.4 has been taken for snow (*i.e.* if $NDSI > 0.4$, then the pixel is snow, else not snow). In the model maker tool of Erdas imagine, two functions were generated to make the numerator and denominator of the NDSI equation. The data also needs to have 100 added to eliminate negative values and also scaled by a factor of 10^4 . For MODIS data, band-4 represents the green band while band-6 represents the short wave infrared band. If summation of band-4 and band-6 is equal to zero (the denominator), the NDSI cannot be obtained as NDSI value will be infinity. Also, a data value of -28672 was ignored since -28672 is the value of pixels of no data. Again, another function in the model maker was created which considers the pixels having NDSI values of greater than or equal to 0.4 as snow. Total 56 NDSI images were prepared from 2002 to 2015 for the months of January, April, July and October. Fig.3.2 gives an overall view of the steps to prepare NDSI maps in the model maker tool of the Erdas Imagine software.

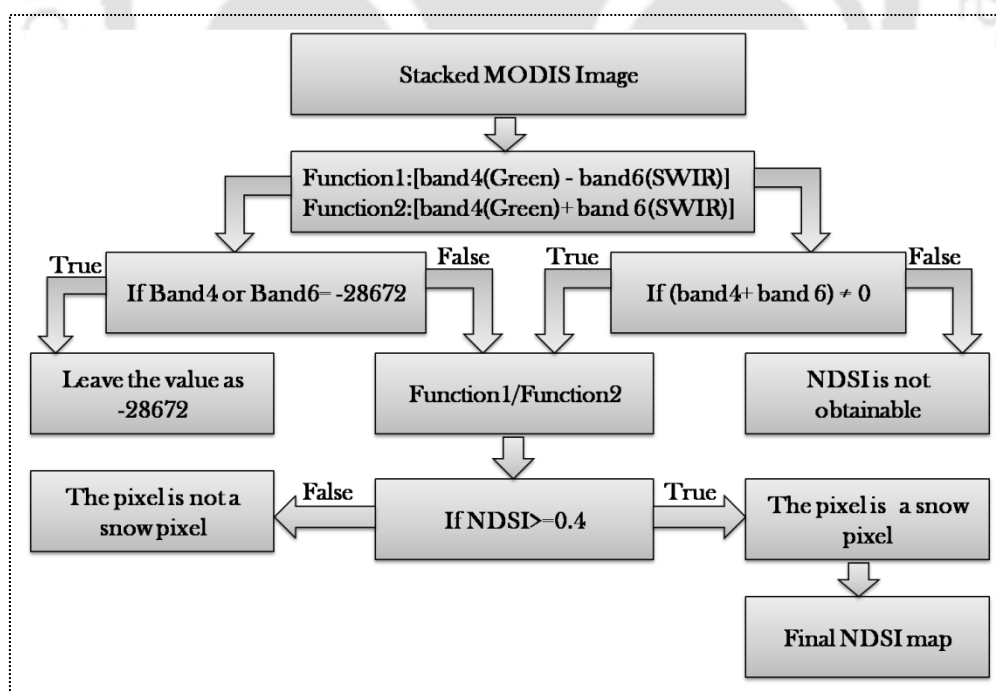


Fig.3.2: Flowchart for preparation of NDSI map in Erdas Imagine

Since water may also have an NDSI of 0.4, an additional test is necessary to separate snow and water. Snow and water may be discriminated because the reflectance of water is less than 11% in band 2. Hence, if the pixels with reflectance in band 2 (0.841- 0.876 μm) was found to be less than 11% even if the NDSI was greater than or equal to 0.4, they were mapped as water. Similarly, for a pixel where the NDSI was greater than or equal to 0.4, but the reflectance in band 4 (0.545-0.565 μm) was less than 10%, it was marked as dark forest (Dozier,1989). The reflectance from the forest areas that consist of dense conifers to less dense deciduous forests is considerably darker than from non-forested areas even with substantial depths of snow. The challenge is to determine the snow cover areas when they may not be directly detectable. To identify the snow covered forests, the NDVI (Normalized Difference Vegetation Index) was examined. If NDSI value of a pixel is less than 0.4 (not snow) but the NDVI is approximately 0.1, the pixel could be snow-covered forest (Hall et al., 2002, Klein et al., 1998). These measures prevent low reflective features like water bodies and dense forest canopies from being misclassified as snow. Fig.3.3 shows in detail, the steps to prepare NDVI in Erdas Imagine software. MODIS bands-2 (0.841-0.876 μm , NIR) and band-1 (0.620-0.670 μm , Red) are used to create NDVI which can be expressed as,

$$NDVI = \frac{MODIS\ band2 - MODIS\ band1}{MODIS\ band2 + MODIS\ band1}$$

In the NDVI model, the following function was added to create snow forest mask:

$$NDVI \geq 0.0\ and\ NDVI < 0.2$$

The created water, forest and NDVI masks were finally applied to the NDSI product to get the final snow map from which the snow cover area can be determined. The values within the NDSI, water, forest and NDVI masks are 1 if true (snow pixel) or 0 if false (non-snow pixel).

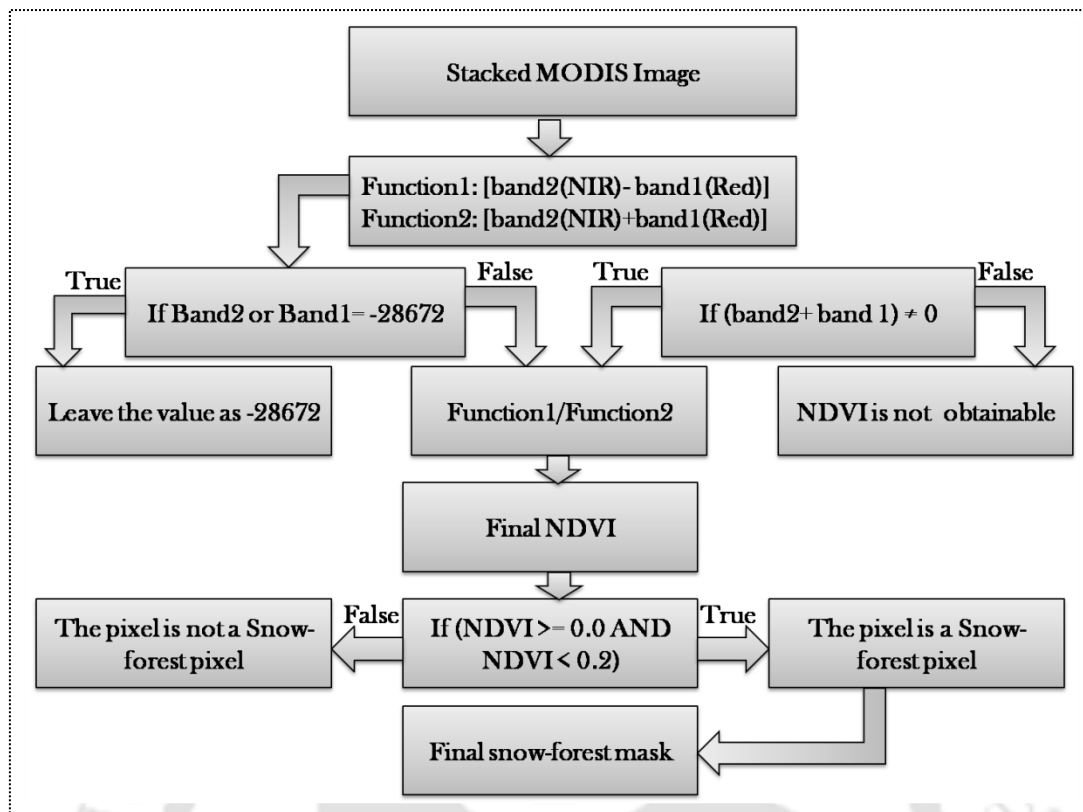


Fig.3.3: Flowchart for NDVI mask prepared in Erdas Imagine

3.2.4 Comparison of the snow maps with Landsat data

Cloud free Landsat satellite data (Landsat 4-5 TM) of 30m resolution acquired on April 15, 2010 has been used to validate the snow map prepared from the MODIS image. MODIS image of the same date has been selected for validation. Two small areas of the MODIS snow map have been compared with the high resolution Landsat data. While interpreting visually, it has been observed that the portions covered by snow for both the MODIS and Landsat images (shown in red rectangle in Fig. 3.4(a) and 3.4(b) were same. Apart from visual interpretation, when the area covered by snow for both the MODIS and Landsat images of the selected portions were calculated, the results were almost equivalent. The NDSI map of the Landsat images were prepared by considering Band-2 (Green, 0.52-0.60 μ m) and Band-5 (Short-wave Infrared, 1.55-1.75 μ m). Fig. 3.4(a) and 3.4(b) show the snow cover map of MODIS image and corresponding Landsat image. For the first portion [Fig.3.4(a)], the area covered by snow in the MODIS image (LHS) was found to be 6012.25 sq.km., while for the Landsat image (RHS) on the same date, it was 6245.65 sq.km. Again, for the other segment [Fig.3.4(b)], the snow cover area in the MODIS image (LHS) was found to be 8393.25 sq.km., while for the Landsat snow map(RHS), it was 8562.25 sq.km. From this validation, it

has been proved that MODIS image can be used to prepare snow maps of large basins. Hence, the MODIS images were used for studying the snow cover area variation in the present study.

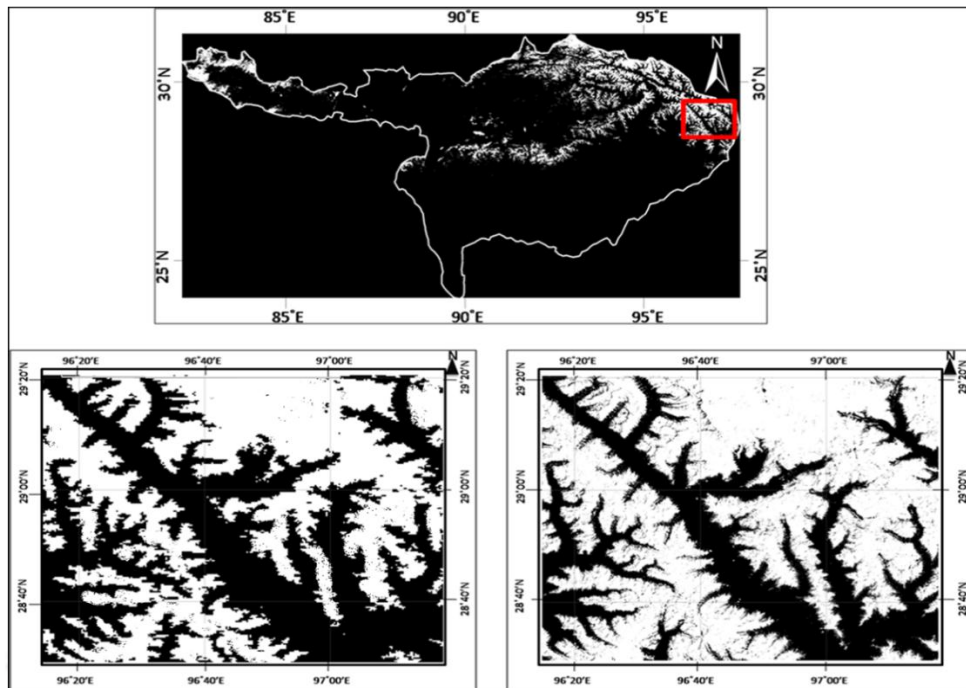


Fig.3.4(a): Comparison of Snow Cover Area of MODIS(LHS) and Landsat (RHS) data for the first portion

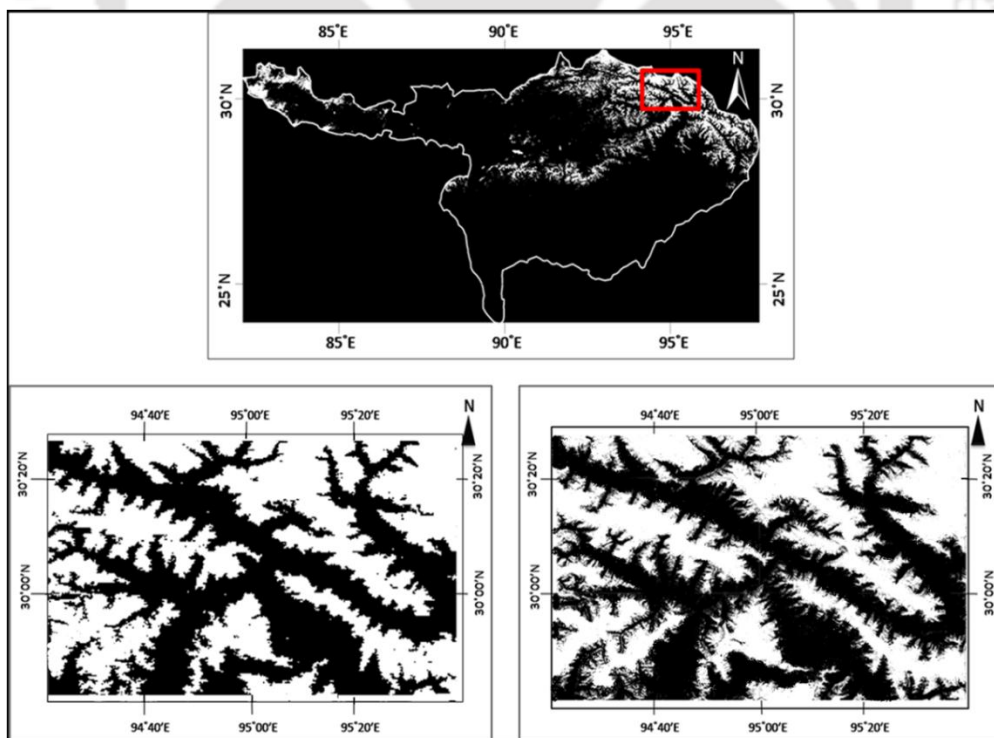


Fig.3.4(b): Comparison of Snow Cover Area of MODIS(LHS) and Landsat (RHS) data for the second portion

3.3 Results and Discussions

3.3.1 Variation of snow cover area with respect to temperature

The snow cover maps for January, April, July and October from 2002 to 2015 have been prepared in the Erdas Imagine software using the methodology discussed above. Fig.3.5 shows an example of the final snow cover map created using the presented methodology. In the image, the white pixels show the snow cover area while black pixels show the non-snow area. All the snow cover area maps from 2002 to 2015 for January, April, July and October are shown in Fig.3.6, 3.7, 3.8 and 3.9 respectively. The total snow cover area for each selected month from 2002 to 2015 along with the temperature of HadCM3 for A2 scenario are given in Table 3.2. It is observed from the table that maximum snow cover area is found either in the month of January or in the month of April.

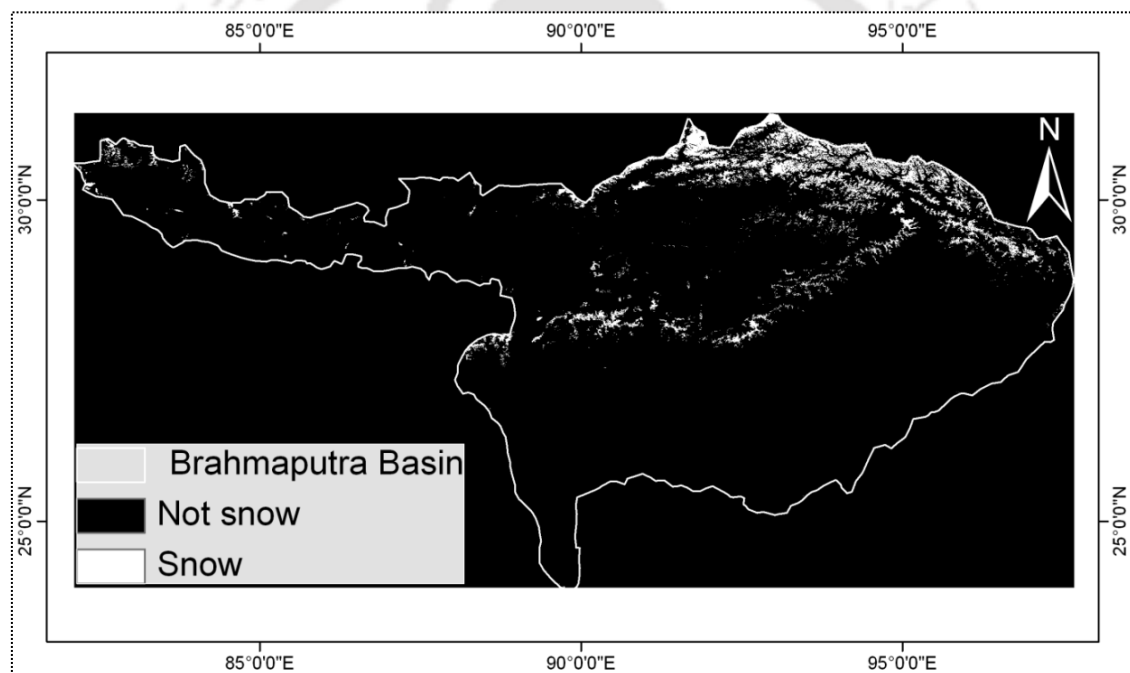
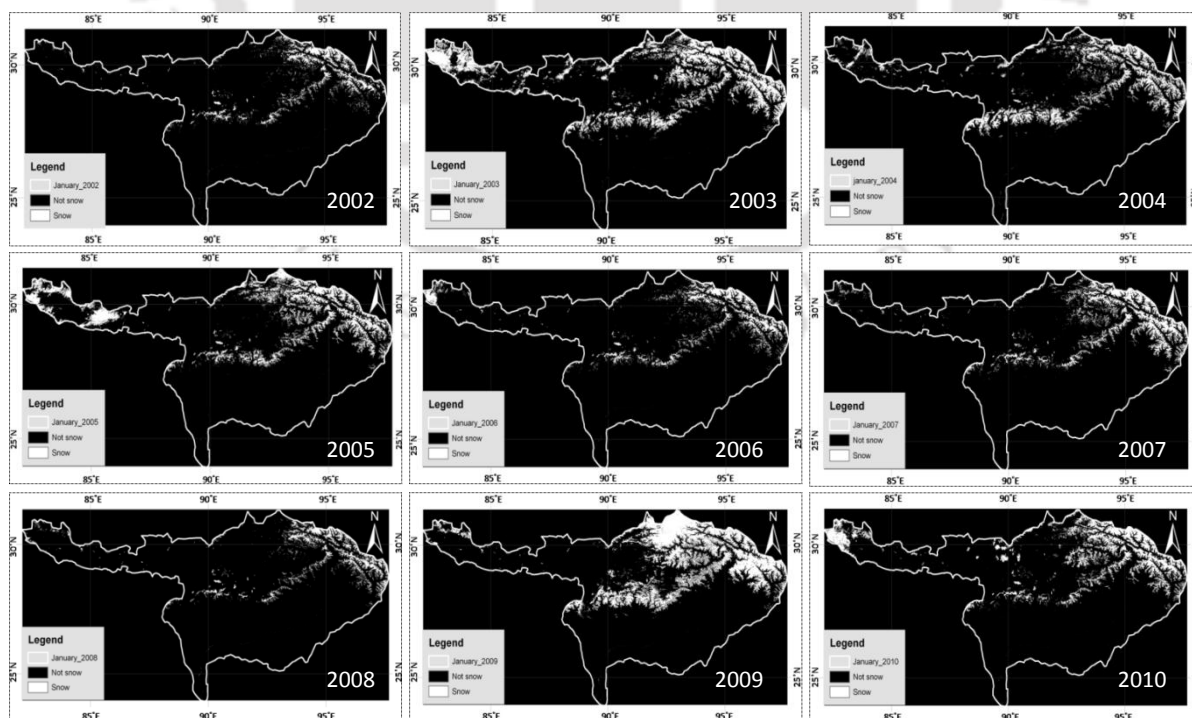


Fig.3.5: Map showing snow cover area of the Brahmaputra River Basin

Table 3.2: Snow Cover Area and temperature for different months

Year	January		April		July		October	
	Snow cover area (sq.km)	Temperature (°C)	Snow cover area (sq.km)	Temperature (°C)	Snow cover area (sq.km)	Temperature (°C)	Snow cover area (sq.km)	Temperature (°C)
2002	30474	-14.92	114588	-2.70	14536	7.91	84551	-0.67
2003	98414	-12.26	99972	-1.62	25851	8.79	21069	-1.05
2004	64472	-14.22	56236	-1.09	23695	7.20	63894	0.93
2005	74004	-11.66	83658	-0.92	11262	7.63	28355	-0.28
2006	37285	-13.87	80162	-3.81	12678	8.85	16157	-2.28
2007	49892	-14.43	87833	0.81	7881	8.16	12347	1.12
2008	29822	-10.20	92263	0.16	15540	7.84	32572	-2.00
2009	112736	-15.55	89539	-1.74	14328	7.75	25427	1.38
2010	66618	-11.43	68848	-0.03	12401	7.96	30162	-3.25
2011	62421	-12.88	74142	-1.69	13038	7.91	13129	1.43
2012	138555	-11.65	89930	-0.82	12236	8.24	20526	0.25
2013	126798	-15.70	52121	0.43	9088	7.33	16915	-1.06
2014	112355	-14.71	50245	-2.88	4503	8.22	9180	0.57
2015	102833	-13.56	51137	-2.13	6584	8.97	9982	0.04



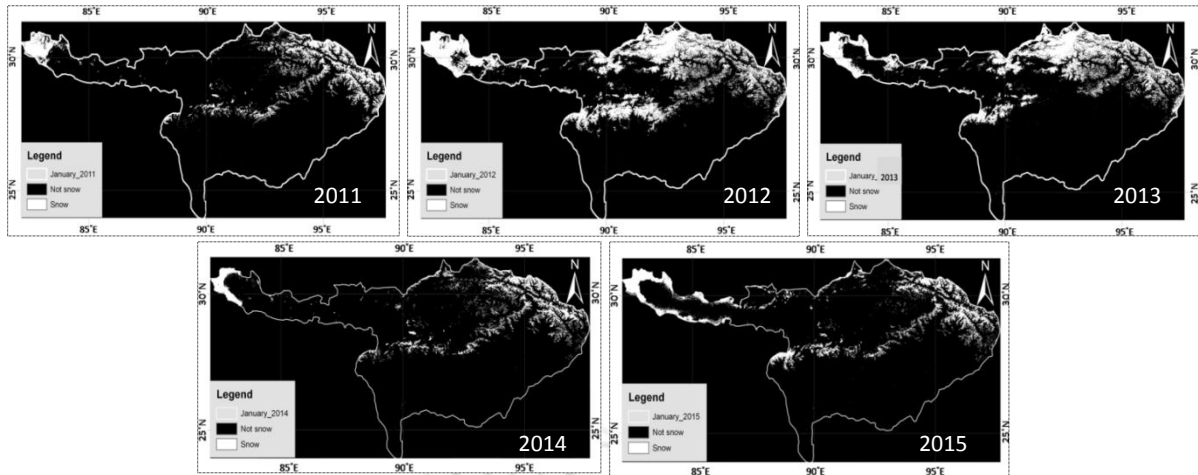


Fig.3.6: Snow Cover Maps of the Brahmaputra basin for January from 2002 to 2015

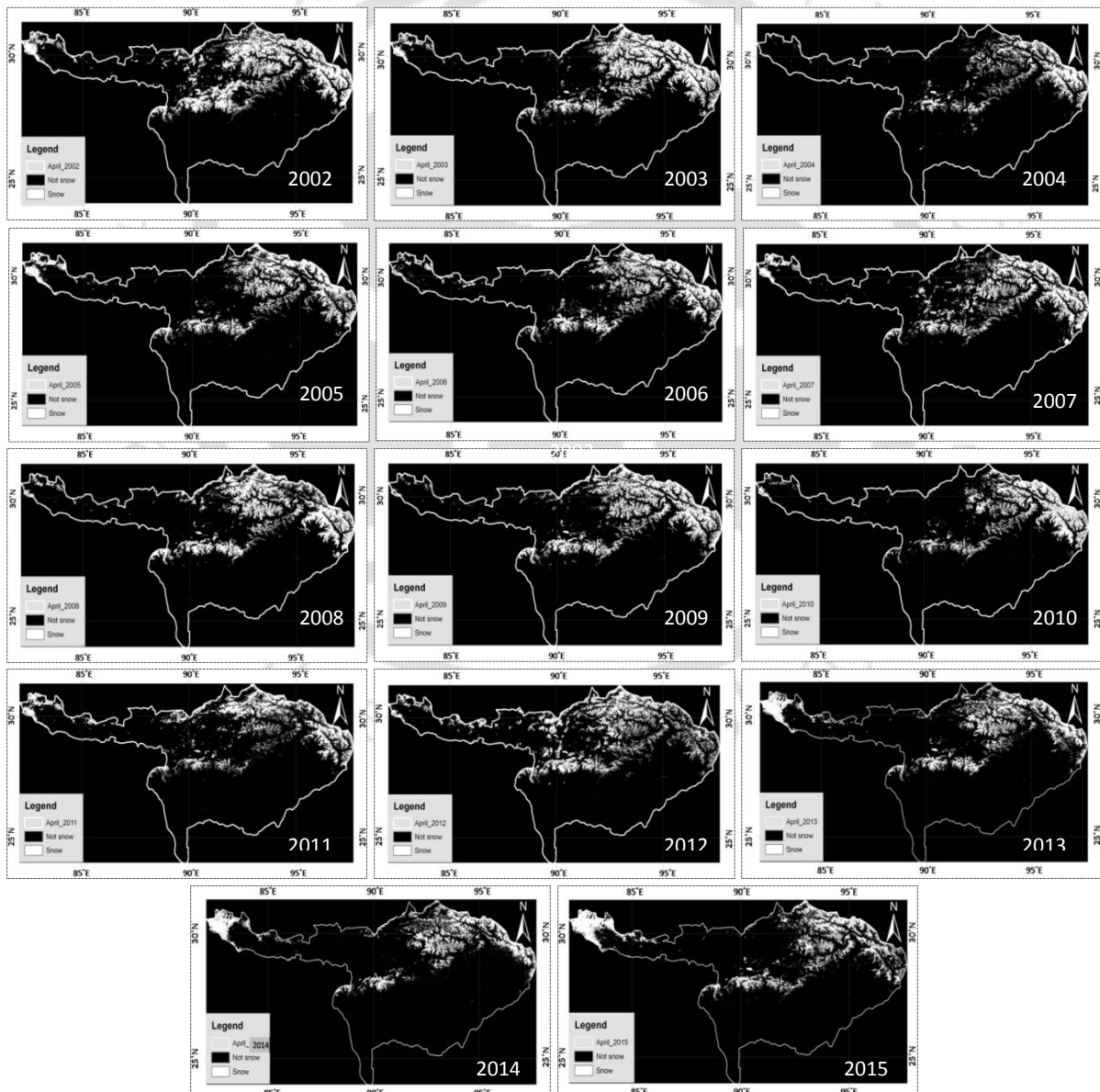


Fig.3.7: Snow Cover Maps of the Brahmaputra basin for April from 2002 to 2015

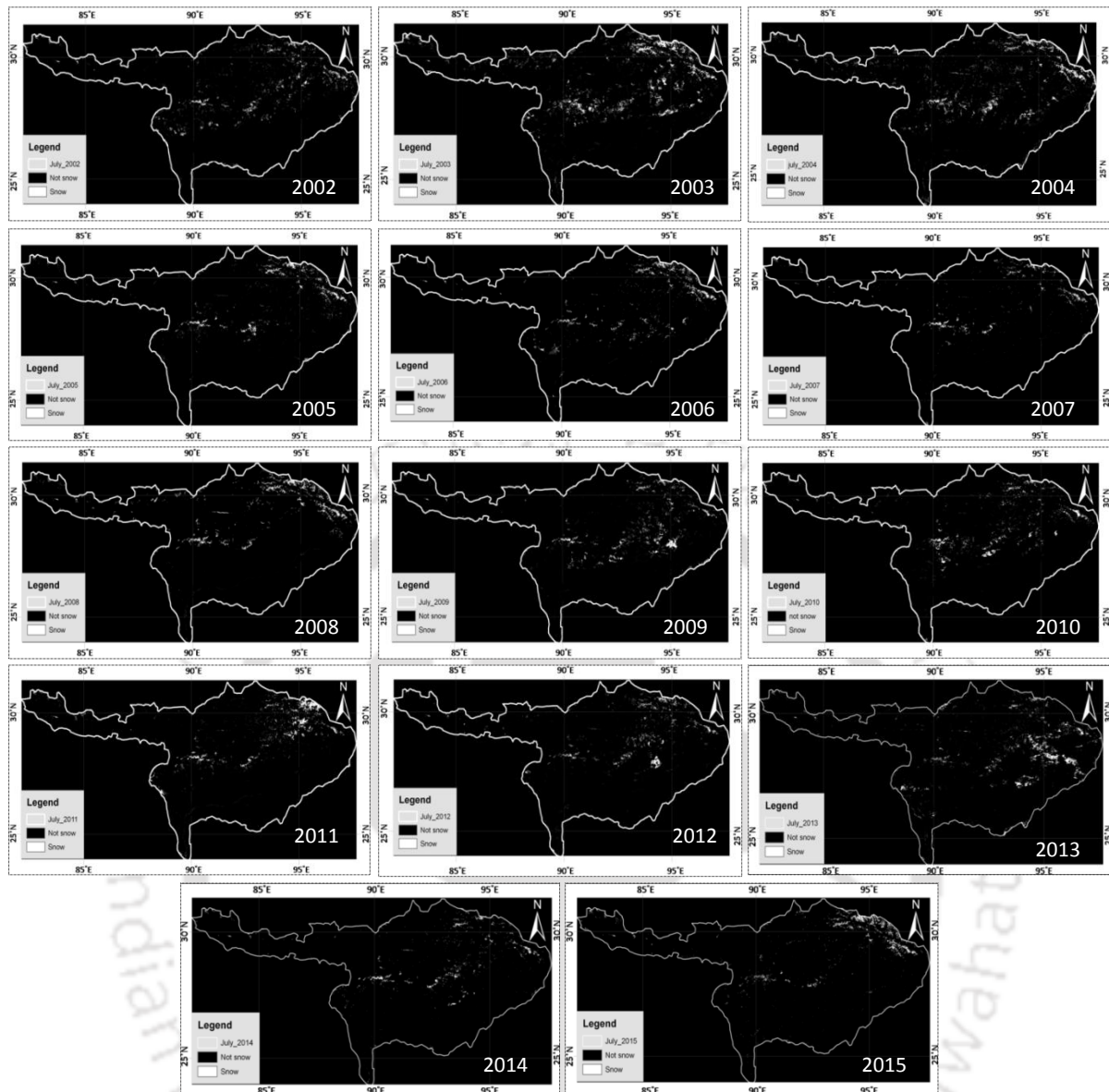
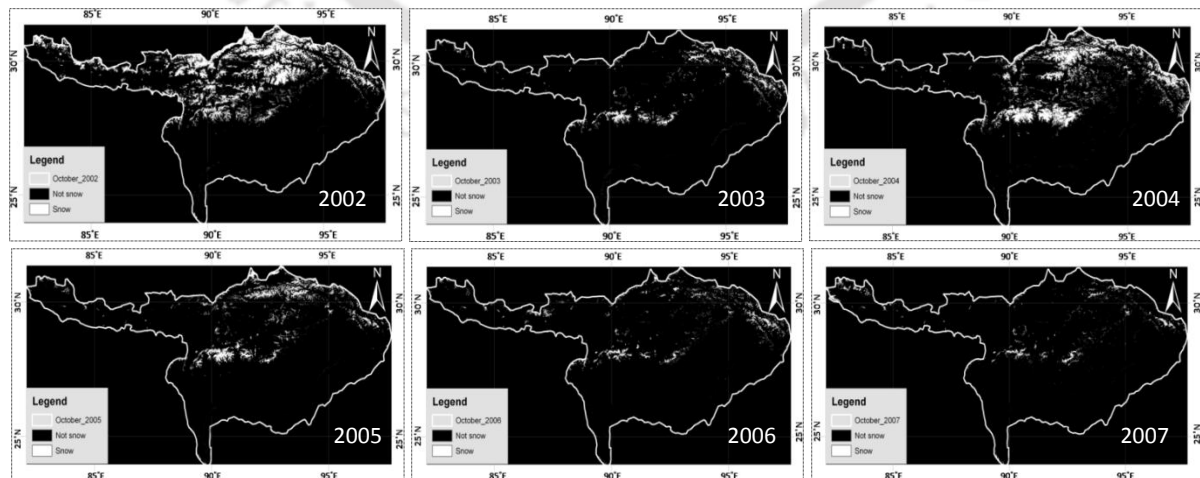


Fig.3.8: Snow Cover Maps of the Brahmaputra basin for July from 2002 to 2015



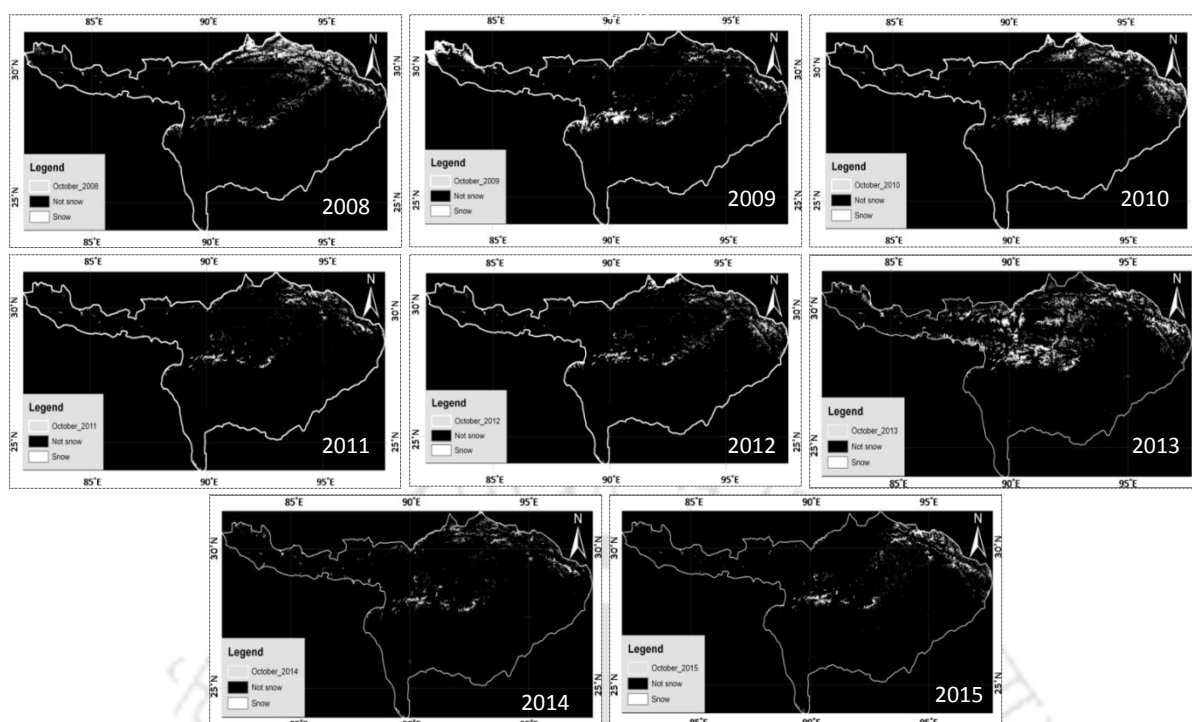
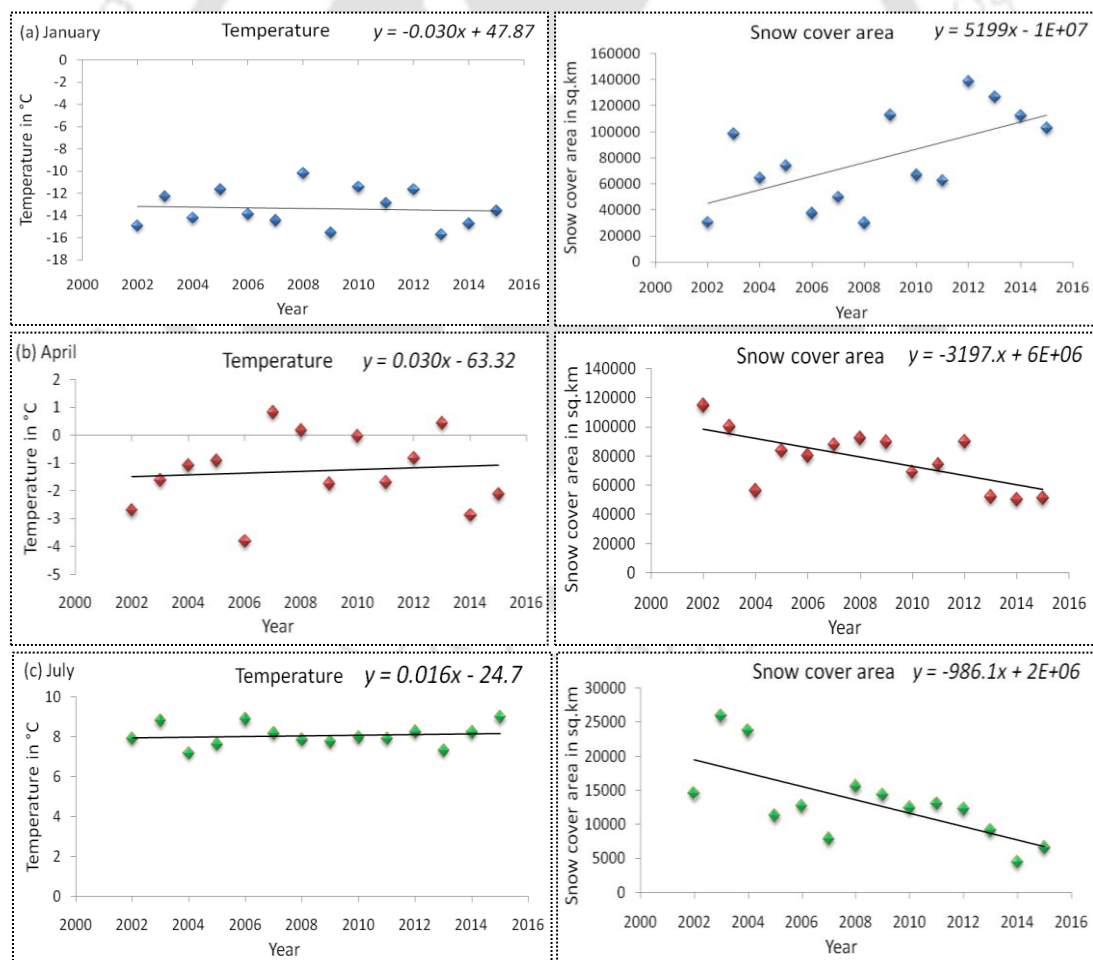


Fig.3.9: Snow Cover Maps of the Brahmaputra basin for October from 2002 to 2015

From Table 3.2, it is observed that the maximum snow cover area has been observed in 2012 for the month of January with a value of 138555sq.km. and the minimum has been observed in 2014 for the month of July with a value of 4503sq.km. The maximum temperature for the entire period from 2002 to 2015 has been observed in 2015 for the month of July (8.97°C) and the minimum has been observed in 2013 for the month of January (-15.70°C). The increasing and decreasing trend of snow cover area with respect to the change in temperature for all the four months from 2002 to 2015 are shown in Fig.3.10 [(a), (b), (c) and (d)]. The results clearly displayed that except for the month of January, the values of temperature taken from the GCM (HadCM3 A2 scenario) for the aforesaid months are increasing gradually from 2002 to 2015 which can be attributed to the fact of global warming. While establishing a relationship between the snow cover area and temperature data, it has been observed that for the month of January, the snow cover area shows an increasing trend with respect to the decreasing trend of temperature. The minimum snow cover during this period was in the year 2008 with a value of 29822 sq. km. and the maximum was in the year 2012 with a value of 138555sq.km. While the minimum temperature was in the year 2013 (-15.70°C) and the maximum was in the year 2008 (-10.20°C). For the entire study period from 2002 to 2015, the effect of temperature on snow melt was found to be the maximum in 2008. For the other three months *i.e.* April, July and October, the results are plotted in Fig. 3.10(b), (c) and (d).

The graphs show that snow cover area for these three months decreases with increase in temperature. Maximum changes have been observed in the month of October. For the month of April, the minimum snow cover was observed in the year 2014 (50246 sq. km.) and the maximum was observed in the year 2002 (114588sq. km.). For July, the minimum was observed in the year 2014 (4503sq. km.) and the maximum was observed in the year 2003 (25851sq. km.). Again, for the month of October, the minimum snow cover area was found to be 9180 sq. km. in the year 2014 while the maximum was found to be 84551sq. km. in the year 2002. In case of temperature, the minimum in the month of April was observed in the year 2006(-3.81 °C) and the maximum was observed in the year 2007 (0.81 °C). For July, the minimum and maximum temperatures were observed in 2004 (7.20°C) and 2015 (8.97°C) respectively. On the other hand, for the month of October, the minimum temperature was observed in the year 2010 (-3.25°C) and the maximum was observed in the year 2011 (1.43°C).



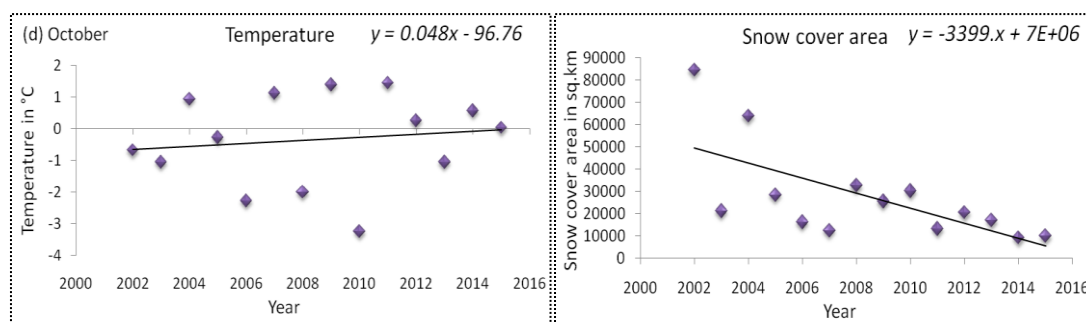


Fig.3.10: Trend showing Variation of Snow Cover Area w.r.t temperature for the month of (a)January, (b) April (c) July and (d) October from 2002 to 2015

Fig. 3.11 shows the percent change in snow cover area from 2003 to 2015 with respect to the snow cover area in 2002 for the months January, April, July and October.

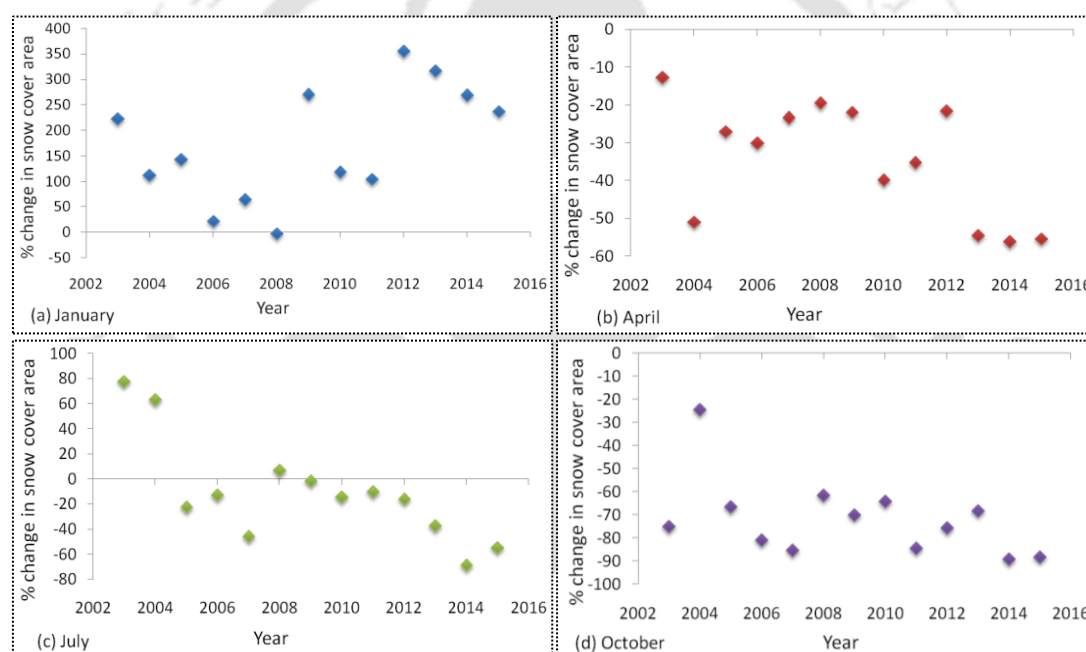


Fig.3.11: Percent change in snow cover area from 2003 to 2015 w.r.t. snow cover area in 2002 for (a) January, (b) April, (c) July and (d) October for the Brahmaputra River basin

It is observed from the above figure that for the month of January, except for 2008 where the snow cover area was less than the snow cover area in 2002, for all other years, the snow cover area increases with respect to the snow cover area in 2002. The maximum increase was observed in 2012 (354.68%) while the minimum increase was observed in 2006 (22.35%). In 2008, the snow cover area decreased by 2.14% with respect to that in 2002.

For the month of April, for each year from 2003 to 2015, the snow cover area was observed to be less than the snow cover area in 2002. The maximum decrease has been observed in

2014 with percent decrease value of 56.15% compared to the snow cover area in 2002. The minimum decrease has been observed in 2003 (12.75%). The snow cover area also decreased significantly in the years 2004, 2013 and 2015 by 50.92%, 54.14% and 55.37% respectively.

For July, the snow cover area were more in 2003, 2004 and 2008 compared to that in 2002. In 2003 and 2004 it increased by 77.84% and 68% respectively. For other years, the snow cover areas were less compared to the snow cover area in 2002. The maximum percent decrease in snow cover area was in 2014, where it decreased by 69.02% with respect to 2002 and the minimum percent decrease was in 2009 where snow cover area decreased by 1.43% compared to that in 2002.

Compared to the snow cover area in 2002, the snow cover areas were less for other years from 2003 to 2015, for the month of October. The maximum reduction in snow cover area was observed in 2014 (89.14%) and the minimum reduction was observed in 2004 (24.43%). Except for the year 2004, the percent decrease in snow cover areas are more than 50% for the rest of the years compared to that in 2002.

Fig.3.12 shows the scatter plot for percentage reduction in average snow cover area of the Brahmaputra River basin from 2003 to 2015 compared to the snow cover area of 2002.

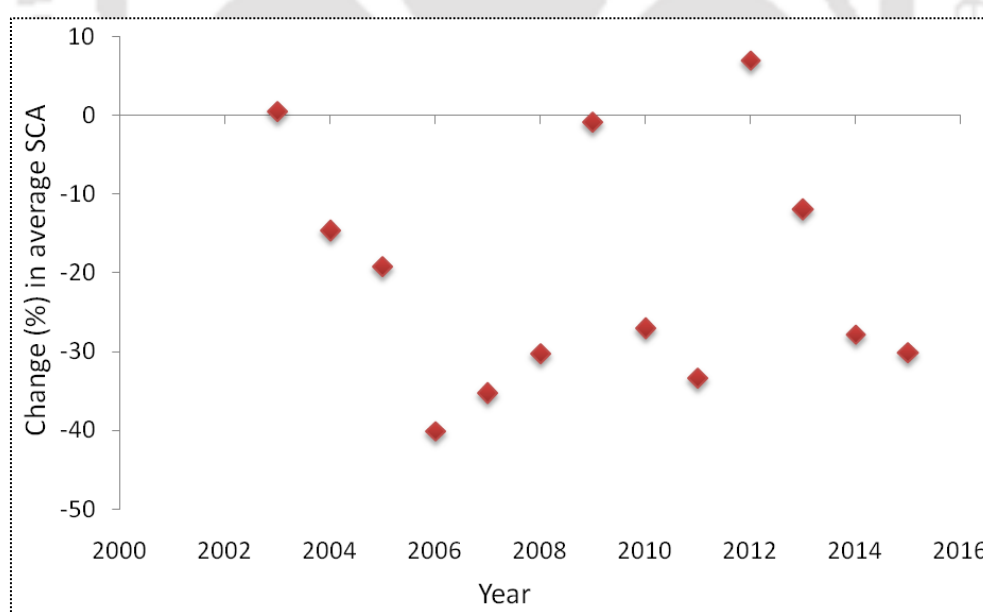


Fig.3.12: Percentage change in average snow cover areas from 2003 to 2015 for the Brahmaputra River basin

It is observed that average snow cover area for 2003 and 2012 increases compared to the snow cover area in 2002 by 0.47% and 7% respectively. For the rest of the years, the average snow cover area of the basin reduces compared to the snow cover area in 2002. The maximum percentage reduction in snow cover area as compared to that of 2002 has been observed for the year 2006 (40.08%) and the minimum percentage reduction was observed in the year 2009 (0.87%). The increase in percentage reduction in snow cover area implies that the river is carrying a significant amount of melting water and is affecting the downstream hydrology of the river Brahmaputra.

Temperature being a dominant factor, this study evaluated the impact of increase in temperature on the snow cover area. Apart from the role of temperature, other factors should also be taken into account to explain the reason behind the difference in snow melt trend of the other three months from that of January. For example, if the snow is older, its albedo will be lower and in such situation it absorbs more solar radiation. Again, if the temperature variation is not significant, snow melts faster in the windy condition than in the calm conditions. According to IPCC (2001a), it is likely that changes in precipitation may occur during winter in Tibet and central Asia. Therefore, such variations should also be considered along with temperature and there is a need to study the combined effect of changes in temperature and precipitation. Once the effect of increase in temperature (no precipitation change) is known, then it is possible to assess the trend of snow cover depletion along with any change in precipitation (Singh and Bengtsson, 2003). For example, under a particular higher temperature scenario, an increase in snowfall will slow down the depletion of snow cover area and, consequently, would prolong the melt season. On the other hand, a reduction in snowfall would accelerate the depletion of snow and the melt season would be reduced.

3.3.2 Effect of change in snow cover area on discharge of the River Brahmaputra

The discharge data collected at Pandu gauge site from 2002 to 2015 has been used to study the effect of change in snow cover area on the discharge of the river Brahmaputra. The increasing and decreasing trends of discharge of Brahmaputra River with respect to the change in snow cover area for the months January, April, July and October from 2002 to 2015 are shown in Fig.3.13 (a,b, c and d).

Table 3.3: Snow Cover Area and discharge for different months

Year	January		April		July		October	
	Snow cover area (sq.km)	Discharge (MCM)	Snow cover area (sq.km)	Discharge MCM)	Snow cover area (sq.km)	Discharge MCM)	Snow cover area (sq.km)	Discharge MCM)
2002	30474	20265	114588	24218	14536	32081	84551	33407
2003	98414	17855	99972	23967	25851	81635	21069	58528
2004	64472	17591	56236	24744	23695	82136	63894	41276
2005	74004	17197	83658	23364	11262	67365	28355	47279
2006	37285	16450	80162	22878	12678	52740	16157	49474
2007	49892	16260	87833	24571	7881	66558	12347	57555
2008	29822	16189	92263	17822	15540	62268	32572	41136
2009	112736	16262	89539	20595	14328	62966	25427	33734
2010	66618	16207	68848	39502	12401	68380	30162	57233
2011	62421	17059	74142	24578	13038	68352	13129	51521
2012	138555	16064	89930	21631	12236	79806	20526	63098
2013	126798	16713	52121	23457	9088	69891	16915	40634
2014	112355	17644	50246	25651	4503	64247	9180	49275
2015	102833	17500	51138	24657	6584	59506	9983	38262

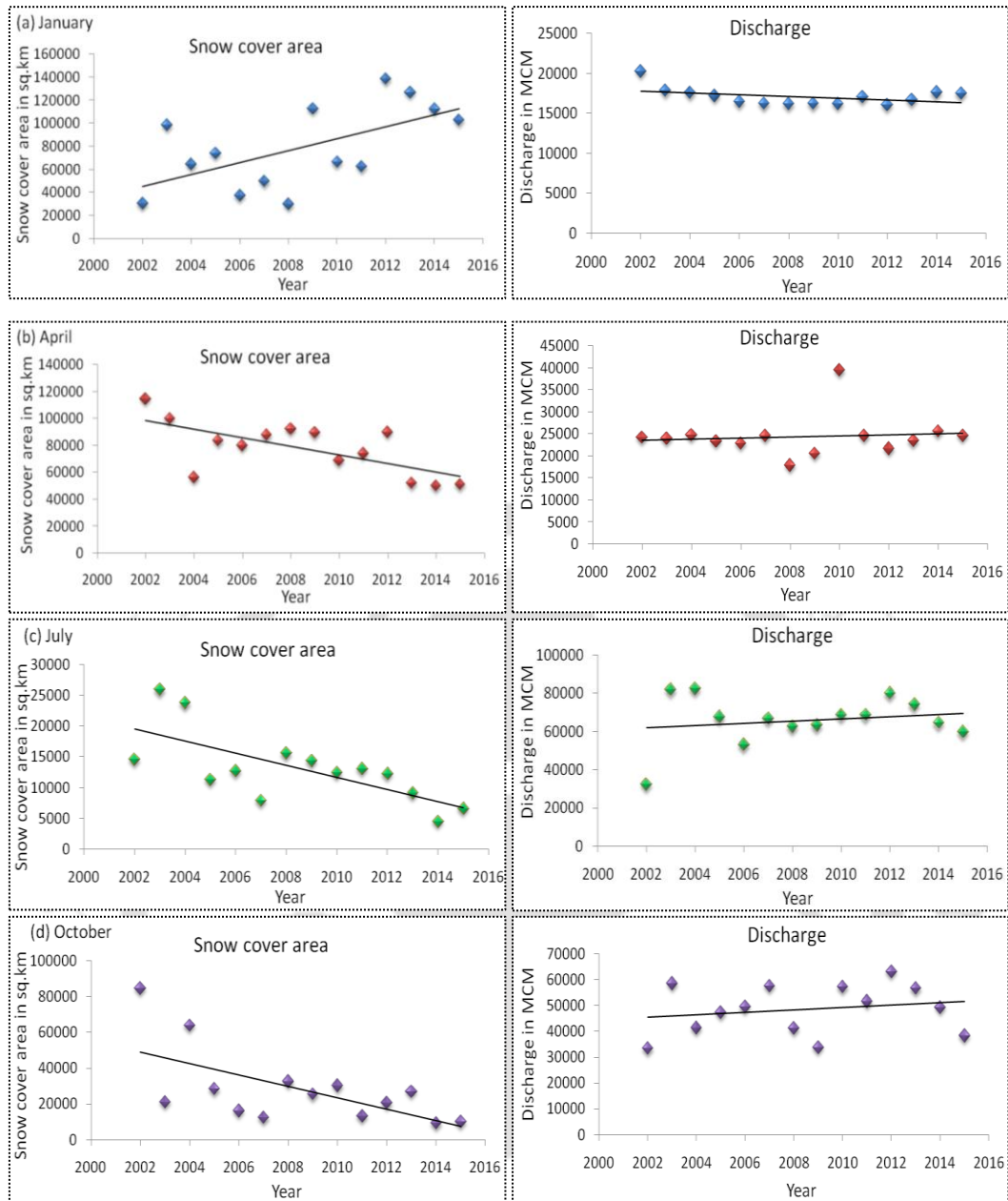


Fig. 3.13: Trend showing variation of discharge w.r.t. snow cover area for the month (a) January, (b) April, (c) July and (d) October.

A relationship has been established between the change in snow cover area and discharge. The output shows that for the month of January, the discharge shows a decreasing trend with respect to the increasing trend of snow cover area. The minimum discharge was observed in the year 2012 (16064 MCM) and maximum was observed in the year 2002 (20265 MCM). For the other three months *i.e.* April, July and October, increasing trends of discharge have been observed with respect to the decreasing trends of snow cover area. This may be attributed to the fact that due to rise in temperature the melting of snow is occurring at the upper catchment of the Brahmaputra River basin and the snowmelt water is contributing to the increase in discharge of the River at the downstream. This in turn is affecting the

downstream hydrology of the basin, causing severe flood in the monsoon season as well as riverbank erosion at some vulnerable points which is definitely a threat to the development of the entire region. For the month of April, the minimum discharge has been observed in the year 2008(17822 MCM) and maximum has been observed in the year 2010 (39502 MCM). For July, minimum has been observed in the year 2002 (32081 MCM) and maximum has been in the year 2004 (82136 MCM). On the other hand, for the month of October, the minimum discharge has been observed in the year 2002(33407 MCM) and maximum has been observed in the year 2012 (63098 MCM). Melting of snow/glacier with respect to the rise in temperature has a major impact on the hydrology of the rivers originating from glaciers. The Brahmaputras responsible for many natural calamities among which flood and erosion are the severe ones. Along with the heavy rainfall of this region, the melting of snow/glacier at the upper catchment of the basin also has a major effect on change in its discharge. In mountain regions particularly, global mean temperature has not been spatially homogeneous. A minor variation in temperature under low magnitude warming is more effective to changes in volume and area of glacier than high magnitude warming. An increased seasonal melt coupled with rains will bring more intense floods to the downstream areas. Impacts of the shrinkage and disappearance of mountain glaciers include changes in the flow characteristics of glacier fed rivers; glacier lake outburst floods (GLOFs) as well as the change in flood severity and frequency. The GLOFs are capable of releasing billions of cubic meter of glacier water, stored for decades without warning to those living at the downstream.

Melting of snow with respect to the rise in temperature has a major impact on the hydrology of the rivers. The flood and river bank erosion caused by the river Brahmaputra at its downstream are the main calamities that affect the livelihood of the people. Though precipitation is considered as the main cause of flood in this region, attention should also be paid to the impact of the contribution of snowmelt water to the discharge of the river. From this study, it has been found that the melting of snow is proportional to rise in temperature. Here a quantitative analysis has been performed to show how much area covered by snow has been reduced due to the rise in temperature from 2002 to 2015 for four different months viz., January, April, July and October. On the basis of these findings, in future, further analysis could be carried out to determine the volume of snowmelt water that contributes to the discharge of the river Brahmaputra. Increase in glacier lakes due to rise in temperature should also be a serious matter of concern. Glacier lakes are formed when the glacier erodes the

land, and then melts, filling the hole or space that it has created. A retreating glacier often left behind large deposits of ice in hollows between hills. As the ice age ended, these melted to create lakes.

The accelerated melting and the accelerated retreat of snow cover area under warmer climate have direct implications on water resources and their distribution in time as well as on the regional climate. The reduction in snow cover area under warmer climate will reduce the volume of snowmelt runoff. Because of major differences in the physical properties of snow and other natural surfaces, the energy balance of the basin will be significantly changed. Evaporation would significantly increase because of higher temperatures and fast conversion of snow cover areas to snow free areas. Moreover, since evaporation from the snow cover area is far lower than from snowfree areas (Bengtsson, 1980), snow-free areas would be exposed to evaporation for longer durations. Under warmer climate, glaciers located in the upper part of the basin will be exposed earlier and this will result in higher melting from the high altitude area (Braithwaite & Olesen, 1989; Braun et al., 1994), which will affect the mass balance of the glaciers. Thus, faster depletion of snow in a basin may influence the total runoff of that particular area and its distribution.

3.4 Conclusions

For hydrological applications, SCA estimates are of primary importance where winter snow accumulation substantially affects spring runoff. In this study, a correlation has been established between change in snow cover area of the Brahmaputra river basin and the change in temperature. There has also been built a relationship between change in snow cover area and change in discharge of the Brahmaputra River. As observed from the results, the snow cover area showed an increasing trend with respect to the decreasing trend of temperature for the month of January. The snow cover areas for other three months *i.e.* April, July and October showed decreasing trends with respect to the increasing trends in temperature. Similarly, for January, with respect to the increasing trend of snow cover area, the discharge showed a decreasing trend. For April, July and October, the discharge showed increasing trends with respect to the decreasing trends of snow cover area.

Conventional methods have limitations in the monitoring of snow cover area in the Himalayan basins because of inaccessibility. Snow by virtue of the high reflectivity is one of the objects on surface of the earth which is readily detected or identified on any visible or near IR remotely sensed image. It has been found from this study that MODIS data can

efficiently be used in mapping snow cover of large areas, because of its good spatial as well as temporal resolution relative to similar sensors such as AVHRR. Since snow reflects more energy in the visible part than in the mid-infrared, the NDSI ratio enhances the contrast between snow and bare ground. Additionally, the reflectance of clouds remains high in MODIS band-6. Thus, the NDSI can discriminate clouds and snow. MODIS snow map prepared by the method of NDSI was found to be accurate when validated with the high resolution LANDSAT data of same date. In both the images, the areas covered by snow for the selected portions were found to be the same. The MODIS product accurately classified snow versus no-snow throughout the Brahmaputra basin on both clear and (partially) cloudy days. The enhanced ability of the MODIS data to detect snow cover area correctly will have the greatest implications for hydrologic modelling and prediction in the Brahmaputra River basin.





CHAPTER 4

STATUS OF SNOWCOVER OF THE SUBANSIRI RIVER BASIN AND ITS IMPACT ON THE DISCHARGE IN THE RIVER

4.1. Introduction

Subansiri River, a north bank tributary of the River Brahmaputra originates in the Himalayas beyond the Great Himalayan range at an altitude of approximately 5340m. The catchment area of the Subansiri River is spread out further than the grand Himalayan mountain ranges, covering Tsona Dzong till the Great Loop of the Tsang Po River in Tibetan Territory. The upper part of the Subansiri basin is covered by snow which starts melting in summer due to increase in temperature. The melting of snow has a major impact on the downstream discharge of the river. Keeping this in mind, the change in snow cover area with respect to the change in temperature has been studied here. The effect of change in snow cover area on the discharge of the river Subansiri has also been analyzed starting from 2002 to 2015 for four different month viz., January, April, July and October.

4.2 Materials used

4.2.1 SRTM DEM data

Shuttle Radar Topographic Mission (SRTM)-DEM at a horizontal spatial resolution of 90 meters has been used in this study to delineate the Subansiri River basin. Digital Elevation Model (DEM) is useful to get various important information including terrain slope, gradient, aspect, contour line, hill shade and view shade. The Shuttle Radar Topography Mission (SRTM) is an international research effort that obtained digital elevation models on a near-global scale from 56° S to 60° N (Nikolakopoulos et al., 2006).

The delineation of the basin has been done in the ILWIS software. ILWIS (Integrated Land and Water Information System) is a GIS / Remote sensing software and is used for both vector and raster processing. Primary data used in ILWIS model to delineate a watershed are DEM and the outlet location of the River. Here in this study, Khabulighat has been considered as the outlet location of the river. The geographic coordinates of Khabulighat are, 94°04'E and 27°01'N.

Version 4.1 of SRTM-DEM datasets, ID 53-06, 53-07, 53-08, 54-06, 54-07, 54-08, 55-06, 55-07, 55-08, 56-06, 56-07 and 56-08 have been downloaded, mosaiced and processed (Fig.4.1). Spatial extent of the datasets are given in Table 4.1

Table 4.1: Spatial extent of the SRTM DEM datasets used to delineate Subansiri basin

SRTM DEM dataset ID	Top left coordinate	Bottom right coordinate
53-06	80° E; 35°N	85°E; 30°N
53-07	80°E; 30°N	85°E; 25°N
53-08	80°E; 25°N	85°E; 20°N
54-06	85°E; 35°N	90°E; 30°N
54-07	85°E; 30°N	90°E; 25°N
54-08	85°E; 25°N	90°E; 20°N
55-06	90°E; 35°N	95°E; 30°N
55-07	90°E; 30°N	95°E; 25°N
55-08	90°E; 25°N	95°E; 20°N
56-06	95°E; 35°N	100°E; 30°N
56-07	95°E; 30°N	100°E; 25°N
56-08	95°E; 25°N	100°E; 20°N

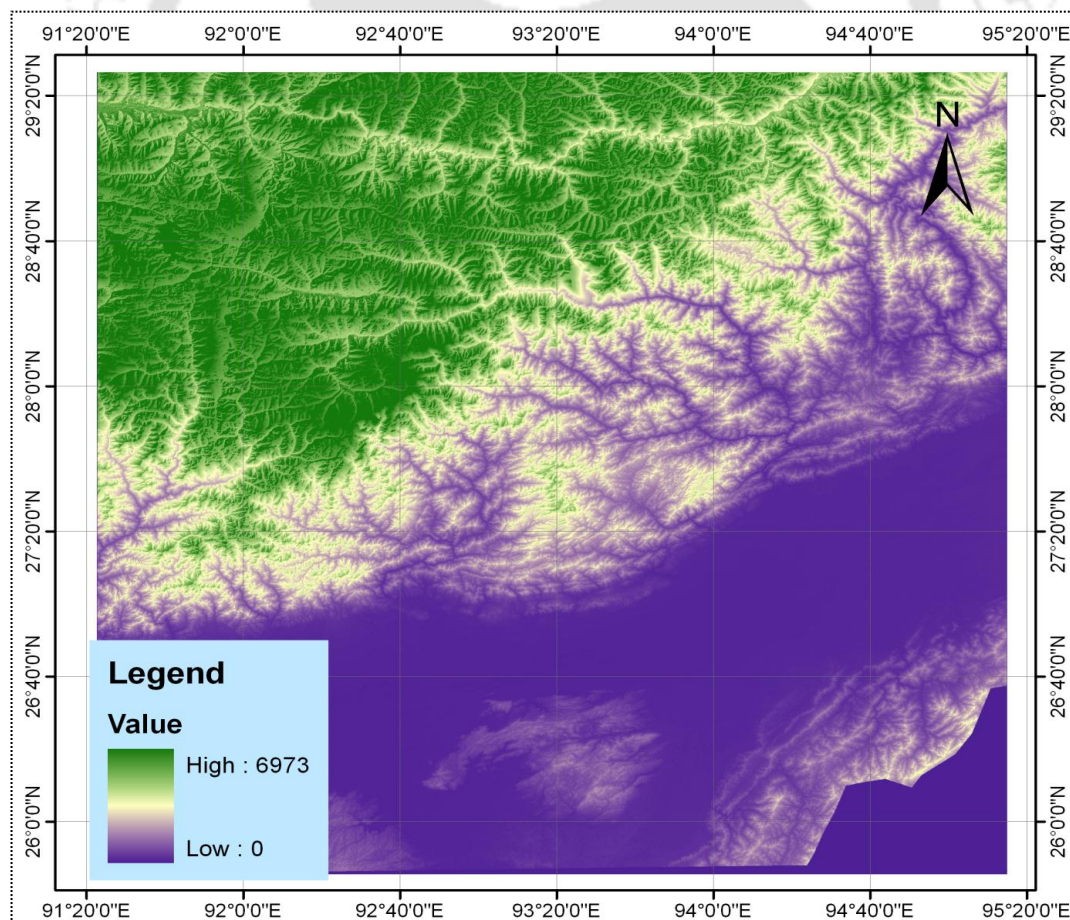


Fig.4.1: Digital Elevation Model, SRTM data

4.2.2 MODIS satellite data

MOD09A1.5 (MODIS/Terra Surface Reflectance 8-Day L3 Global 500m SIN Grid) of 500m resolution consisting of seven bands (band-1 to band-7) used to determine the snow cover area of the Subansiri river basin.

4.2.3 Temperature data

The gridded temperature data of HadCM3 (Hadley center Coupled Model version 3) model of A2 scenario having spatial resolution of $2.5^{\circ} \times 3.75^{\circ}$ (latitude by longitude) have been used to get the average temperature of the Subansiri River basin. There is only one HadCM3 point that falls inside the basin. Three other HadCM3 points that fall around the basin have also been considered to determine the average temperature of the basin. Table 4.2 gives the geographic coordinates of the four HadCM3 GCM points.

Table 4.2: Geographic coordinates of the GCM points

HadCM3 points	Geographic coordinates
(1)	93.75°E, 27.50°N
(2)	93.75°E, 30.00°N
(3)	90.00°E, 30.00°N
(4)	90.00°E, 27.50°N

4.2.4 Discharge data

The daily discharge data of Subansiri River at Khabulighat gauge station from 1990 to 2015 have been collected from the Water Resources Department, Govt. of Assam to study the variation of discharge with respect to the change in snow cover area.

4.3 Methodology

4.3.1 Watershed delineation

Accurate delineation of watershed is very important as it plays an important role in the management of the watershed (Donia, N., 2009). The traditional method of catchment area delineation from topographic maps by drawing lines to connecting elevation points and contour lines is not an easy task to precisely define the watershed lines and related hydrographic and morphometric parameters in plane land areas (Altansukh, 2012). The manual delineation of drainage networks and catchments from topographic maps has been widely replaced by the automatic extraction from Digital Elevation Model (Bastawesy et al., 2008). In the present study, the Subansiri river basin has been delineated using ILWIS model.

The steepest slope method has been used to determine the flow direction. Fig. 4.2 gives the flowchart showing the methodology to delineate watershed from DEM.

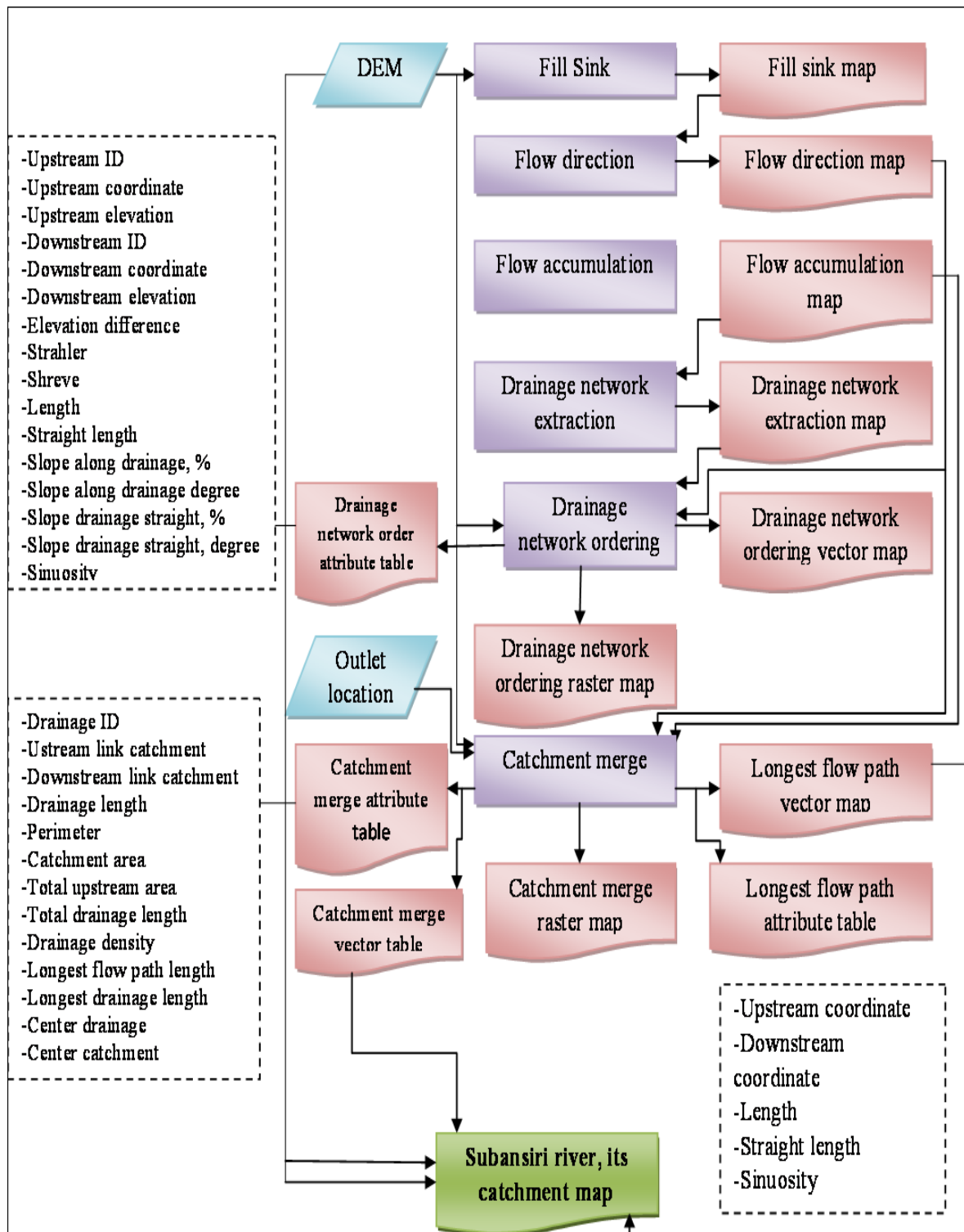


Fig.4.2: Methodology of ILWIS model used for delineation of the Subansiri catchment

The SRTM DEM has been processed in the above seven phases as shown in the flowchart to get the catchment area of the Subansiri river basin. The various operations performed are, fill sink, flow direction, flow accumulation, drainage network extraction, drainage network ordering, catchment extraction and catchment merge. The intermediate results produced while running the model are shown in Fig. 4.3. The Subansiri basin with its flow directions and the longest flow path is shown in Fig. 4.4.

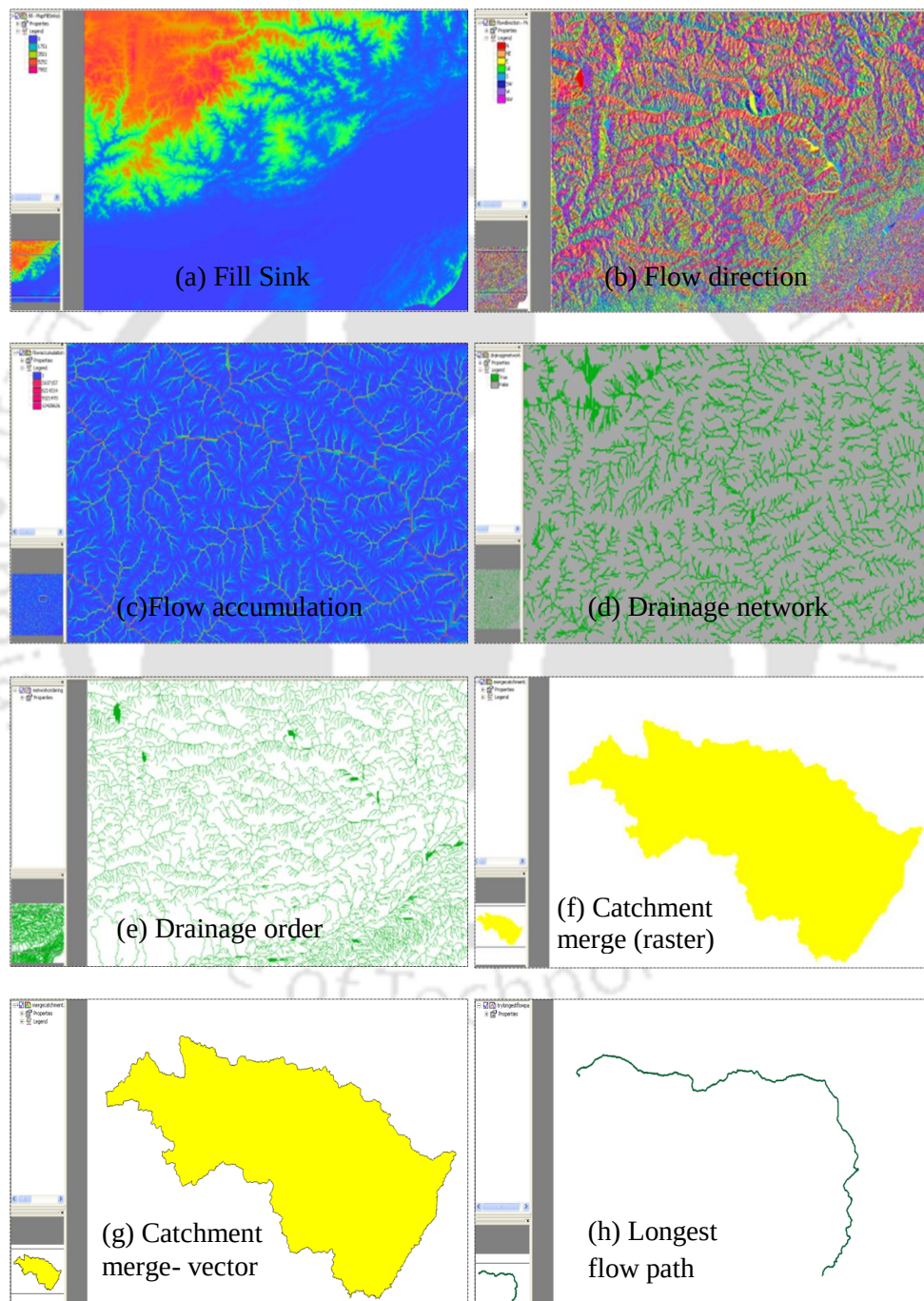


Fig.4.3: Some intermediate results obtained from ILWIS model

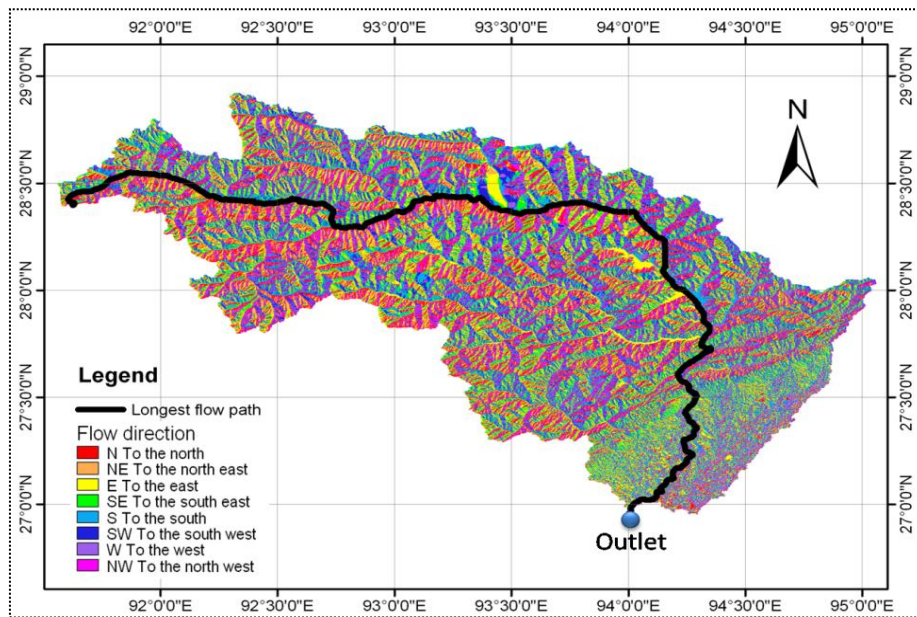


Fig.4.4: The Subansiri Catchment showing the Flow direction and the longest flow path

4.3.2 Snow cover area study of the Subansiri River Basin

The NDSI method as explained in Chapter 3 to determine the snow cover area of the Brahmaputra river basin has also been used to determine the snow cover area of the Subansiri River basin. The variations of snow cover area with respect to temperature have been analyzed for January, April, July and October from 2002 to 2015. The four HadCM3 GCM points considered (Table 4.2) to determine the average temperature of the basin are shown in Fig. 4.5.

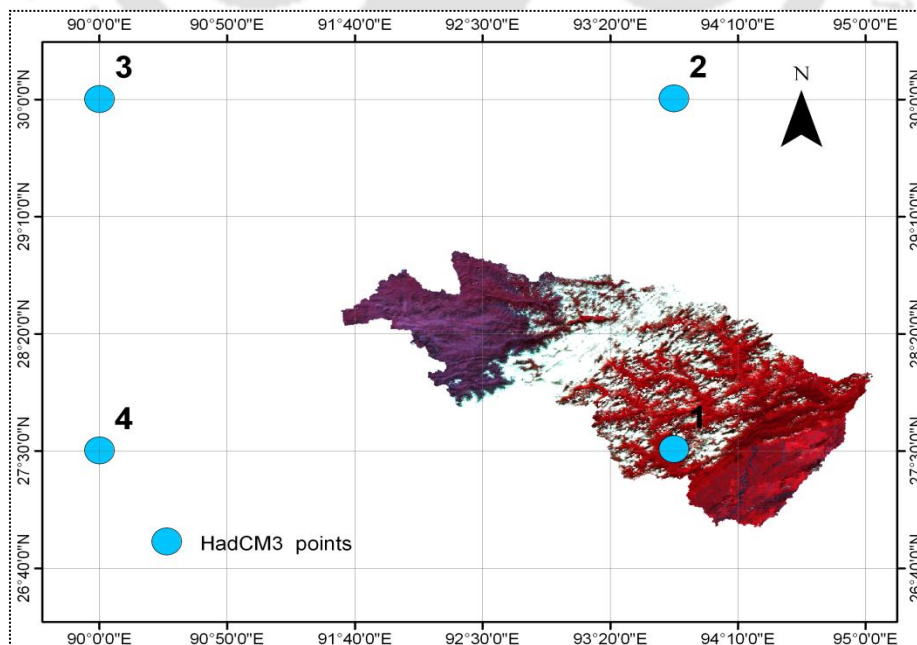


Fig.4.5: Locations of four HadCM3 GCM points considered for the Subansiri basin

4.3.3 Effect of change in snow cover area on discharge of river Subansiri

The snow cover areas obtained from the NDSI method have been used to study impact of variations of snow cover area on the discharge of the river Subansiri.

4.4 Results and Discussions

4.4.1 Geomorphologic parameters of the Subansiri River and its basin

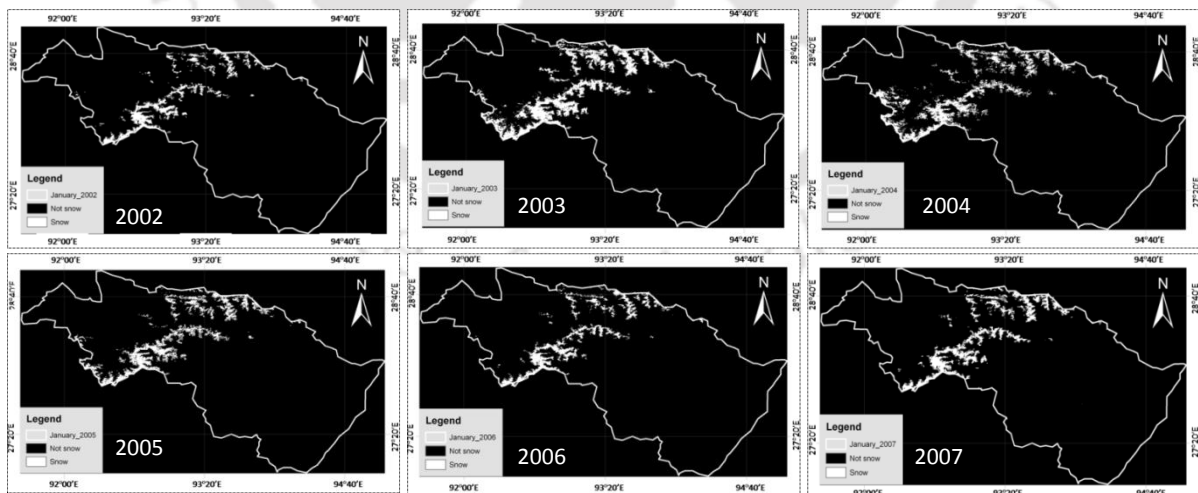
According to the final result of ILWIS model, which was run on SRTM-DEM, the perimeter of the catchment area is 1407.29 km, area of the catchment is 34246.19 km², overall length of the drainage is 10049.66 km, drainage density is 0.29 km/km², length of longest flow path is 533.14 km, length of the Subansiri River is 533.14 km, centre of the catchment according to half of the length of the longest flow path is 28°22'26.2"N, 93°37'48.38"E, geographic coordinate of Subansiri river head is 28°24'18.2"N, 91°37'32.93"E, elevation of the river head is 5030m, geographic coordinate of the Subansiri river mouth is 26°57'44.2"N, 94°00'00"E, elevation of the river mouth is 87m, elevation difference is 4943m, catchment centre is 27°56'14.2"N, 93°56'48.38"E, according to Strahler ordering system the river belongs to 6th order and sinuosity is 1.87. Drainage density is a very useful index of basin characteristics as it affects the magnitude of streamflow from a drainage basin (Kirkby and Chorley, 1967). The high drainage density of Subansiri catchment reflects that it is a highly dissected basin and has a relatively rapid hydrologic response to rainfall events compared to a low drainage density basin with slow hydrologic response.

4.4.2 Variation of snow cover area with respect to change in temperature

The snow cover area maps from 2002 to 2015 for January, April, July and October are shown in Fig.4.6, 4.7, 4.8 and 4.9 respectively. Table 4.3 gives the total area covered by snow for each selected month and the temperature data of HadCM3 for A2 scenario for the Subansiri River basin. The maximum snow cover area has been observed either in the month of January or in the month of April.

Table 4.3: Snow Cover Area and temperature for different months for Subansiri River basin

Year	January		April		July		October	
	Snow cover area (sq.km)	Temperature (°C)	Snow cover area (sq.km)	Temperature (°C)	Snow cover area (sq.km)	Temperature (°C)	Snow cover area (sq.km)	Temperature (°C)
2002	1697	-3.06	5154	6.81	1067	13.57	1593	4.93
2003	3502	-5.23	4249	7.53	2623	11.59	865	6.25
2004	2908	-5.18	2500	7.55	2162	11.87	1319	5.46
2005	2510	-4.90	2010	5.77	709	12.95	1042	3.94
2006	1803	-5.31	3067	9.10	903	12.51	803	6.83
2007	2216	-3.05	3743	8.43	353	12.15	1056	3.56
2008	1527	-6.30	2478	7.53	673	12.63	985	7.07
2009	3766	-4.09	2630	8.61	650	12.20	766	4.19
2010	2218	-4.76	2543	7.59	938	13.06	1063	7.21
2011	2037	-3.28	1081	8.42	604	12.84	665	6.00
2012	3876	-8.43	3945	9.03	420	12.01	1076	4.99
2013	3550	-6.28	1227	8.66	749	12.04	1316	4.60
2014	2301	-4.78	1330	7.06	617	12.98	864	5.10
2015	1678	-6.78	1112	7.35	446	13.24	574	6.06



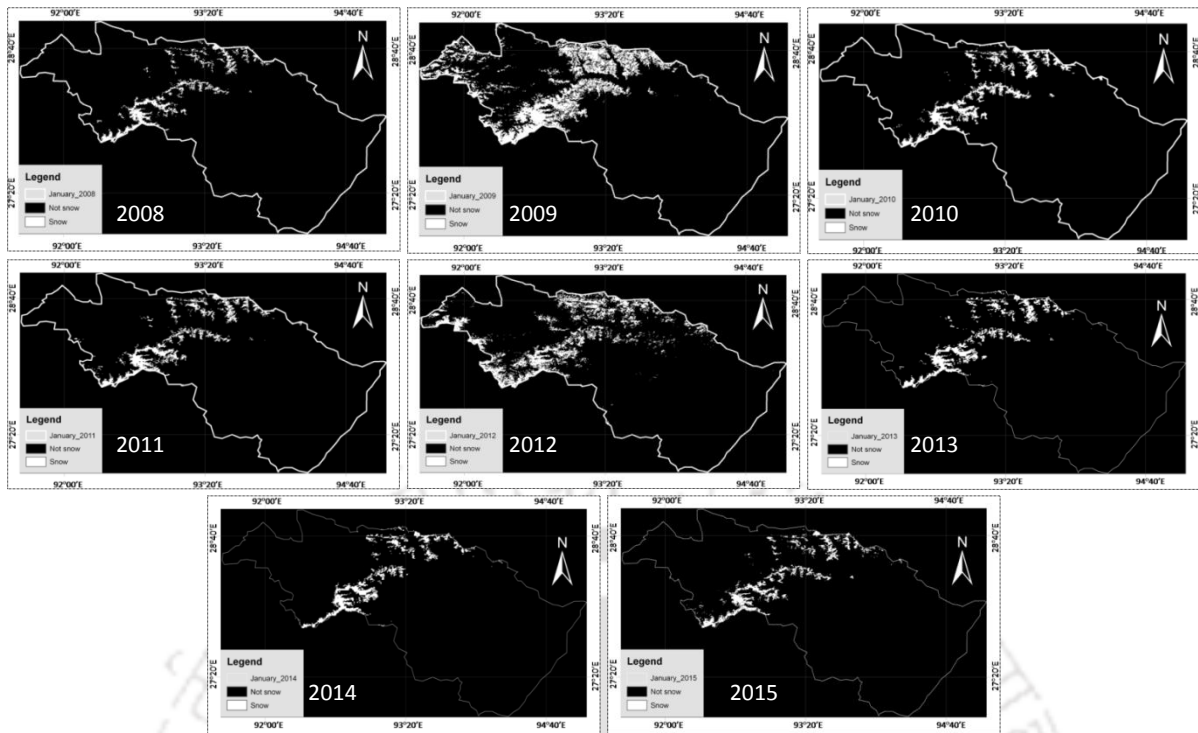
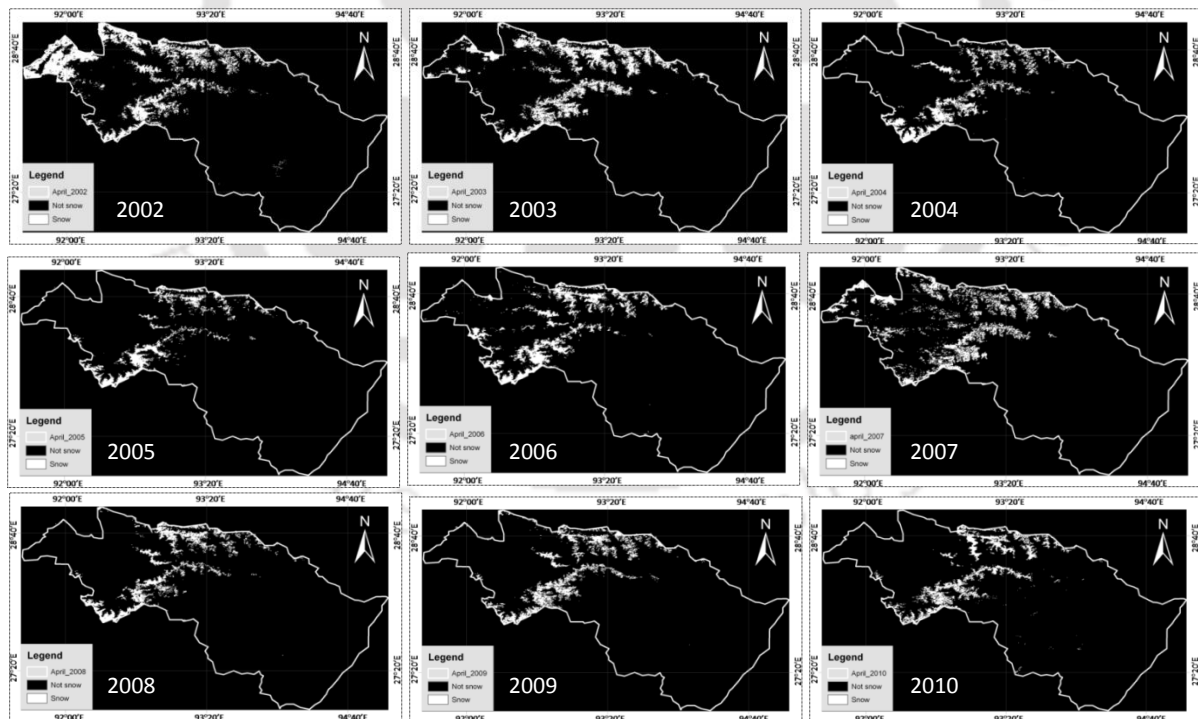


Fig.4.6: Snow Cover Maps of the Subansiri basin for January from 2002 to 2015



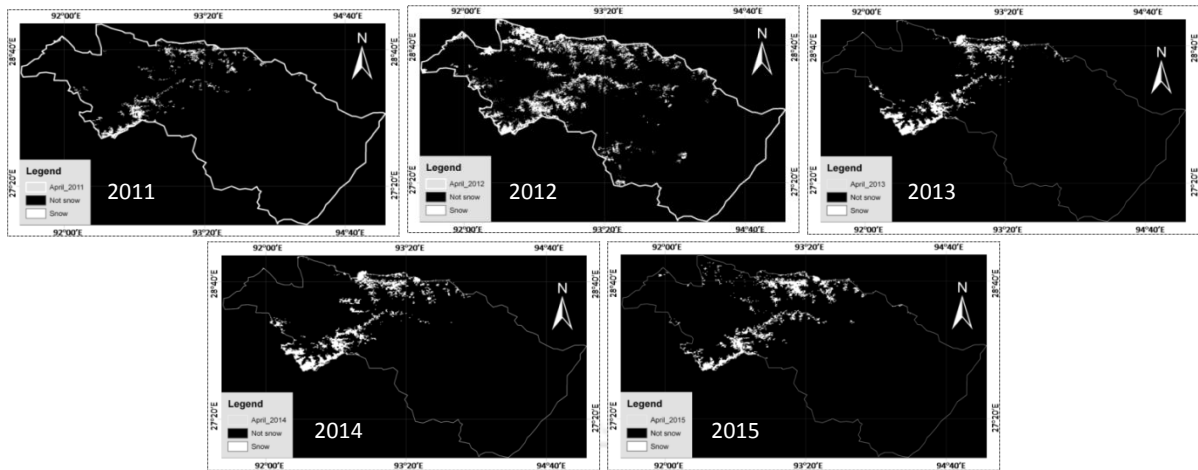


Fig.4.7: Snow Cover Maps of the Subansiri basin for April from 2002 to 2015

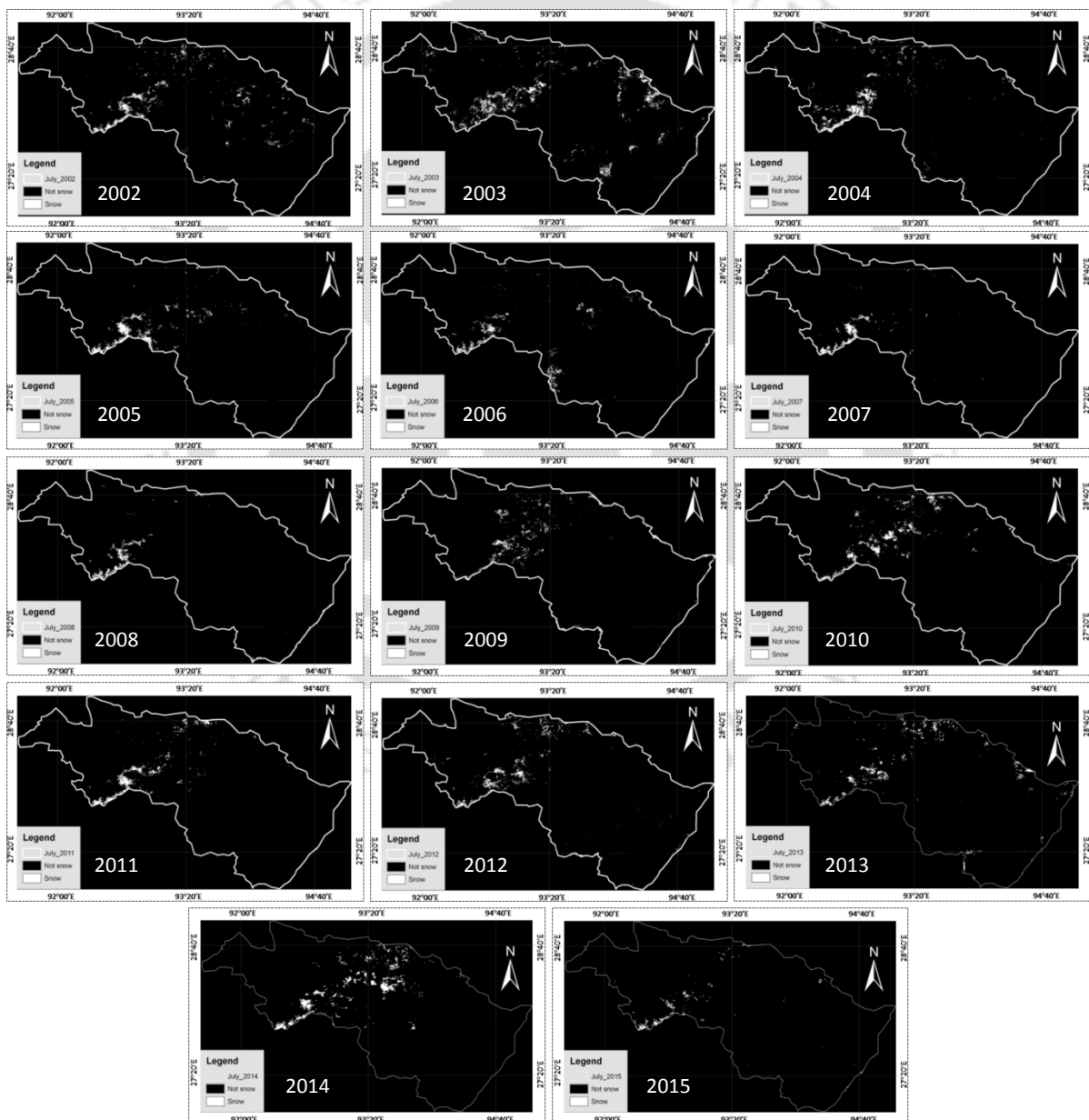


Fig.4.8: Snow Cover Maps of the Subansiri basin for July from 2002 to 2015

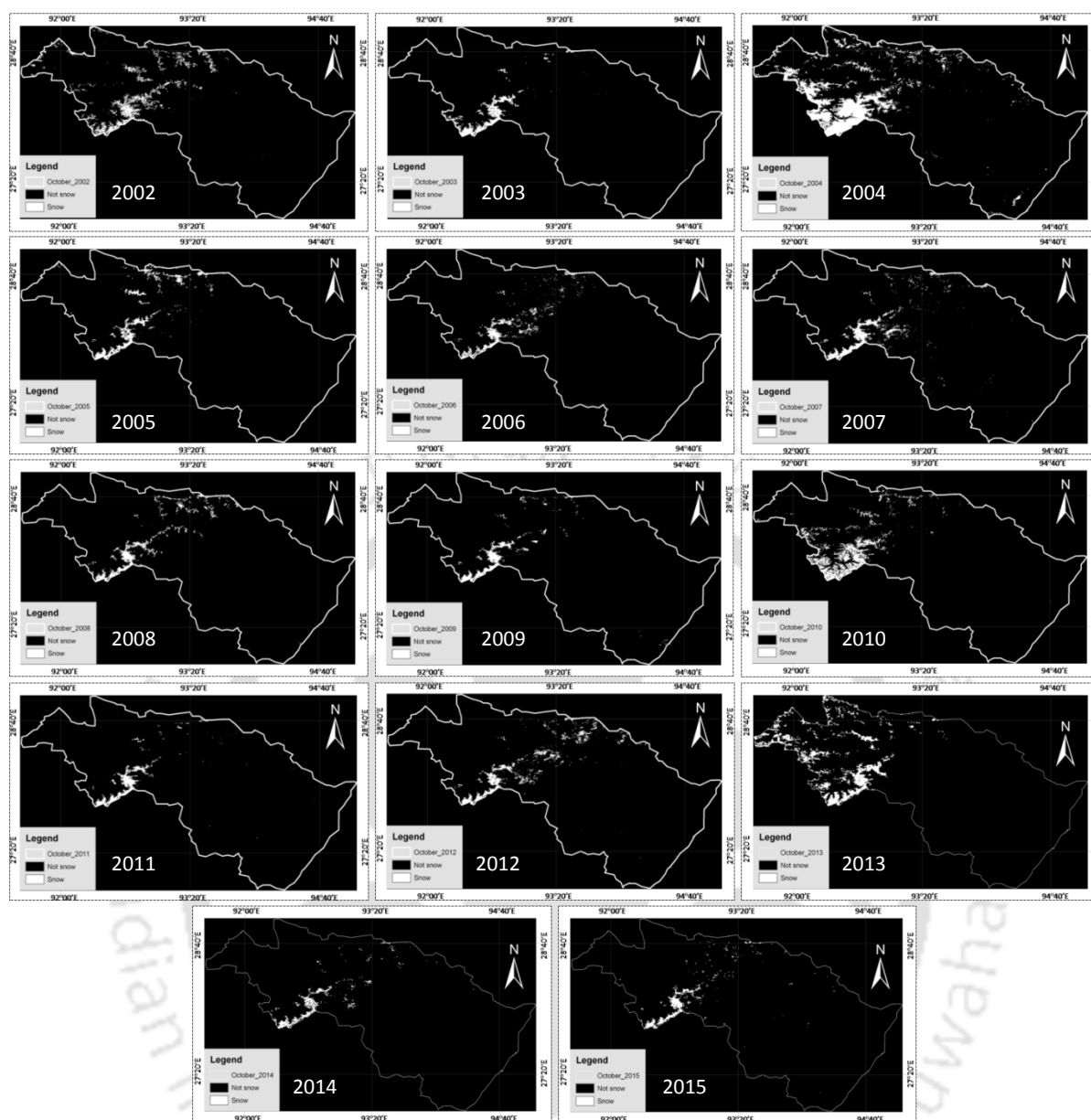
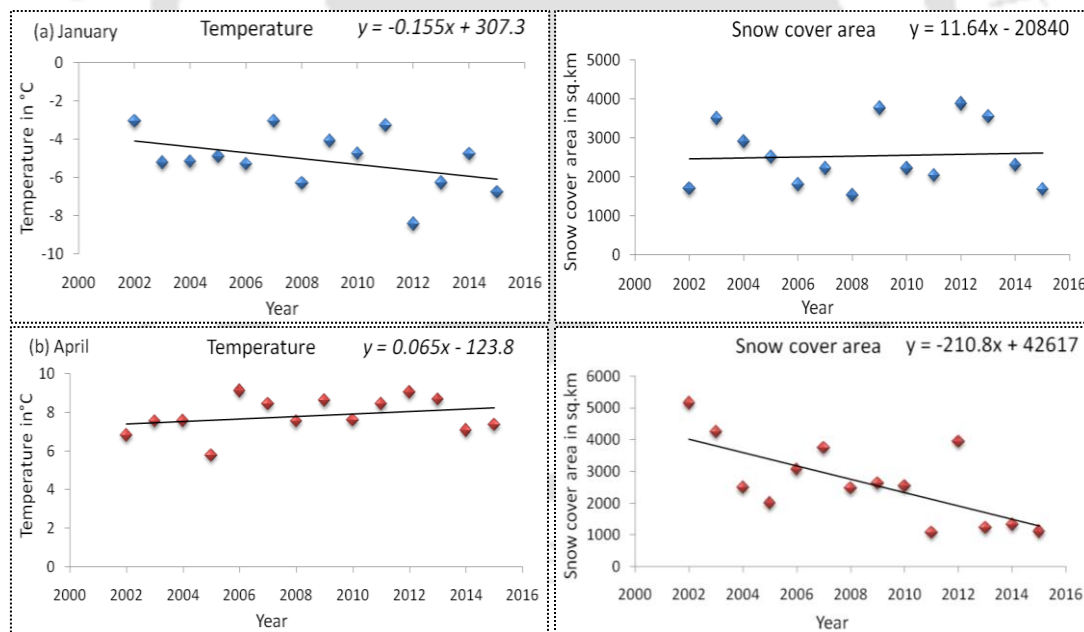


Fig.4.9: Snow Cover Maps of the Subansiri basin for October from 2002 to 2015

From the Table 4.3, it has been observed that the maximum snow cover area has been observed in 2002 for the month of April with a value of 5154 sq.km. and the minimum has been observed in 2007 for the month of July with a value of 353 sq.km. The maximum temperature for the entire period from 2002 to 2015 has been observed in 2002 for the month of July (13.57°C) and the minimum has been observed in 2012 for the month of January (-8.43°C). The increasing and decreasing trend of snow cover area with respect to the change in temperature for all the four months from 2002 to 2015 are shown in Fig.4.10 [(a), (b) (c) and (d)]. It has been observed that for the month of January, the snow cover area shows an increasing trend with respect to the decreasing trend of temperature. The minimum snow cover during this period was in the year 2008 with a value of 1527 sq. km. and the maximum

was in the year 2012 with a value of 3876 sq.km. While the minimum temperature was in the year 2012 (-8.43 °C) and maximum was in the year 2007 (-3.05 °C).

For the other three months *i.e.* April, July and October, the graphs show decreasing trends of snow cover areas with respect to the increasing trends of temperature. For the month of April, the minimum snow cover area was observed in the year 2011 (1081 sq.km.) and the maximum was observed in the year 2002 (5154 sq.km.). For July, the minimum was observed in the year 2007 (353 sq.km.) and the maximum was observed in the year 2003 (2623 sq.km.). Again, for the month of October, the minimum snow cover area was observed in the year 2015 (574 sq. km.) and the maximum was observed in the year 2002 (1593 sq.km.). In case of temperature, the minimum in the month of April was observed in 2005 (5.77 °C) and maximum was observed in the year 2006 (9.10 °C). For July, the minimum and maximum temperatures were observed in 2003 (11.59°C) and 2002 (13.57°C) respectively. On the other hand, for the month of October, the minimum temperature was observed in the year 2007 (3.56 °C) and maximum was observed in the year 2010 (7.21°C).



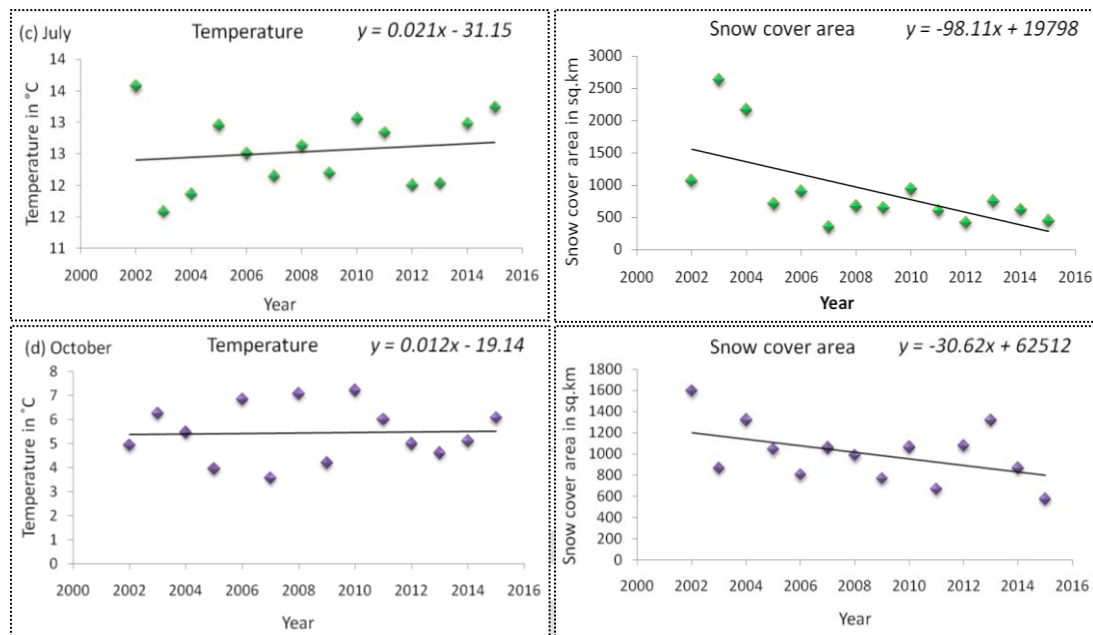


Fig. 4.10: Trend showing Variation of Snow Cover Area w.r.t temperature for the month of (a)January,(b) April (c) July and (d) October from 2002 to 2015 in the Subansiri river basin

The percentage change in snow cover area from 2003 to 2015 by taking the snow cover area in 2002 as the base has also been studied. Fig. 4.11 gives the scatter plots of the percentage change in snow cover area of the Subansiri basin from 2003 to 2015 with respect to the snow cover area in the year 2002 for the four different months.

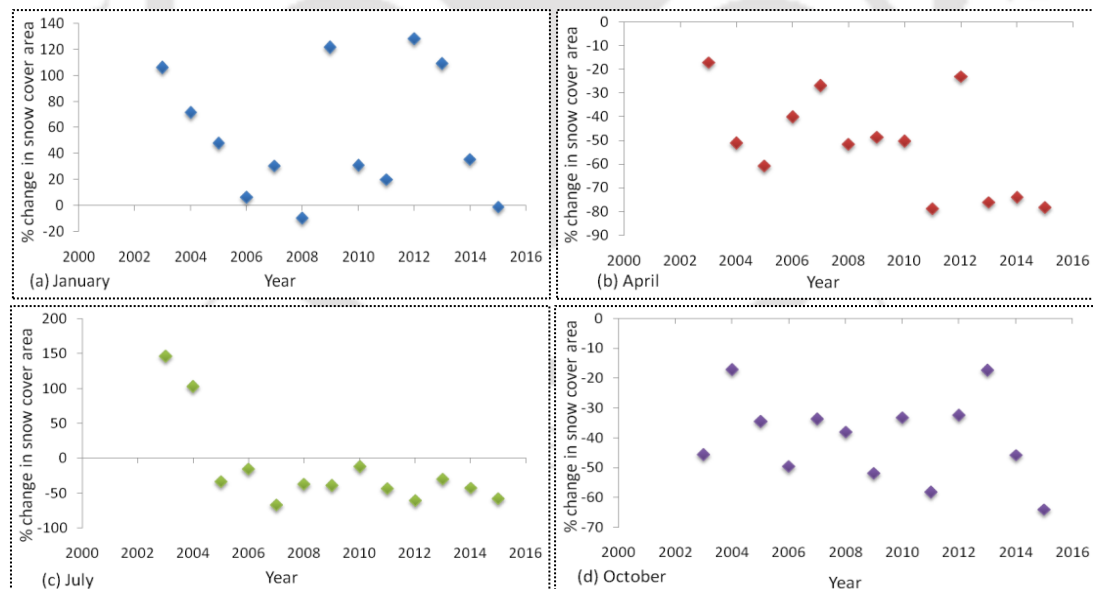


Fig.4.11: Percent change in snow cover area from 2003 to 2015 w.r.t. snow cover area in 2002 for (a) January, (b) April, (c) July and (d) October for the Subansiri river basin

It is observed from the figure that, for the month of January, except in 2008 and 2015, the snow cover area increases for each year from 2003 to 2014 compared to that in 2002. In 2008, it reduces by 10.02% while in 2015, it reduces by 1.12%. The maximum and the

minimum increase has been observed in 2012 and in 2006 where the snow cover area increases by 128.40% and 6.25% respectively compared to that in 2002. Percentage increases were also significant in 2004, 2009 and 2013 with values 71.36%, 121.92% and 109.19% respectively.

For the month of April, compared to 2002, the snow cover areas for the other years from 2003 to 2015 show lesser values. From percentage reduction scatter plot (Fig. 4.6(b)), it is seen that the maximum and the minimum reduction were in 2011 (78.90%) and 2003 (17.08%) respectively. Also, significant reductions have been observed in 2004, 2005, 2008, 2010, 2013, 2014 and 2015 where snow cover areas reduced by 51.21%, 60.77%, 51.64%, 50.37%, 76.05%, 74.04% and 78.30% respectively with respect to the area covered by snow in 2002.

For the month of July, the snow cover area first increases for 2003 and 2004 compared to that in 2002 with percentage increase values of 145.83% and 102.62% respectively. For the rest of the years i.e. from 2005 to 2015, the snow cover area show lesser values than that in 2002. The maximum and the minimum reductions were observed in 2007(66.92%) and in 2010 (12.09%). More than 50% reductions were also observed in 2012 and 2015 with values 60.64% and 58.20% respectively.

Similar to the month of April, for the month of October too, the snow cover areas from 2003 to 2015 are less compared to the snow cover area of 2002. The maximum and the minimum reductions have been observed in 2015 and in 2004 where the areas covered by snow were reduced by 63.97% and 17.20% respectively. Years 2006, 2009 and 2011 also show significant reduction in snow cover areas with values 49.59%, 51.91% and 58.25% respectively.

The scatter plot for the percentage change in average snow cover area from 2003 to 2015 taking the snow cover area of 2002 as the base is shown in Fig.4.12. It is observed that average snow cover area for 2003 increases compared to the snow cover area in 2002 by 18.16%. For the rest of the year i.e. from 2004 to 2015, the average snow cover area of the basin reduces compared to the area covered by snow in 2002. The maximum percentage reduction in snow cover area as compared to that of 2002 has been observed for the year 2015 (59.95%) and the minimum percentage reduction was in the year 2012 (2.05%). High percentage reductions have also been observed for the years 2011 and 2014 with values 53.88% and 46.26% respectively.

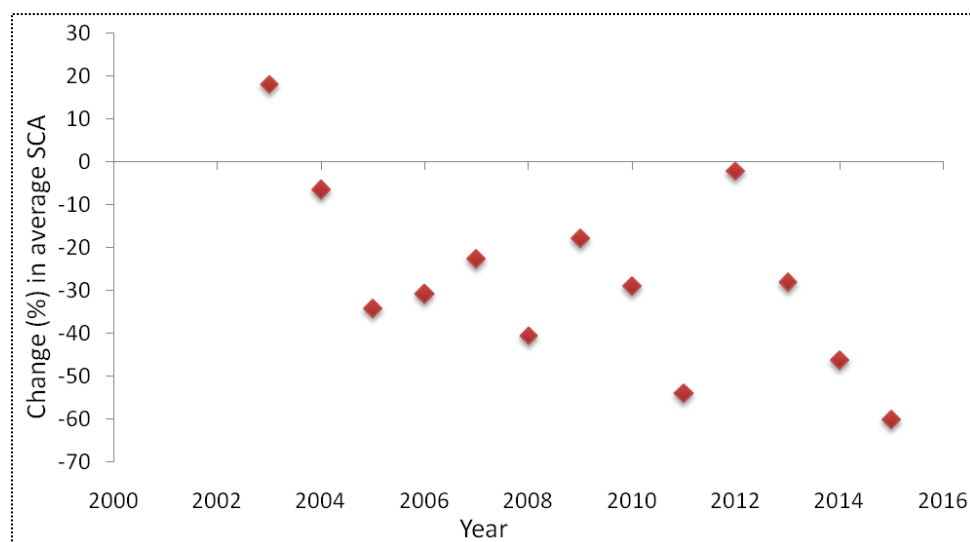


Fig. 4.12: Percentage change in average snow cover area from 2003 to 2015 for the Subansiri river basin

4.4.3 Effect of change in snow cover area on discharge of River Subansiri

The discharge data collected at Khabulighat gauge site from 2002 to 2015 has been used to study the effect of change in snow cover area on the discharge of river Subansiri. Table 4.4 gives the total area covered by snow for each related month and the discharge of Subansiri river for different months. The increasing and decreasing trend of discharge of Subansiri River with respect to the change in snow cover area for the months January, April, July and October from 2002 to 2015 are shown in Fig.4.13 (a,b, c and d).

Table 4.4: Snow Cover Area and discharge for different months for Subansiri

Year	January		April		July		October	
	Snow cover area (sq.km)	Discharge (MCM)	Snow cover area (sq.km)	Discharge (MCM)	Snow cover area (sq.km)	Discharge (MCM)	Snow cover area (sq.km)	Discharge (MCM)
2002	1697	1921	5154	3707	1067	9768	1593	3443
2003	3502	1902	4249	4200	2623	6054	865	2472
2004	2908	1876	2500	5135	2162	9032	1319	4440
2005	2510	2051	2010	4296	709	4667	1042	1844
2006	1803	1825	3067	4131	903	10902	803	3876
2007	2216	1950	3743	3840	353	9527	1056	2826
2008	1527	1846	2478	3552	673	9245	985	4066
2009	3766	1993	2630	3455	650	6359	766	3724

2010	2218	1899	2543	4705	938	3459	1063	3416
2011	2037	1933	1081	3238	604	8207	665	3968
2012	3876	1849	3945	6025	420	7321	1076	3592
2013	3550	1900	1227	4331	749	8762	1316	3610
2014	2301	1928	1330	4198	617	12652	864	4187
2015	1678	1774	1112	3901	446	11118	574	2309

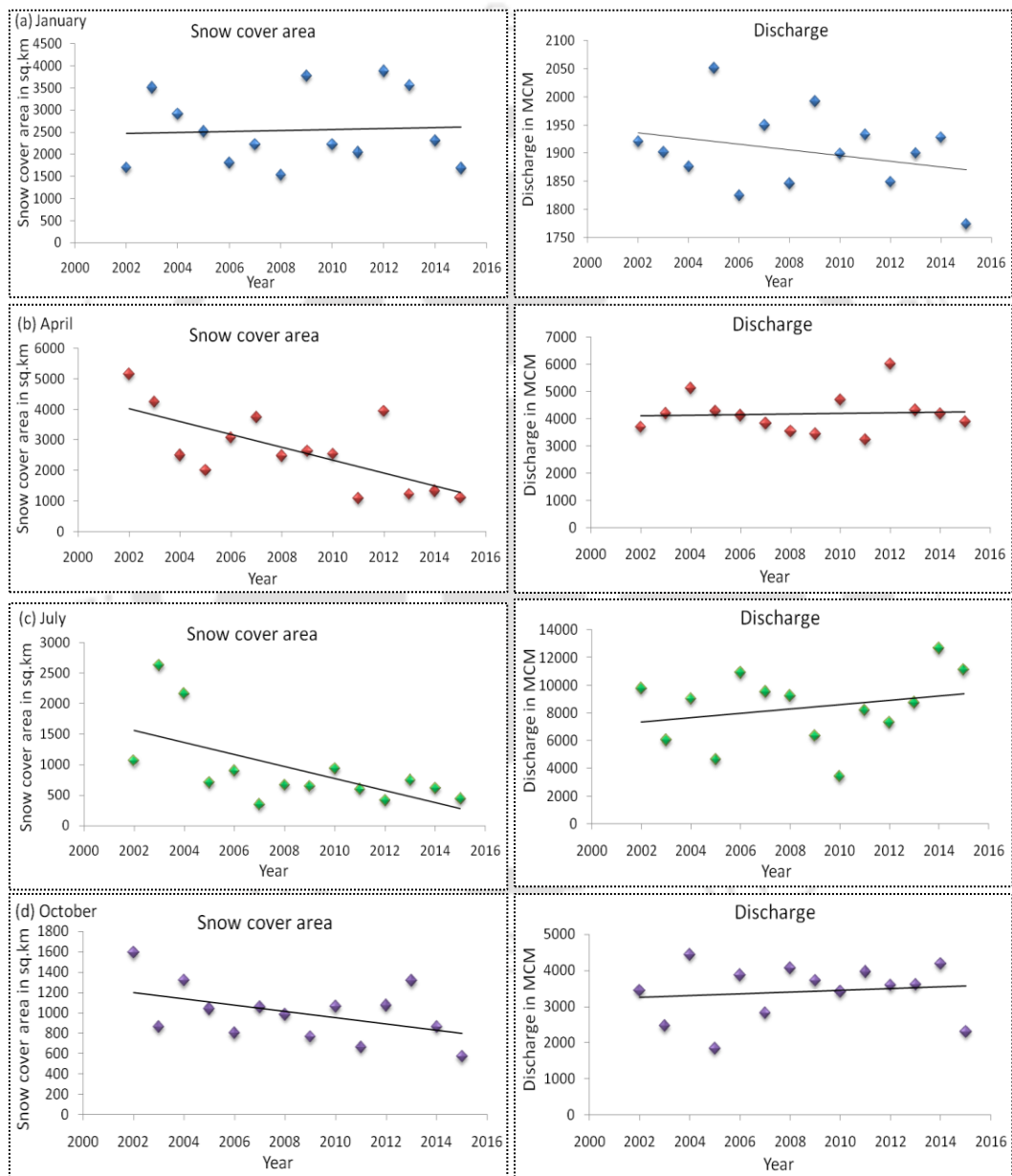


Fig. 4.13: Trend showing variation of discharge w.r.t snow cover area for the month (a) January, (b) April, (c) July and (d) October

From the graphs, it is observed that for the month of January, the discharge shows a decreasing trend with respect to the increasing trend of snow cover area. The minimum discharge was in the year 2015 (1774 MCM) and maximum was in the year 2005 (2051 MCM).

For the other three months *i.e.* April, July and October, corresponding to the decreasing trends in snow cover areas the discharge shows increasing trends. For the month of April, the minimum discharge has been observed in the year 2011(3211 MCM) and maximum has been observed in the year 2012 (6025 MCM). For July, minimum has been observed in the year 2010 (3459 MCM) and maximum has been in the year 2014 (12652 MCM). On the other hand, for the month of October, the minimum discharge has been observed in the year 2003(2472 MCM) and maximum has been observed in the year 2004 (4440 MCM).

The Subansiri basin experiences the highest temperature from June to the beginning of October and begins to drop by the end of November (Gogoi et al., 2013). Such high temperature is responsible for melting of snow at the upper part of the catchment. Snowmelt water in turn contributes to the discharge of the river at downstream. Apart from the snowmelt water, the heavy rainfall that occurs in the basin during the months June through September is also responsible for heavy discharge of the river in downstream. The reason behind heavy rainfall during this period is that, during the pre-monsoon months of April and May, North East India receives a fairly good amount of rainfall on account of large scale thunder storm activity over this region causing a favorable antecedent condition of saturated ground and nearly bank full stage in rivers (Gogoi et al., 2013). The resultant heavy discharge in turn is responsible for high flood and erosion in the lower part of the basin in Assam. Generally, high floods occur in the months of June, July and August. The contribution of Subansiri River is estimated to be about 10 percent of the total discharge of Brahmaputra River (Bakalial et al., 2014). Thus, the huge discharge developed at the downstream of Subansiri River finally leads to heavy discharge of the river Brahmaputra which is one of the major causes of flood and erosion in the State of Assam and in the entire Brahmaputra valley.

4.5 Conclusions

In this study, the variations of snow cover area of Subansiri river basin with respect to change in temperature have been studied from 2002 to 2015 for the months January, April, July and October. For this, the Subansiri River catchment area has first been delineated in ILWIS software by taking the SRTM DEM data of 90m spatial resolution and catchment outlet at Khabulighat for the input parameters. Various geomorphologic parameters have been defined by ILWIS model out of which few parameters defined the catchment area and rest defined the river morphology. The total length of Subansiri River has been found to be 533.14 km. Elevation of the river head and mouth is 5030m and 87m respectively. Hence, elevation difference is 4943m. Therefore, drainage slope is 0.0093.

A correlation has been made between change in snow cover area of the Subansiri river basin with the change in temperature for four different month viz., January, April, July and October starting from 2002 to 2015. It has been found from this study that except for the month of January, the snow cover area for other three months *i.e.* April, July and October showed decreasing trends with respect to the increasing trendsof temperature.

The effect of change in snow cover area on discharge of the river Subansiri has also been studied for the same four different months from 2002 to 2015. The discharge of Subansiri River at Khabulighat outlet has been used for the analysis. The results showed that snow cover area and discharge of the river gave a reverse relationship *i.e.* when the snow cover area showed a decreasing trend the discharge showed an increasing trend and vice versa. This implies that the melting of snow at the upper part of the Subansiri catchment has contribution towards the discharge of the river in downstream.

CHAPTER 5

LAND USE/LAND COVER CHANGE DETECTION STUDY OF THE BRAHMAPUTRA AND THE SUBANSIRI RIVER BASINS USING REMOTE SENSING AND GIS

5.1 Introduction

The term “land use” and “land cover” (LULC) are often used simultaneously to describe maps that provide information about the types of features found on the earth’s surface (land cover) and the human activity that is associated with them (land use) (Shetty et al., 2005). Originally, the kind and state of vegetation such as forest cover or grass cover were referred to as land cover, but in subsequent usage, it has broadened to include various structures such as buildings, pavements and other natural environment like soil type, biodiversity, surface water and ground water (Chen et al., 2008 and Meyer, 1995). Assessment of land use/land cover has become one of the most important parameters for proper and meaningful management of land resources. Land use/land cover information of an area is helpful in better assessment of relationship of cropland, forestland, settlement, wetlands etc. with river flowing through the area. Land use/landcover changes is a widespread and accelerating process, mainly driven by natural phenomena and anthropogenic activities, which in turn drive changes that would impact natural ecosystem (Ruiz-Luna and Berlanga-Robles, 2003; Turner and Ruscher, 2004). Land use/land cover change detection is essential as it is an indicator of climate change as well as it helps in better assessment of landscape dynamic during a particular period of time.

In the present study, the land use/land cover change detection has been performed for both the Brahmaputra and the Subansiri River basins from 2002 to 2012 for three different months viz., January, April and October. The supervised classification method and the maximum likelihood classifier algorithm are used to classify the satellite images.

5.1.1 Methods of LULC change detection study

LULC changes are important elements of the global environmental change processes (Jaisawal et al., 2001). Satellite remote sensing is a potentially powerful means of monitoring

land-use change at high temporal resolution and lower costs than those associated with the use of traditional methods (El-Raey et al., 1995). The synoptic view, repetitive coverage and real time data acquisition are three main advantages that make remote sensing data very useful. The satellite imageries, therefore, enable to accurately compute various LULC categories and help in maintaining the spatial data infrastructure which is very essential for monitoring urban expansion and land use studies (Mukherjee, 1987). There are two basic methods to study the LULC change detection. These are pixel-to-pixel comparison and post-classification comparison (Jaisawal et al., 1999). In the post classification method, two or more images of different dates are first classified separately and then are compared (Pilon et al., 1988; Fung and Zhang, 1989). It is considered to be one of the most appropriate and commonly used methods for change detection (Jensen, 1996).

5.1.2 Image Classification

The overall objective of image classification is to automatically categorize all pixels in an image into land cover classes or themes. Normally, multispectral data are used to perform the classification, and the spectral pattern present within the data of each pixel is used as numerical basis for categorization. The various image classification techniques can be broadly classified into two categories: deterministic and fuzzy classifications.

5.1.2.1 Deterministic Classification

In deterministic classification, a pixel will fall into one and only one category devoting 100% of its information to the class it is assigned. Deterministic classification can further be divided into four more categories. These are: (i) Manual classification, (ii) Semi-automated (supervised) digital classification, (iii) Automated (unsupervised) digital classification and (iv) Knowledge base classification.

5.1.2.1.1 Manual Classification

Manual classification of satellite data is done by delineating polygons around the pixels that belong to the same class based on color, texture, tone, pattern and shape. If the analyst has a previous knowledge of the area to be classified as well as knowledge of reflectance properties of the ground materials, then manual classification technique is considered as an effective method of classifying land cover. It can be done through on-screen digitization or classifying hard copies.

5.1.2.1.2 Automated Supervised Classification

Supervised classification can be defined normally as the process of samples of known identity to classify pixels of unknown identity (Kumar and Singh, 2013). Samples of known identity are those pixels located within training areas. In this method, the area of interest is delineated and stored for use in the supervised classification algorithm. The user defines the original pixels that contain similar spectral classes representing certain land cover class. In other words, in supervised classification, spectral signatures are collected from specified locations (training sites) in the image by digitizing various polygons overlaying different land use types. The spectral signatures are then used to classify all pixels in the scene. Generally, the supervised classification is followed by knowledge-based expert classification systems depending on reference maps to improve the accuracy of the classification process (Xiuling et al., 2006 and Berberoglu et al., 2007). As the “User-Defined Polygon” function involves a high degree of user control, it reduces the chance of underestimating class variance in supervised classification (Moller-Jensen, 1997).

The basic steps involved in a typical supervised classification procedure are,

I. The training stage

In this step, training fields *i.e.* the areas of known identity are delineated on a satellite image. It is necessary for the analyst to know the correct class for each area. The objective is to identify a set of pixels that accurately represent spectral variation present within each information region (Kumar and Singh, 2013). The key characteristics of training area are, shape, location, number, placement and uniformity.

II. Selection of Appropriate Classification Algorithm

Various supervised classification algorithms may be used to assign an unknown pixel to one of a number of classes. Parametric classification algorithms assume that the observed measurement vectors for each class in each spectral band during the training phase of the supervised classification are Gaussian in nature, *i.e.* they are normally distributed. Nonparametric classification algorithms make no such assumption. Among the most frequently used classification algorithms are the parallelepiped, minimum distance and maximum likelihood decision rules.

Parallelepiped Classification Algorithm

This is a widely used decision rule based on simple Boolean “and/or” logic. Leica (2002a) gave the basic concept of the parallelepiped decision rule. He said that in this decision rule,

the data file values of the candidate pixel are compared to the *a priori* set higher and lower limits of every signature in every band. When the data values of a pixel fall in between the threshold values in the signature data for each band, then that pixel is automatically assigned to the class that corresponds the signature. As shown in Fig.5.1, all the pixels inside the rectangle *i.e.* the parallelepipeds are the members of the same land cover class. Those pixels far from the centre and near to the corners usually do not have the same attribute as the other members of the class. Apart from that several pixels also fall outside the parallelepipeds. In such case, the analyst defines some parametric decision rules and distributes them into the available land cover classes or they are assigned as unclassified. The parallelepiped algorithm is considered as computationally efficient method of classifying remote sensing data. The disadvantage of this method is that sometimes the parallelepipeds overlap because of which chances are there that an unknown pixel might satisfy the criteria of more than one class. In such case, it is assigned to the first class for which it meets all the criteria.

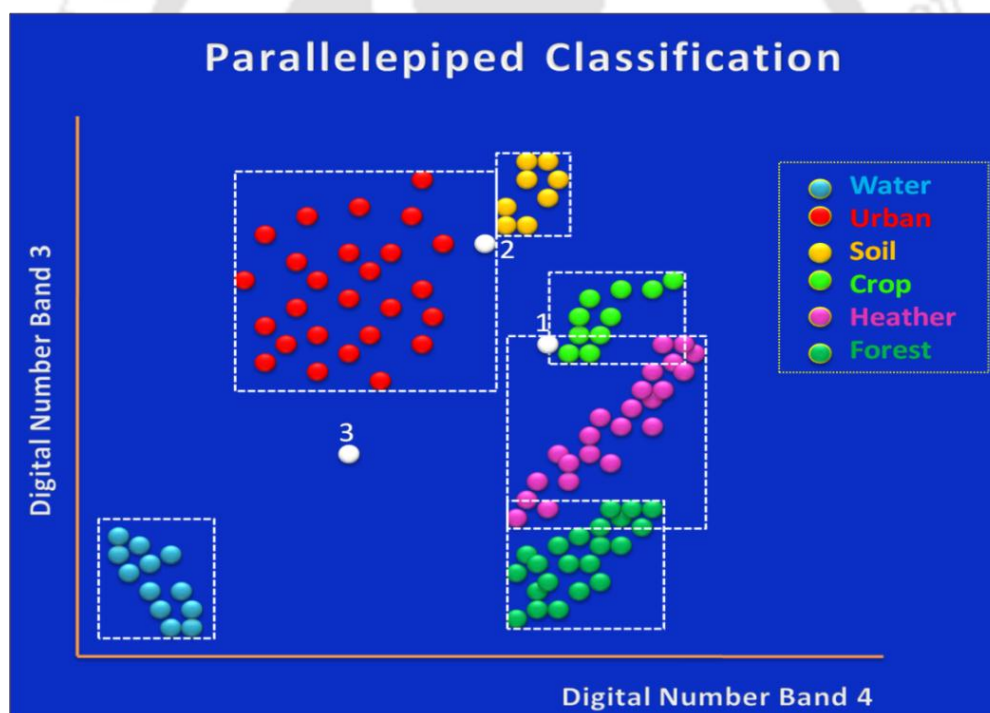


Fig. 5.1: Parallelepiped Classification

Minimum distance to means classification algorithm

Like the parallelepiped algorithm, it requires that the user provides the mean vectors for each class in each band from the training data. To perform minimum distance classification, a program must calculate the distance to each mean vector, from each unknown pixel. It is

possible to calculate this distance using Euclidean distance based on the Pythagorean Theorem.

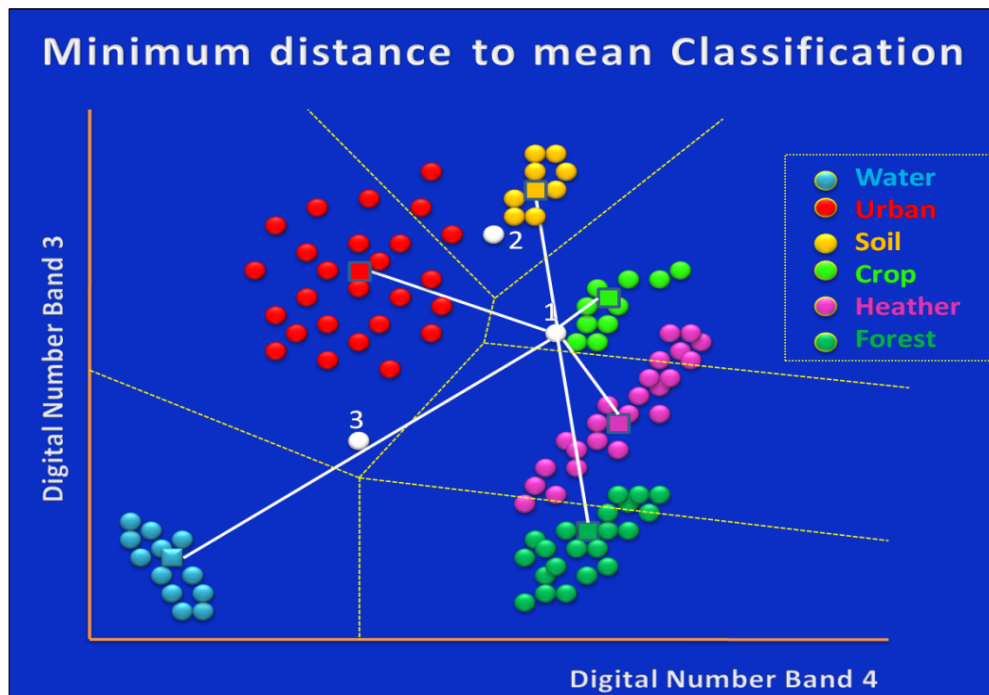


Fig. 5.2: Minimum distance to mean classification

Maximum likelihood classification algorithm

The basic assumption of Maximum Likelihood Classifier (MLC) algorithm is that a pixel has a certain probability of belonging to a particular class. These probabilities are equal for all classes and the input data in each band follows the Gaussian (normal) distribution function (Lillesand et al., 2004). The MLC functions by using the band means and standard deviations from field collected data in order to project land cover classes as centroids in feature space (Muzein, 2006). The Maximum Likelihood Classification tool considers both the variances and covariances of the class signatures when assigning each cell to one of the classes represented in the signature file. With the assumption that the distribution of a class sample is normal, a class can be characterized by the mean vector and the covariance matrix. Given these two characteristics for each cell value, the statistical probability is computed for each class to determine the membership of the cells to the class. When the default EQUAL a priori option is specified, each cell is classified to the class to which it has the highest probability of being a member. The advantage of Maximum Likelihood method is its use of well-developed probability theory.

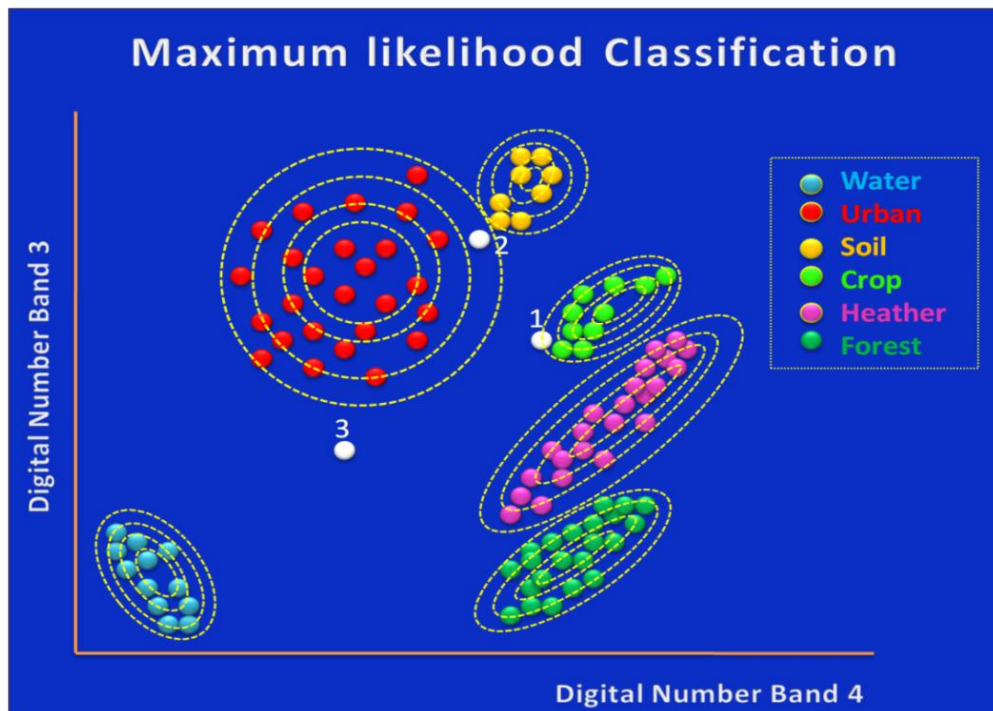


Fig.5.3: Maximum likelihood classification

5.1.2.1.3 Unsupervised Classification

The unsupervised approach attempts spectral grouping that may have an unclear meaning from the user's point of view. Unsupervised classifiers do not utilize training data as the basis for classification. Rather, this family of classifiers involves algorithms that examine the unknown pixels in an image and aggregate them into a number of classes based on the natural groupings or clusters present in the image values. It performs very well in cases where the values within a given cover type are close together in the measurement space and data in different classes are comparatively well separated.

The classes that result from unsupervised classification are spectral classes because they are based solely on the natural groupings in the image values, the identity of the spectral classes will not be initially known. The analyst must compare the classified data with some form of reference data (such as larger scale imagery or maps) to determine the identity and informational value of the spectral classes.

There are numerous clustering algorithms that can be used to determine the natural spectral groupings present in dataset. One common form of clustering, called the "k-means" approach also called as ISODATA (Iterative Self-Organizing Data Analysis Technique) accepts from the analyst a number of clusters to be located in the data. Because the k-means approach is

iterative, it is computationally intensive. Therefore, it is often applied to image subareas rather than to full scenes.

Advantages of unsupervised classification

Advantages of unsupervised classification (relative to supervised classification) can be enumerated as follows:

- a) No extensive prior knowledge of the region is required
- b) The opportunity for human error is minimized
- c) Unique classes are recognized as distinct units

Disadvantages of unsupervised classification

Disadvantages and limitations arise primarily from a reliance on “natural” grouping difficulties in matching these groups to the informational categories that are of interest to the analyst.

- a) Unsupervised classification identifies spectrally homogeneous classes within the data; these classes do not necessarily correspond to the information categories that are of interest to the analyst. As a result, the analyst is faced with the problem of matching spectral classes generated by the classification to the informational classes that are required by the ultimate user of the information.
- b) Spectral properties of specific information classes will change over time (on a seasonal basis as well as over the year). As a result, relationships between informational classes and spectral classes are not constant and relationships defined for one image can seldom be extended to others.

5.1.2.2 Knowledge Base Classification

Knowledge Base Classification (KBC) method is especially applicable when spectral information alone is not adequate for proper classification (Hansen et al., 2000; Defries et al., 2000). Example may be drawn from a forest cover where forest in a lowland or highland responds almost similarly to the incoming radiation in all spectral ranges. In such case, elevation information is required to mark out these two classes. Such additional information is easily accommodated by the KBC method. KBC is used mostly as a post classification procedure to refine the previously classified images. One more advantage of KBC method is its convenience for land cover classification that involves fine scale temporal resolutions.

5.1.2.3 Fuzzy/Soft Classification

Fuzzy classification is a relatively new method of classification. Here, the fuzzy logic concept is employed to address the problem of mixed pixels. Unlike the conventional classification techniques where every pixel is treated as full member of one of the classes in the thematic map or completely excluded from those classes, fuzzy logic assigns the degree of membership of each pixel to each land cover class (Kruse, 1993).

An attempt has been made in this study to map out the status of land use/cover of both the Brahmaputra and the Subansiri River basins in view to detect the changes that have taken place in the basins during the period from 2002 to 2012 for three different months viz., January, April and October using geospatial techniques.

5.2 Materials and Methods

5.2.1 Data used

MODIS image MOD09A1.5 of 500m resolution starting from the year 2002 to 2012 for three different months, viz., January, April and October have been used to prepare the land use/land cover maps.

5.2.2 Database preparation

These MODIS datasets were imported in ERDAS Imagine version 9.1 (LeicaGeosystems, Atlanta, U.S.A.), satellite image processing software to create a false color composite (FCC). The layer stack option in image interpreter tool box was used to generate FCCs for the study areas.

5.2.3 Land use/land cover change detection and analysis

To work out the LULC classification, supervised classification method with maximum likelihood algorithm was applied in the ERDAS Imagine 9.1 Software. Over 80 training points were repeatedly selected from the whole study area by drawing a polygon around training sites of interests.

Maximum likelihood algorithm (MLC) as described above is one of the most popular supervised classification methods which is based on the probability that a pixel belongs to a particular class. This theory assumes that these probabilities are equal for all classes as well as the input bands have normal distributions. The disadvantage of this algorithm is that it heavily relies on a normal distribution of the data in each input band and there is a tendency

to over classify the signatures with relatively large values in the covariance matrix. Also this method requires long computational time.

Five different land use/cover types are identified in the study area viz., (i) bare soil (BS) (ii) surface water bodies (SWB) (iii) dense vegetation (DV) (iv) light vegetation (LV) and (v) snow cover area (SCA). For performing LULC change detection, a post-classification detection method was employed. Classified images of different months were compared in order to determine quantitative aspects of the changes for the periods from 2002 to 2012 for the months of January, April and October. Quantitative area data of the overall land use/cover changes as well as gains and losses in each category between 2002 and 2012 were then compiled.

5.3 Results and Discussions

The LULC maps for the Brahmaputra and the Subansiri River basins have been prepared for January, April and October by Supervised classification method using the maximum likelihood classification algorithm in the Erdas Imagine 9.1 software. The area covered by different LULC classes for both the river basins from 2002 to 2012 for January, April and October have been determined and the change detection has been analyzed accordingly.

5.3.1 LULC change detection analysis for Brahmaputra river basin

5.3.1.1 Change detection analysis for the month of January

The areas covered by different LULC classes for the month of January from 2002 to 2012 are given in Table 5.1. Fig. 5.4 shows the pie diagrams depicting the percent of total area covered by each LULC class.

Table 5.1: Area covered by different LULC classes in Brahmaputra basin for the month of January from 2002 to 2012

LULC Classes	Year wise area covered ($\times 10^4 \text{ km}^2$)										
	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
BS	24.71	19.47	19.61	20.06	24.40	23.81	26.31	19.46	21.03	22.42	15.74
SWB	7.10	7.47	10.31	9.03	5.35	3.85	4.36	8.94	7.35	7.87	9.96
DV	15.39	17.33	13.93	20.68	17.39	17.84	22.61	18.92	20.08	13.47	7.77
LV	17.12	13.28	16.90	10.27	16.87	16.97	11.32	8.86	12.54	17.37	20.62
SCA	3.38	10.16	6.95	7.68	3.69	5.23	3.11	11.51	6.70	6.58	13.60

It is seen that area covered by bare soil has always been the maximum except for the year 2012, where area covered by light vegetation was the maximum. The increase in light vegetation can be attributed to the fact of increasing urbanisation and agricultural land due to increase in population.

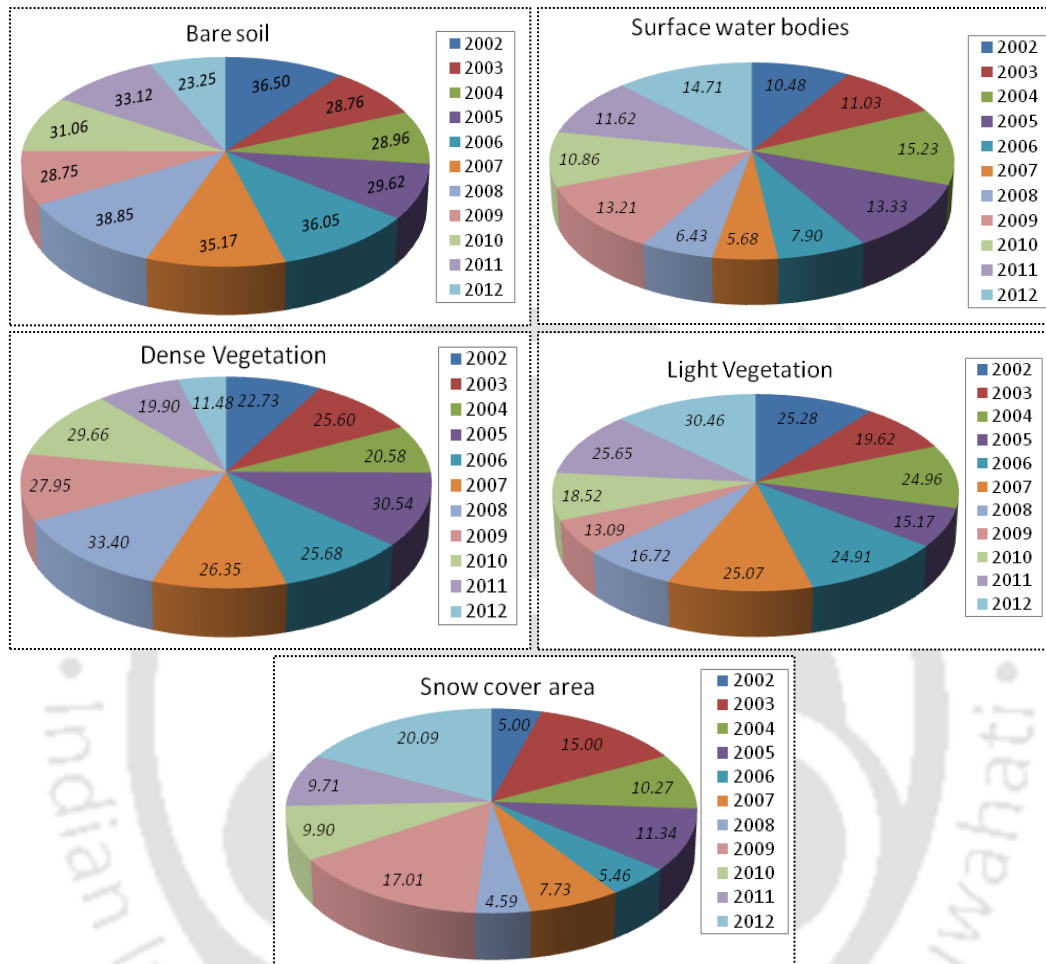


Fig. 5.4: Pie diagrams showing percent of total area covered by different LULC classes in the Brahmaputra River basin from 2002 to 2012 for the month of January

The maximum area covered by bare soil has been observed in 2008 with a value of 38.85% of the total basin area and the minimum was observed in the year 2012 with a value of 23.25% of the total area of the Brahmaputra basin. Area covered by surface water bodies was the maximum in 2004 (15.23%) and minimum in 2007 (5.68%). Percent of total area covered by dense vegetation was the maximum in 2008 with a value of 33.40% and was the minimum in 2012 with a value of 11.48%. For light vegetation and snow cover area the maximum were in 2012 (30.46% and 20.09% respectively) while the minimum were in 2009 (13.09%) and 2008(4.59%) respectively.

The trend analysis for each LULC class for the month of January from 2002 to 2012 are presented graphically in Fig. 5.5.

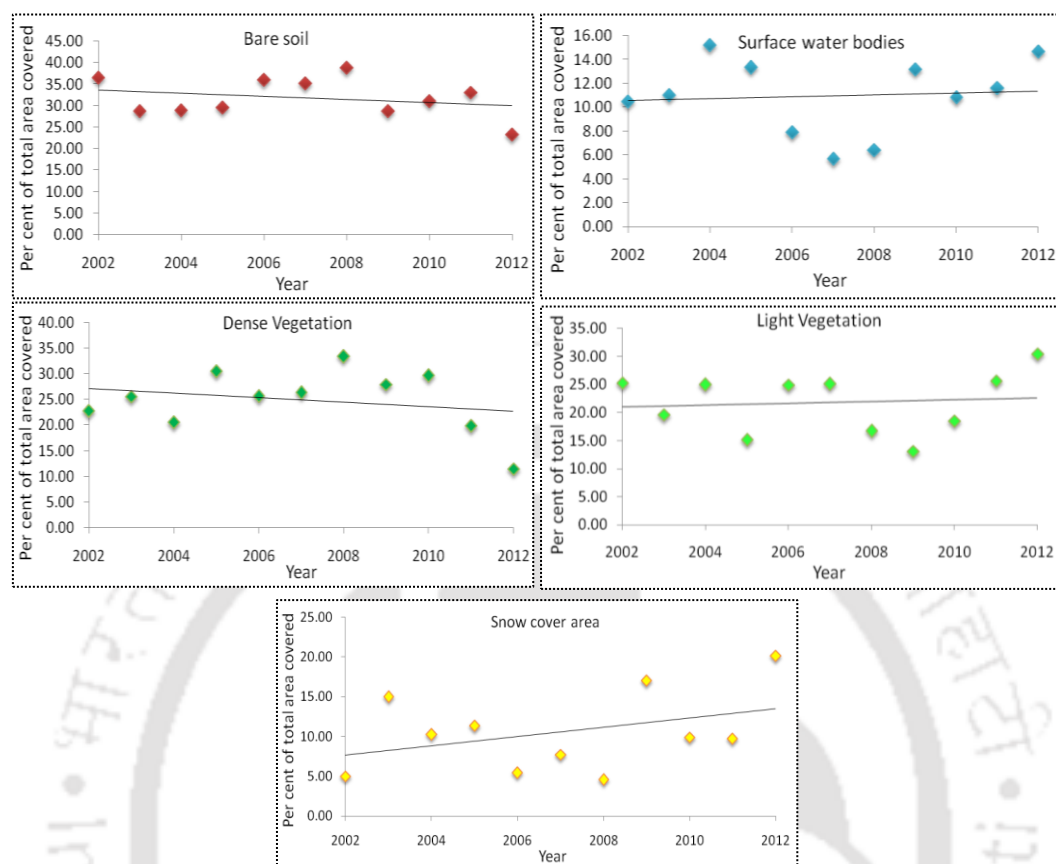


Fig. 5.5: Trends showing percent of total area covered by different LULC classes for the Brahmaputra River basin from 2002 to 2012 for the month of January

From Fig. 5.5 it is observed that for bare soil and dense vegetation, the percent of total area covered show decreasing trends from 2002 to 2012 while percent of total area covered by surface water bodies, light vegetation and snow cover area show increasing trends. The increased snow cover area and surface water bodies might have occupied the bare land leading to decrease in the area covered by bare soil. The reason behind decrease in dense vegetation and increase in light vegetation may be that deforestation occurred during this period which had been covered by agricultural lands.

The land use/land cover maps of the Brahmaputra River Basin prepared by supervised classification method in Erdas Imagine software for the Month of January from 2002 to 2012 are shown in Fig. 5.6.

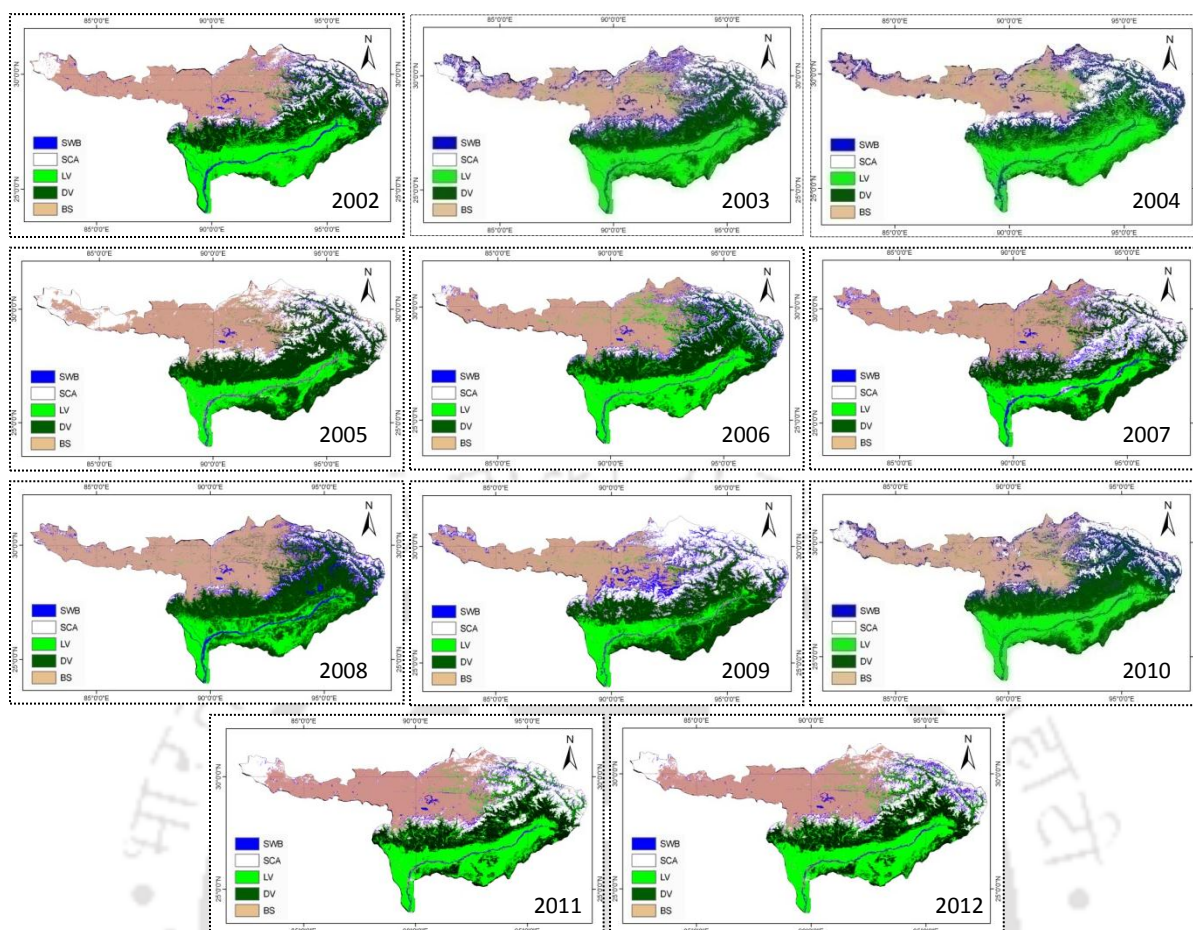


Fig. 5.6: LULC maps of Brahmaputra river basin for the month of January from 2002 to 2012

The yearly changes of each LULC class from 2002 to 2012 for the month of January has also been analyzed and are shown in Table 5.2.

Table 5.2: Year wise Changes in Brahmaputra basin for different LULC classes from 2002 to 2012 for the month of January

Year	LULC Classes				
	BS (%)	SWB(%)	DV(%)	LV(%)	SCA(%)
2002-03	-7.74	0.55	2.87	-5.66	10
2003-04	0.2	4.2	-5.02	5.34	-4.73
2004-05	0.66	-1.9	9.96	-9.79	1.07
2005-06	6.43	-5.43	-4.86	9.74	-5.88
2006-07	-0.88	-2.22	0.67	0.16	2.27
2007-08	3.68	0.75	7.05	-8.35	-3.14
2008-09	-10.1	6.78	-5.45	-3.63	12.42
2009-10	2.31	-2.35	1.71	5.43	-7.11
2010-11	2.06	0.76	-9.76	7.13	-0.19
2011-12	-9.87	3.09	-8.42	4.81	10.38

For bare soil, maximum decrease has been observed during 2008-09 where it decreased by 10.1% and the maximum increase was during 2005-06 where it increased by 6.43%. Surface water bodies increased the most during 2008-09 (6.78%) and decreased the most during 2005-06 (5.43%). The maximum decrease in dense vegetation has been observed during 2010-11 (9.76%) and the maximum increase was observed during 2004-05 (9.96%). The maximum decrease in light vegetation and snow cover area were during 2004-05 (9.79%) and 2009-10(7.11%) respectively, while the maximum increases were during 2005-06 (9.74%) and 2011-12 (10.38%) respectively.

By taking the values of area covered by different LULC classes in the years 2002 and 2012, the overall change that has taken place in the entire decade for the month of January has been analyzed and is represented graphically in Fig. 5.7. The area covered by each LULC class along with the percent of total basin area and overall changes occurred in the entire period from 2002 to 2012 are given in Table 5.3.

Table5.3:Area and amount of change in different LULC categories in the Brahmaputra basin during 2002 to 2012 for the month of January

LULC Classes	Year				Change 2002-2012	
	2002		2012			
	Area(km ²)	%	Area(km ²)	%	Area(km ²)	%
Bare soil	247127	36.50	157436	23.25	-89691	-13.25
Surface water bodies	70983	10.48	99613	14.71	28630	4.23
Dense vegetation	153890	22.73	77715	11.48	-76175	-11.25
Light vegetation	171176	25.28	206223	30.46	35047	5.18
Snow cover area	33841	5.00	136030	20.09	102189	15.09

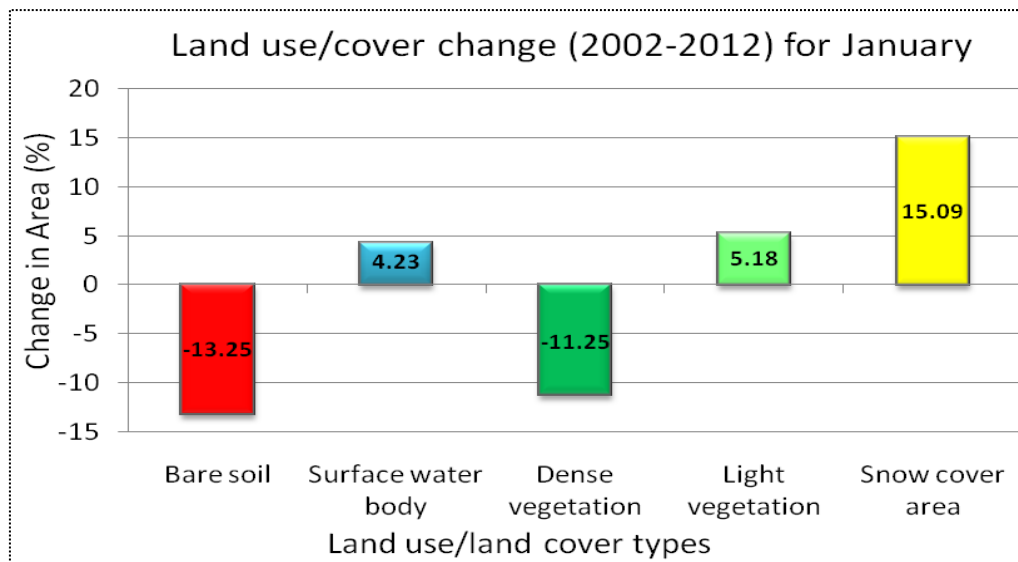


Fig. 5.7: LULC change in the Brahmaputra River basin during 2002 to 2012 for January

While analyzing the LULC changes in the entire period from 2002 to 2012, it is seen that in case of Brahmaputra River basin for the month of January, area covered by surface water bodies, light vegetation and snow cover area increased and area covered by bare soil and dense vegetation decreased. The bare soil has decreased from 247127km² in 2002 to 157436km² in 2012 which accounts for 13.25%. The surface water body has increased from 70983 km² in 2002 to 99613 km² in 2012 which accounts for 4.23% of the total study area. The dense vegetation has decreased from 153890km² in 2002 to 77715km² in 2012 which accounts for 10.57 %. Again, light vegetation has increased from 2002 (171176km²) to 2012 (206223km²) which accounts for 5.18%. The snow cover area has increased from 33841km² in 2002 to 102189km² in 2012 with percent increase of 15.09%. The increases in snow cover area, surface water bodies and light vegetation led to the decrease in the other classes.

5.3.1.2 Change detection analysis for the month of April

The area covered by each LULC class from 2002 to 2012 for the month of April has been determined and are tabulated in Table 5.4. The percent of total area covered by each class are expressed as pie diagrams in Fig. 5.8.

Table 5.4: Area covered by different LULC classes in Brahmaputra basin for the month of April from 2002 to 2012

LULC Classes	Year wise area covered ($\times 10^4 \text{km}^2$)										
	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
BS	17.04	18.63	21.18	22.12	19.87	23.56	18.08	21.21	12.70	17.39	14.95
SWB	9.02	8.15	11.33	9.44	8.12	3.55	12.00	9.31	6.99	11.18	9.93
DV	16.60	16.14	13.52	15.89	11.95	17.05	14.85	14.17	17.68	16.27	13.95
LV	13.91	15.06	15.87	12.23	19.43	14.54	13.18	13.62	23.26	15.13	19.63
SCA	11.13	9.72	5.81	8.03	8.34	9.01	9.60	9.40	7.08	7.74	9.24

The Table 5.4 shows that during this decade, area covered by bare soil, surface water bodies, dense vegetation, light vegetation and snow cover area were the maximum in 2007, 2008, 2010, 2010 and 2002 respectively. The minimum areas of these classes have been found in 2010, 2007, 2006, 2005 and 2004 respectively.

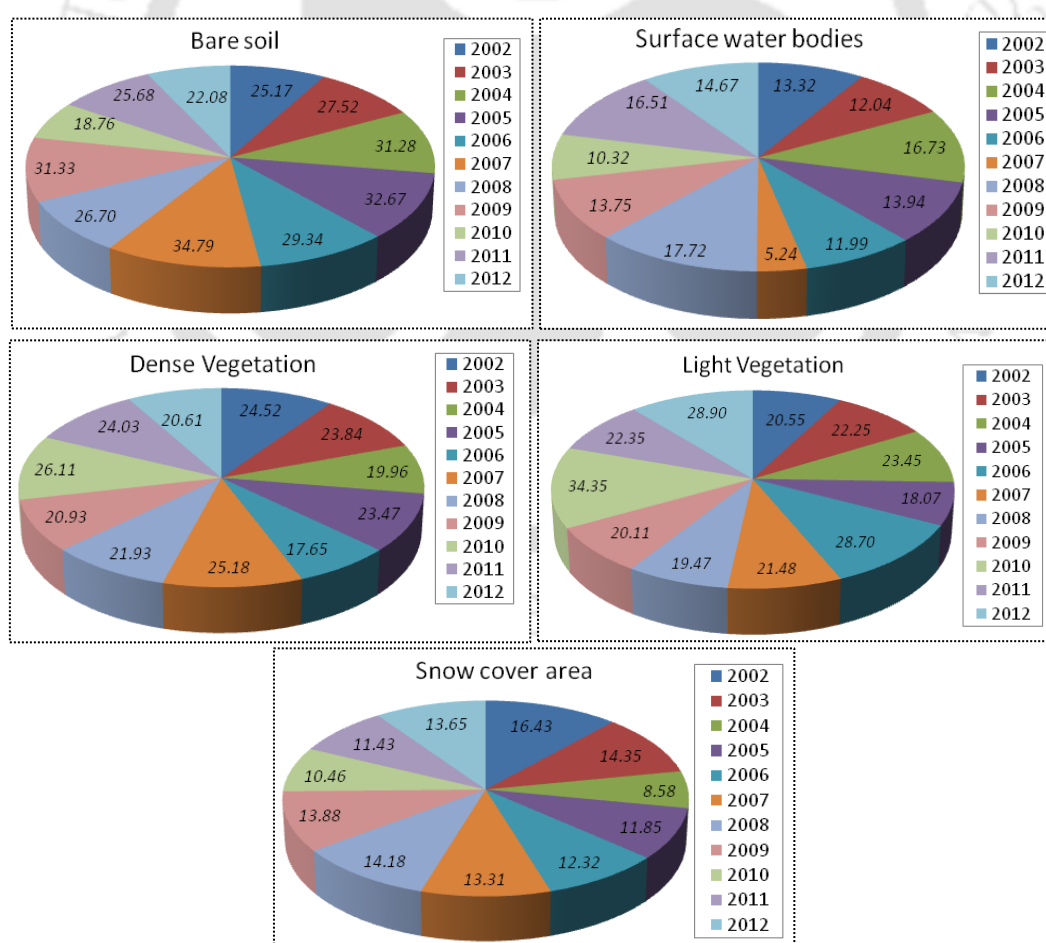


Fig. 5.8: Pie diagrams showing percent of total area covered by different LULC classes in the Brahmaputra River basin from 2002 to 2012 for the month of April

It is observed that the maximum per cent of total area covered by bare soil during the time period was in the year 2007 with a value of 34.79% of the total basin area, while the minimum was in the year 2010 with a value of 18.76% of the total area. Area covered by surface water bodies was the maximum in 2008 (17.72%) and the minimum was observed in 2007 (5.24%). Percent of total area covered by dense vegetation was the maximum in 2010 with a value of 26.11% and was the minimum in 2006 with a value of 17.65%. For light vegetation and snow cover area, the maximum were observed in 2010 (34.35%) and 2002 (16.43%) respectively while the minimum were observed in 2005 (18.07%) and 2004 (8.58%) respectively.

Fig. 5.9 gives the trend analysis of percent of total area of the Brahmaputra basin covered by each LULC class from 2002 to 2012 for the month of April.

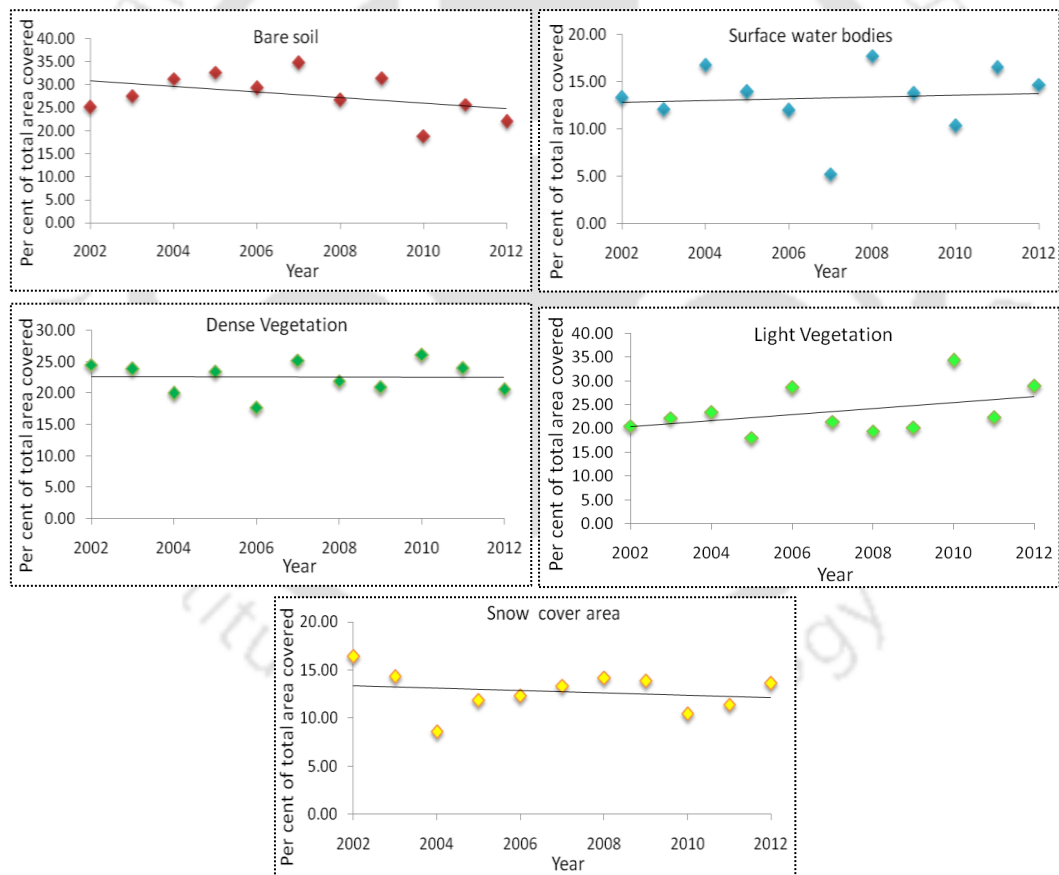


Fig. 5.9: Trends showing percent of total area covered by different LULC classes for the Brahmaputra River basin from 2002 to 2012 for the month of April

It is clear from the figure that except for light vegetation and surface water bodies where increasing trends are observed, all other LULC classes show decreasing trends from 2002 to 2012. Deforestation and development of agricultural land due to the increase in population

might have led to the increase in light vegetation and decrease in bare land and dense vegetation. In other words, the decreased bare soil, dense vegetation and snow cover area had been covered with light vegetation and surface water bodies.

The LULC maps for the month of April from 2002 to 2012 are given in Fig. 5.10.

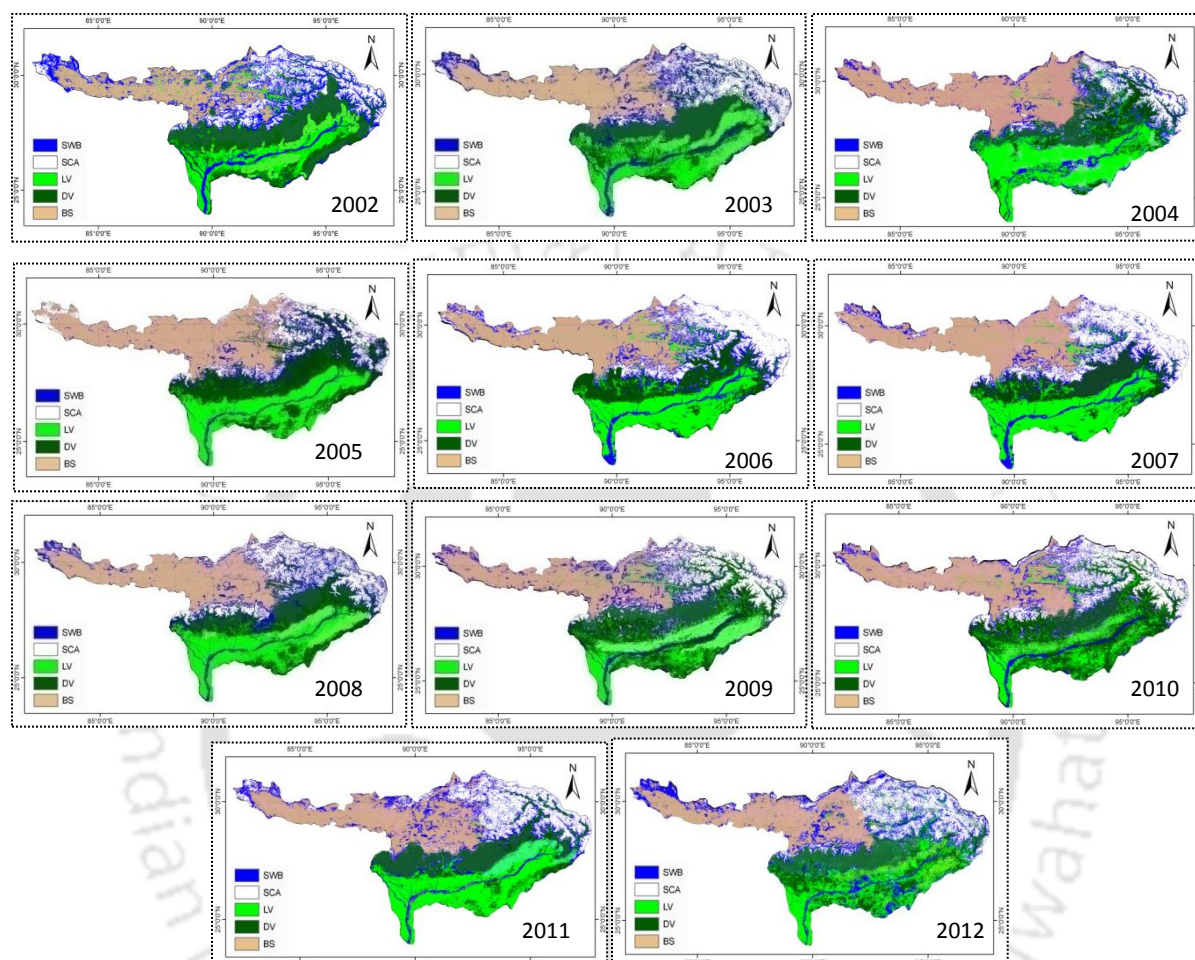


Fig. 5.10: LULC maps of the Brahmaputra River basin for the month of April from 2002 to 2012

The yearly changes taken place in the Brahmaputra basin for each LULC class from 2002 to 2012 for the month of April are shown in Table 5.5.

Table 5.5: Year wise Changes in Brahmaputra basin for different LULC classes from 2002 to 2012 for the month of April

Year	LULC Classes				
	BS (%)	SWB (%)	DV (%)	LV (%)	SCA (%)
2002-2003	2.35	-1.28	-0.68	1.70	-2.08
2003-2004	3.76	4.69	-3.88	1.20	-5.77
2004-2005	1.39	-2.79	3.51	-5.38	3.28
2005-2006	-3.33	-1.95	-5.82	10.63	0.46

2006-2007	5.45	-6.75	7.53	-7.22	0.99
2007-2008	-8.10	12.48	-3.25	-2.01	0.87
2008-2009	4.63	-3.97	-1.00	0.64	-0.30
2009-2010	-12.57	-3.43	5.18	14.24	-3.42
2010-2011	6.92	6.19	-2.08	-12.00	0.97
2011-2012	-3.61	-1.84	-3.42	6.55	2.22

The maximum increase in bare soil, surface water bodies, dense vegetation, light vegetation and snow cover area have been observed during 2010-11, 2007-08, 2006-07, 2009-10 and 2004-05 with percent increase values of 6.92%, 12.48%, 7.53%, 14.24% and 3.28% respectively. The maximum decrease for these classes have been observed in 2009-10, 2006-07, 2003-04, 2010-11 and 2003-04 where the areas decreased by 12.57%, 6.75%, 3.88%, 12% and 5.77% respectively.

The overall changes that have taken place in the decade (from 2002 to 2012) for the month of April were analyzed and are represented in Fig. 5.11. The changes are tabulated in Table 5.6.

Table 5.6: Area and amount of change in different LULC categories in the Brahmaputra basin during 2002 to 2012 for the month of April

LULC categories	Year				Change 2002-2012	
	2002		2012			
	Area(km ²)	%	Area(km ²)	%	Area(km ²)	%
Bare soil	170432	25.17	149473	22.08	-20959	-3.09
Surface water bodies	90196	13.32	99342	14.67	9145	1.35
Dense vegetation	165978	24.52	139502	20.61	-26476	-3.91
Light vegetation	139148	20.55	196314	28.90	57166	8.35
Snow cover area	111262	16.43	92386	13.65	-18875	-2.79

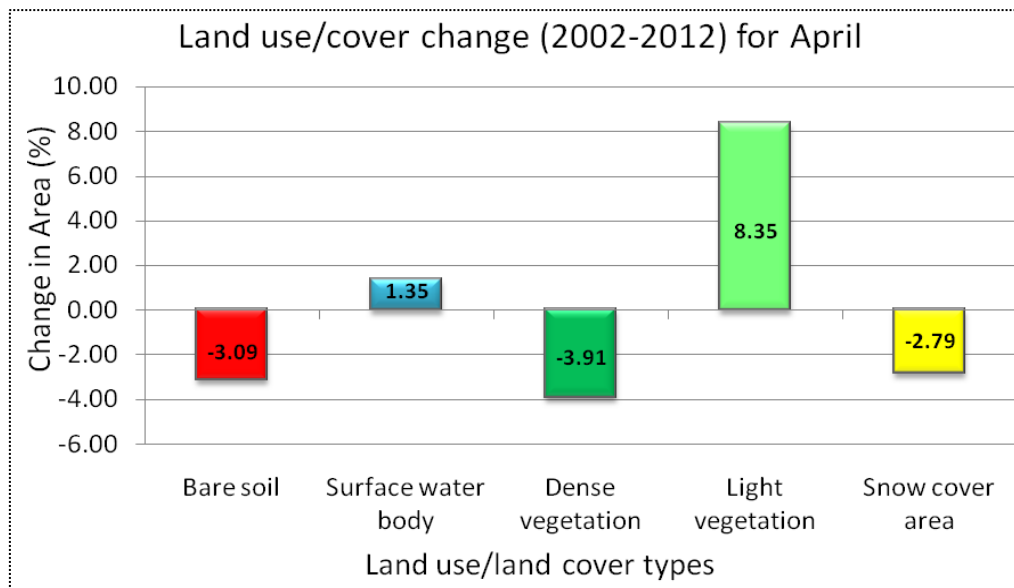


Fig. 5.11: LULC change in the Brahmaputra River basin during 2002 to 2012 for April

For the entire period from 2002 to 2012, it is seen that for the month of April, area covered by light vegetation and surface water bodies had increased and area covered by other classes had decreased. The bare soil decreased from 170432km^2 in 2002 to 149473km^2 in 2012 which accounts for 3.09%. The surface water body increased from 90196 km^2 in 2002 to 99342 km^2 in 2012 which accounts for 1.35% of the total study area. The dense vegetation decreased from 165978km^2 in 2002 to 139502km^2 in 2012 which accounts for 3.91 %. Again, light vegetation increased from 2002 (139148km^2) to 2012 (196314km^2) which accounts for 8.35%. The snow cover area has decreased from 111262km^2 in 2002 to 92386km^2 in 2012 which accounts for 2.79% of the total area of the basin. The increased light vegetation depicts the increase in population in the basin as more land had been used for agricultural purpose.

5.3.1.3 Change detection analysis for the month of October

The areas covered by each LULC class from 2002 to 2012 for the month of October are given in Table 5.7. The percent of total area covered by each class are expressed as pie diagrams as shown in Fig. 5.12.

Table 5.7: Area covered by different LULC classes in Brahmaputra basin for the month of October from 2002 to 2012

LULC Classes	Year wise area covered ($\times 10^4 \text{km}^2$)										
	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
BS	16.30	21.81	19.45	18.73	22.68	23.34	23.76	25.64	21.30	22.67	24.77
SWB	9.15	7.90	8.09	6.44	6.87	3.09	3.46	2.41	5.35	7.27	4.26
DV	15.07	15.90	16.38	22.72	18.35	17.85	16.47	14.90	12.49	10.62	11.07
LV	18.54	19.75	17.71	16.91	17.94	21.93	20.59	21.81	25.32	25.49	25.31
SCA	8.64	2.35	6.07	2.90	1.86	1.50	3.43	2.93	3.24	1.66	2.29

Areas covered by bare soil, surface water bodies, dense vegetation, light vegetation and snow were the maximum in 2009, 2002, 2005, 2011 and 2002 respectively while the areas covered by these classes were the minimum in 2002, 2009, 2011, 2005 and 2007 respectively.

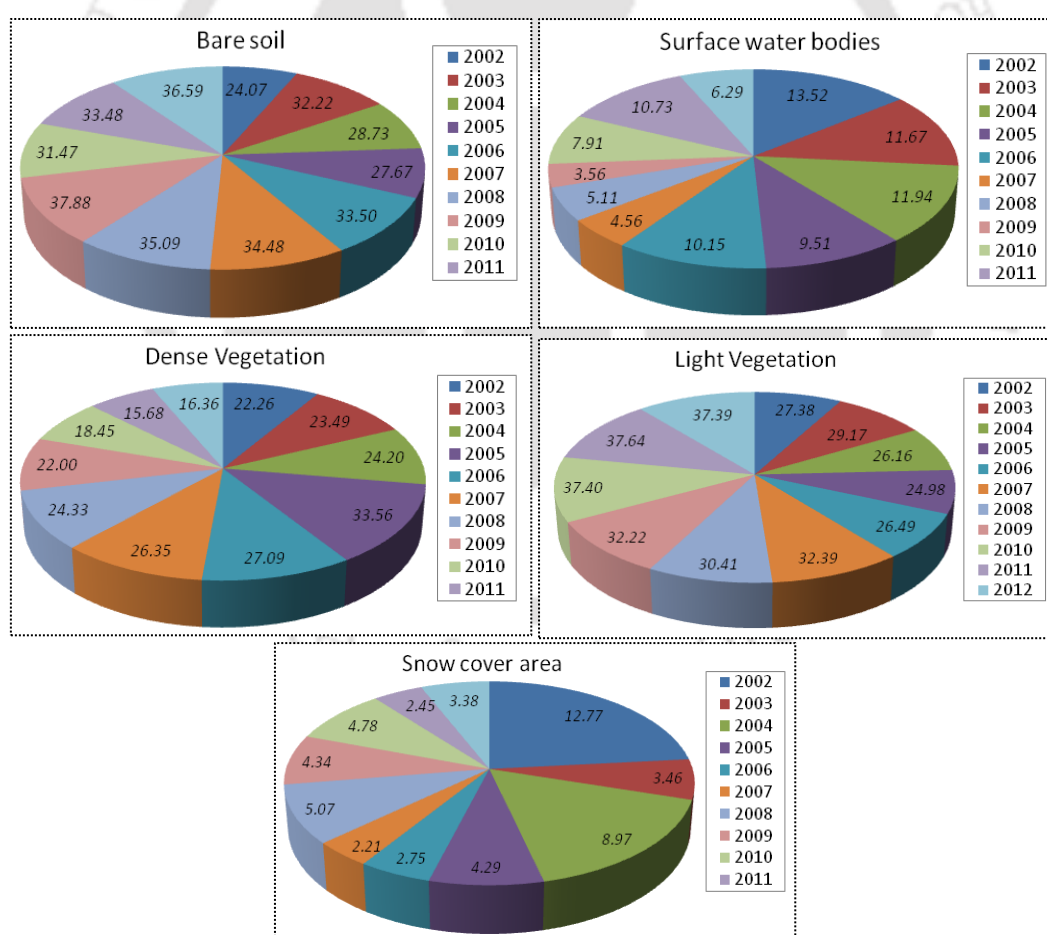


Fig. 5.12: Pie diagrams showing percent of total area covered by different LULC classes in the Brahmaputra River basin from 2002 to 2012 for the month of October

For bare soil, the maximum percent of total area covered has been observed in 2009 with a value of 37.88% of the total area and minimum was in the year 2002 with a value of 24.07% of the total area of the Brahmaputra basin. Percent of total area covered by surface water bodies was the maximum in 2002 (13.52%) and minimum in 2009 (3.56%). Per cent of total area covered by dense vegetation was maximum in 2005 with a value of 33.56% and was minimum in 2011 with a value of 15.68%. For light vegetation and snow cover area the maximum were in 2011 (37.39%) and 2002 (12.77%) respectively while the minimum were in 2005 (24.98%) and 2007 (2.21%) respectively.

Fig.5.13 shows the trend analyses for each land use/land cover class during 2002-12.

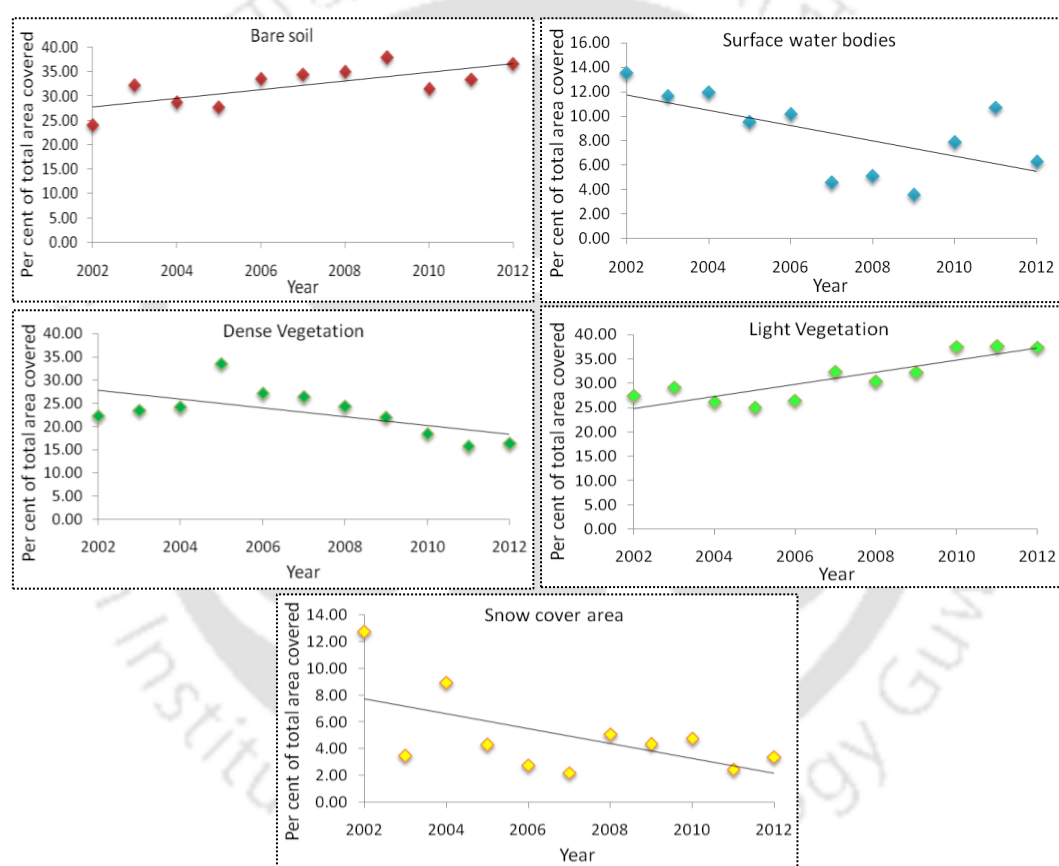


Fig. 5.13: Trends showing percent of total area covered by different LULC classes for the Brahmaputra River basin from 2002 to 2012 for the month of October

It is observed that for surface water bodies, dense vegetation and snow cover area, the percent of total area covered show decreasing trends from 2002 to 2012 while percent of total area covered by bare soil and light vegetation show increasing trends during this period.

The LULC maps for the month of October from 2002 to 2012 are given in Fig. 5.14.

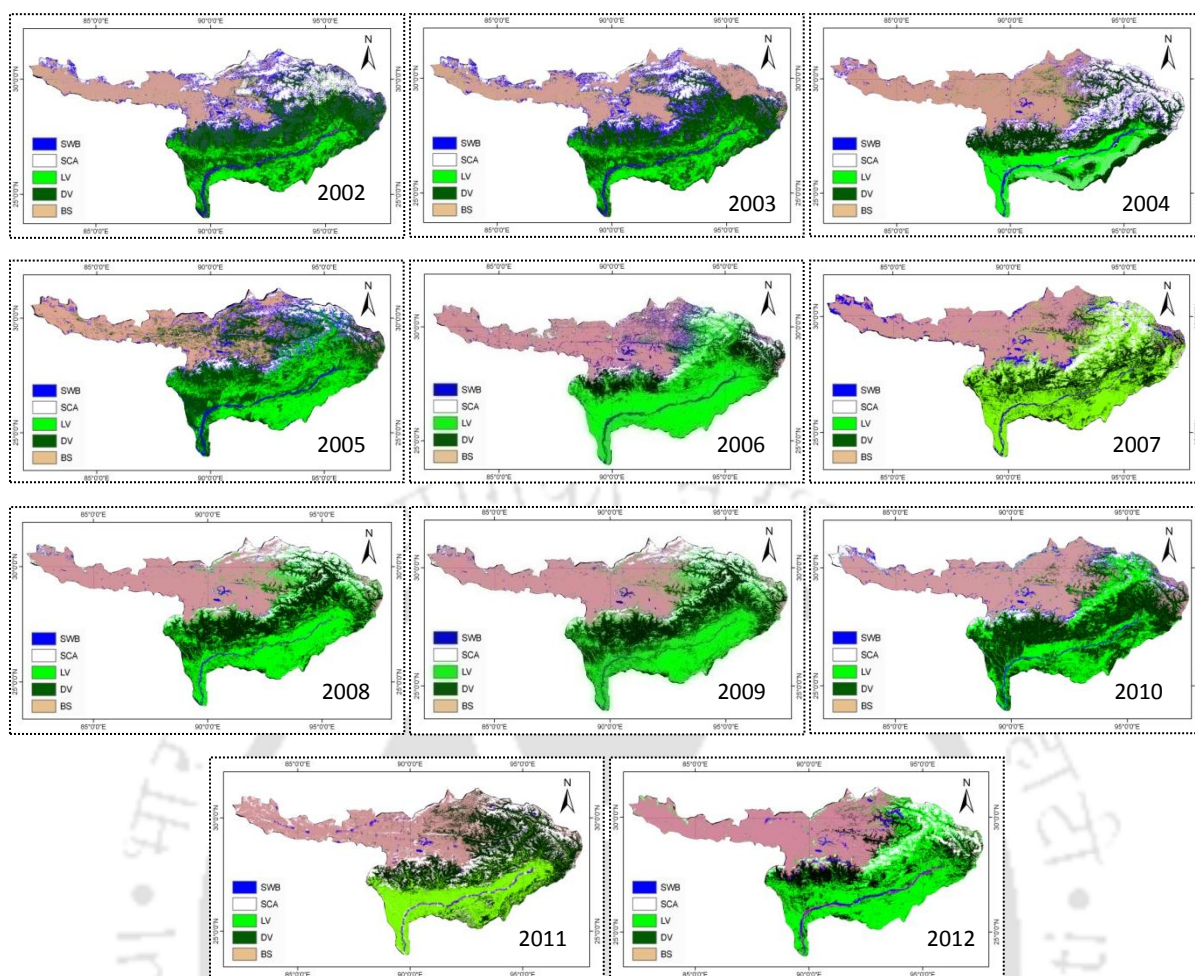


Fig. 5.14: LULC maps of the Brahmaputra River basin for the month of October from 2002 to 2012

The changes taken place in each year for each LULC class from 2002 to 2012 are given below in Table 5.8.

Table 5.8: Year wise Changes in Brahmaputra basin for different LULC classes from 2002 to 2012 for the month of October

Year	LULC Classes				
	BS (%)	SWB(%)	DV(%)	LV(%)	SCA(%)
2002-2003	8.14	-1.85	1.23	1.79	-9.30
2003-2004	-3.49	0.27	0.72	-3.01	5.50
2004-2005	-1.05	-2.43	9.36	-1.18	-4.68
2005-2006	5.83	0.65	-6.47	1.51	-1.53
2006-2007	0.98	-5.60	-0.74	5.90	-0.54
2007-2008	0.61	0.55	-2.02	-1.98	2.86
2008-2009	2.79	-1.55	-2.33	1.81	-0.73
2009-2010	-6.41	4.35	-3.55	5.18	0.44
2010-2011	2.01	2.83	-2.77	0.24	-2.33
2011-2012	3.11	-4.44	0.68	-0.25	0.92

The maximum positive changes for bare soil, surface water bodies, dense vegetation, light vegetation and surface water bodies have been observed during 2002-03 (8.15%), 2009-10 (4.35%), 2004-05 (9.36%), 2009-10 (5.18%) and 2007-08 (2.86%) respectively. The maximum negative changes for these classes have been observed during 2009-10 (6.41%), 2006-07 (5.60%), 2005-06 (6.47%), 2003-04 (3.01%) and 2004-05 (4.68%) respectively.

The overall changes taken place for the different land use/land cover classes during the entire decade from 2002 to 2012 are given in Table 5.9. The graphical representation is shown in Fig. 5.15.

Table 5.9: Area and amount of change in different LULC categories in the Brahmaputra basin during 2002 to 2012 for the month of October

LULC Classes	Year				Change 2002-2012	
	2002		2012			
	Area(km ²)	%	Area(km ²)	%	Area(km ²)	%
Bare soil	162987	24.07	247716	36.59	84729	12.52
Surface water bodies	91515	13.52	42585	6.29	-48930	-7.23
Dense vegetation	150705	22.26	110747	16.36	-39957	-5.90
Light vegetation	185379	27.38	253106	37.39	67727	10.01
Snow cover area	86431	12.77	22862	3.38	-63569	-9.39

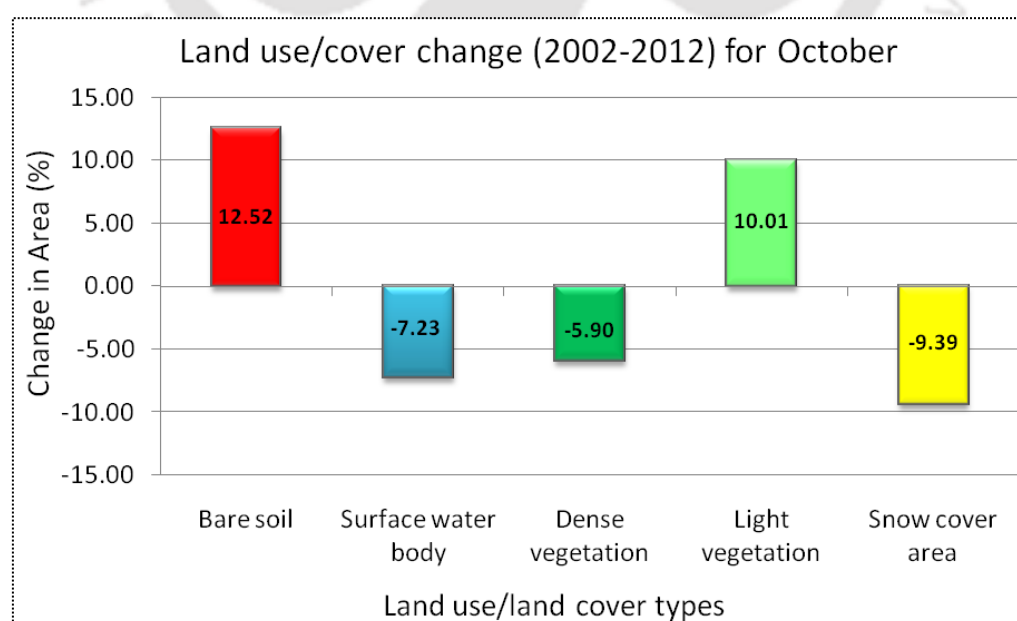


Fig. 5.15: LULC change in the Brahmaputra River basin during 2002 to 2012 for October

For the entire period from 2002 to 2012, it is seen that for the month of October, bare soil has increased from 162987km² in 2002 to 247716km² in 2012 which accounts for 12.52%. The surface water body has decreased from 91515 km² in 2002 to 42585 km² in 2012 which accounts for 7.23%. The dense vegetation has decreased from 150705km² in 2002 to 110747km² in 2012 which accounts for 5.90%. Again, light vegetation has increased from 2002 (185379km²) to 2012 (253106km²) which accounts for 10.01%. The snow cover area has decreased from 86431km² in 2002 to 22862km² in 2012 which accounts for 9.39%. The reason behind decrease in dense vegetation and surface water bodies is basically the increase in population and use of more land for agricultural purpose due to which light vegetation increased in the basin.

5.3.2 LULC change detection analysis for Subansiri river basin

The land use/land cover change detection study has also been done for the Subansiri River basin for the three different months of January, April and October. The details of the analysis are explained in the following sections.

5.3.2.1 Change detection analysis for the month of January

The areas covered by different LULC classes in the Subansiri basin for the month of January from 2002 to 2012 are given in Table 5.10. Fig.5.16 shows the pie diagram for percent of total area covered by each LULC class

Table 5.10: Area covered by different LULC classes in Subansiri basin for the month of January from 2002 to 2012

LULC Classes	Year wise area covered ($\times 10^3 \text{km}^2$)										
	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
BS	4.76	5.77	5.71	9.28	9.47	9.47	10.13	6.08	7.41	9.65	7.87
SWB	1.19	3.29	5.63	0.75	1.57	3.10	2.52	5.55	2.27	0.88	3.72
DV	19.04	14.22	12.75	12.85	13.07	11.61	11.75	9.03	11.53	11.91	10.62
LV	7.26	7.52	7.07	8.77	8.22	7.69	8.51	7.71	10.92	9.71	8.28
SCA	1.99	3.45	3.09	2.59	1.92	2.37	1.34	5.88	2.11	2.10	3.75

Bare soil, surface water bodies, dense vegetation, light vegetation and snow cover area covered the maximum areas of the total basin area in 2008, 2004, 2002, 2010 and 2009 respectively. However, the areas covered by these classes were found to be minimum in 2002, 2005, 2009, 2004 and 2008 respectively.

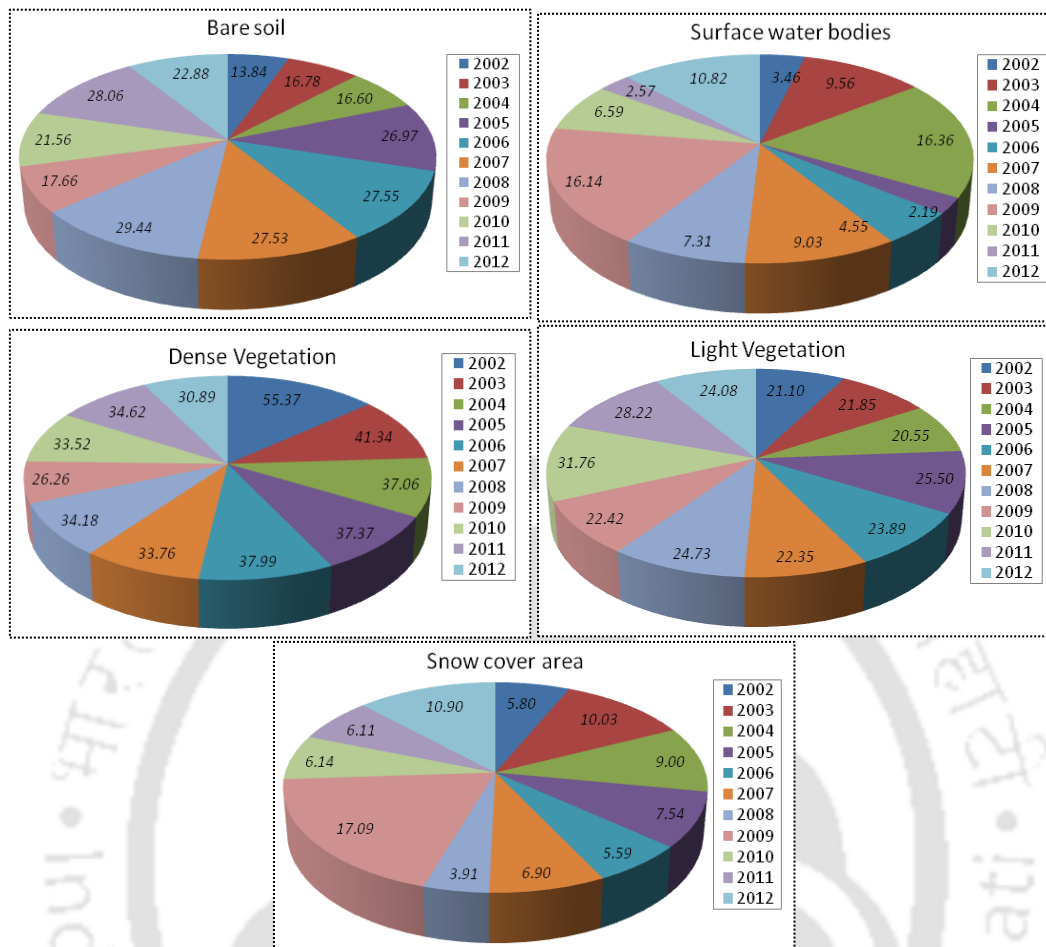


Fig. 5.16: Pie diagrams showing percent of total area covered by different LULC classes in the Subansiri River basin from 2002 to 2012 for the month of January

During 2002 to 2012, the area covered by bare soil was found to be the maximum in the year 2008 where 29.44% of the total area was covered by bare soil and the minimum was observed in the year 2002 with a value of 13.84% of total area. Area covered by surface water bodies and dense vegetation were found to be maximum in 2004 (16.36% of total area) and 2002(55.37% of total area) respectively. For these two LULC classes, the area covered has been observed to be minimum in 2005 (2.19% of total area) and 2009 (26.26% of total area) respectively. For the remaining two classes *i.e.* light vegetation and snow cover area, the maximum area covered were in 2010(31.76% of total area) and 2009 (17.09% of total area) respectively while minimum areas covered by these classes have ben observed in 2004 (20.55% of total area) and 2008 (3.91% of total area) respectively.

Fig.5.17 shows the trend analysis for each class from 2002 to 2012.

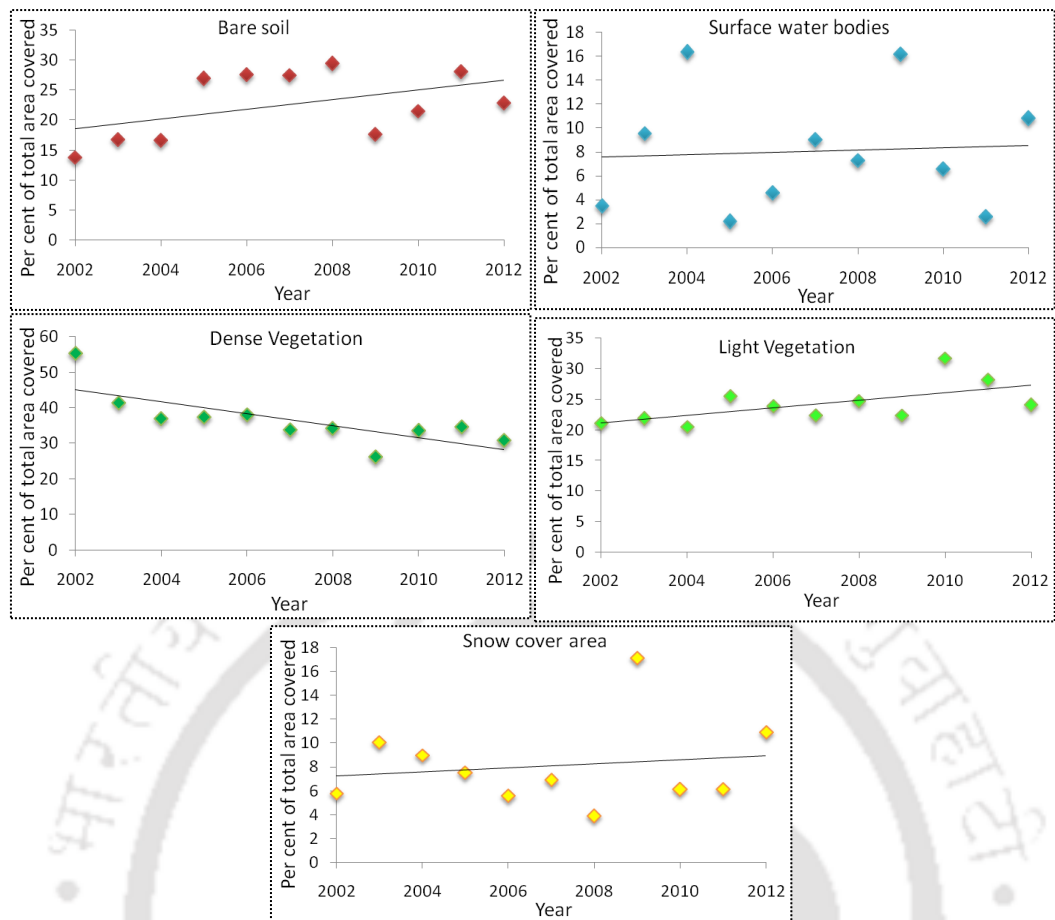
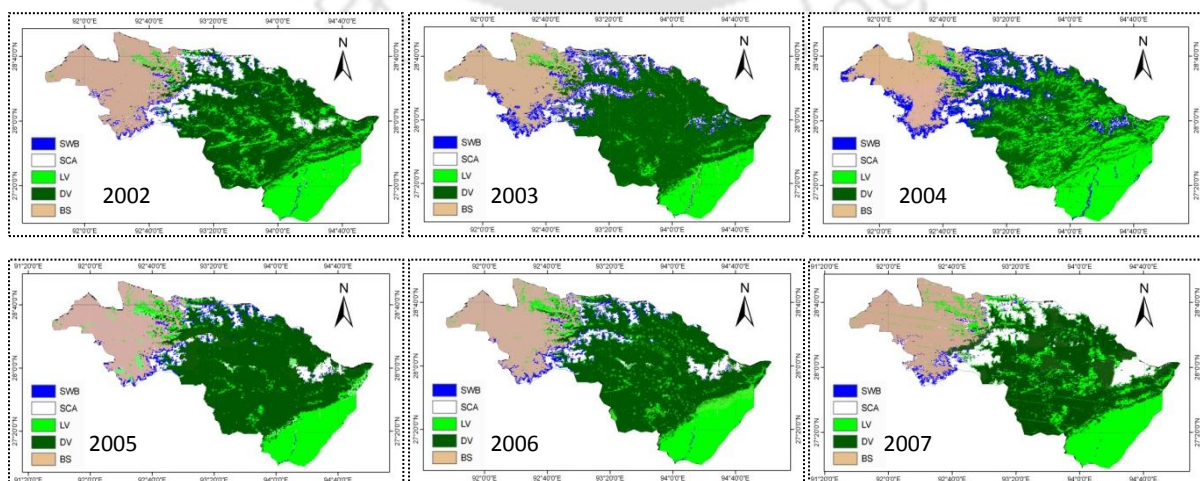


Fig. 5.17: Trends showing percent of total area covered by different LULC classes for the Subansiri River basin from 2002 to 2012 for the month of January

It is seen that except for dense vegetation, all other LULC classes show increasing trends in the Subansiri basin for the month of January.

The LULC maps prepared for the Subansiri basin for the month of January from 2002 to 2012 are given in Fig. 5.18.



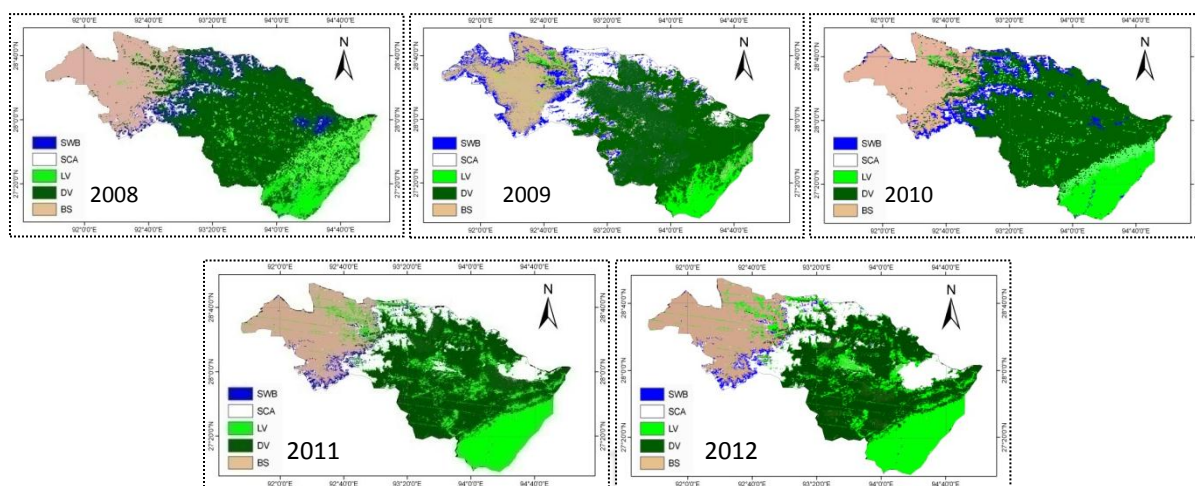


Fig. 5.18:LULC maps of Subansiri River basin for the month of January from 2002 to 2012

The changes taken place in each year for each of the LULC classes from 2002 to 2012 are given below in Table 5.11.

Table 5.11: Year wise Changes in Subansiri basin for different LULC classes from 2002 to 2012 for the month of January

Year	LULC Classes				
	BS (%)	SWB (%)	DV (%)	LV (%)	SCA (%)
2002-2003	2.95	6.10	-14.03	0.75	4.24
2003-2004	-0.18	6.80	-4.28	-1.30	-1.04
2004-2005	10.37	-14.16	0.30	4.95	-1.46
2005-2006	0.58	2.36	0.62	-1.61	-1.95
2006-2007	-0.02	4.48	-4.23	-1.54	1.32
2007-2008	1.91	-1.71	0.42	2.37	-2.99
2008-2009	-11.78	8.82	-7.91	-2.31	13.18
2009-2010	3.89	-9.55	7.26	9.35	-10.94
2010-2011	6.50	-4.02	1.10	-3.54	-0.04
2011-2012	-5.17	8.25	-3.73	-4.15	4.79

The maximum increase in bare soil has been observed during 2004-05 where bare soil increased by 10.37% and the maximum decrease has been observed in 2008-09 where it decreased by 11.78%. For surface water bodies, dense vegetation, light vegetation and snow cover area, the maximum increase have been observed during 2008-09 (8.82%), 2009-10 (7.26%), 2009-10 (9.35%) and 2008-09 (13.18%). The maximum decreases for these classes were observed during 2004-05 (14.16%), 2008-09 (7.91%), 2011-12 (4.15%) and 2009-10 (10.94%) respectively.

The change in land use/land cover classes for the entire decade from 2002 to 2012 are shown in Table 5.12 and are represented in Fig. 5.19.

Table 5.12: Area and amount of change in different LULC categories in the Subansiri basin during 2002 to 2012 for the month of January

LULC Classes	Year				Change 2002-2012	
	2002		2012			
	Area(km ²)	%	Area(km ²)	%	Area(km ²)	%
Bare soil	4759	13.90	7869	22.88	3110	9.05
Surface water bodies	1190	3.47	3719	10.82	2529	7.36
Dense vegetation	19044	55.61	10625	30.89	-8419	-24.48
Light vegetation	7259	21.20	8281	24.08	1022	2.98
Snow cover area	1993	5.82	3748	10.90	1754	5.10

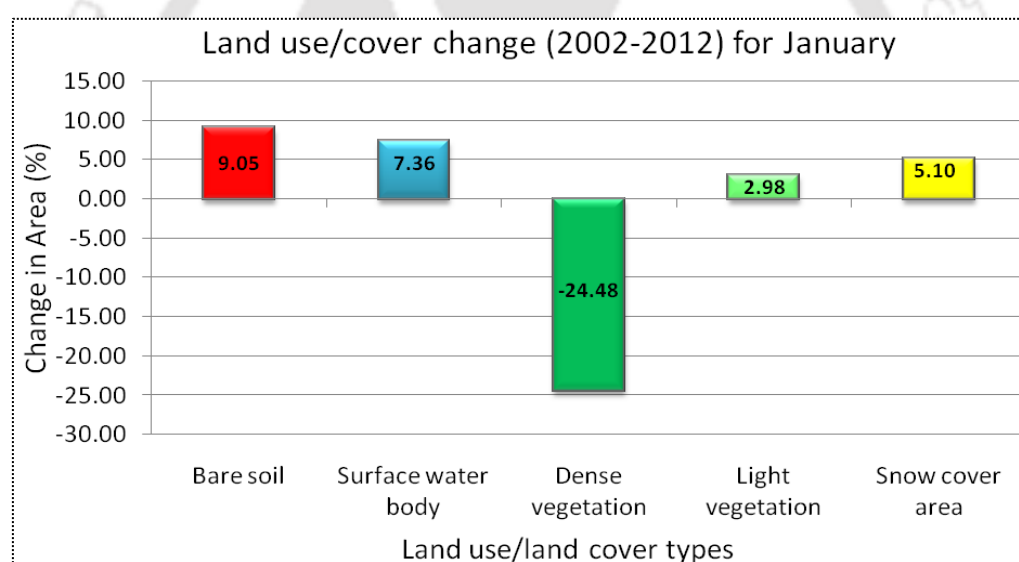


Fig. 5.19: LULC change in the Subansiri River basin during 2002 to 2012 for January

During the decade from 2002 to 2012, it is observed that in case of Subansiri basin for the month of January, bare soil has increased from 4759km² in 2002 to 7869km² in 2012 which accounts for 9.05%. The surface water body has increased from 1190 km² in 2002 to 3719 km² in 2012 which accounts for 7.36% of the total study area. The dense vegetation has decreased from 19044km² in 2002 to 10625km² in 2012 which accounts for 24.48%. Again, light vegetation has increased from 2002 (7259km²) to 2012 (8281km²) which accounts for 2.98%. The snow cover area has increased from 1993km² in 2002 to 3748km² in 2012 which

accounts for 5.1% of the total area of the basin. A very significant decrease in dense vegetation is observed here as it had been occupied by all other increased classes.

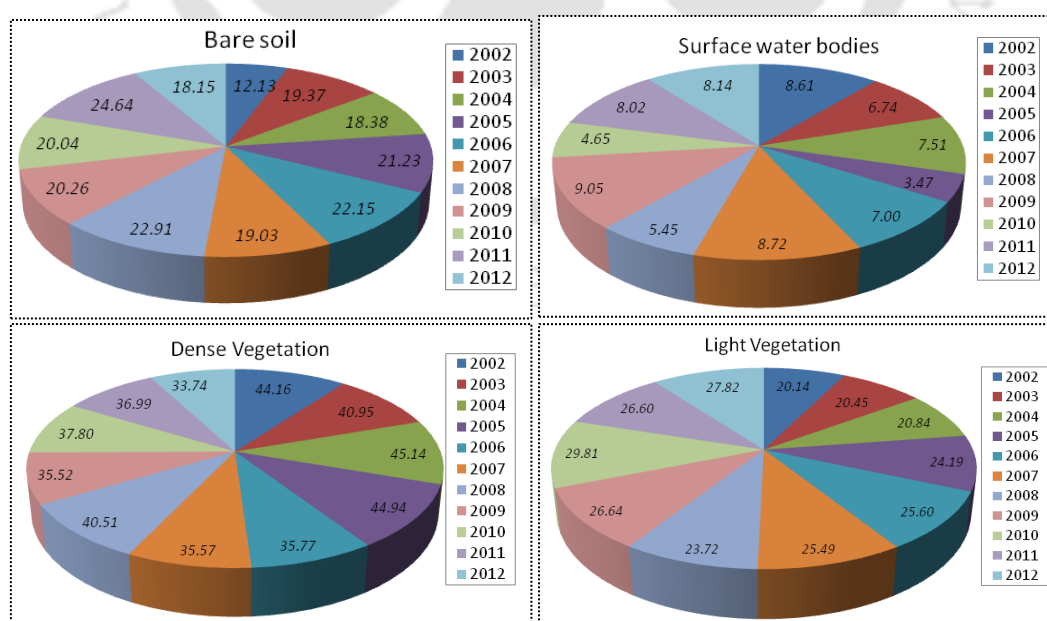
5.3.2.2 Change detection analysis for the month of April

The area covered by each LULC class from 2002 to 2012 for Subansiri basin for the month of April has been determined and are given in Table 5.13. The percent of total area covered by each class are shown as pie diagrams as shown in Fig. 5.20.

Table 5.13: Area covered by different LULC classes in Subansiri basin for the month of April from 2002 to 2012

LULC Classes	Year wise area covered ($\times 10^3 \text{km}^2$)										
	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
BS	4.17	6.66	6.32	7.30	7.62	6.55	7.88	6.97	6.89	8.48	6.24
SWB	2.96	2.32	2.58	1.19	2.41	3.00	1.88	3.11	1.60	2.76	2.80
DV	15.19	14.09	15.53	15.46	12.30	12.23	13.93	12.22	13.00	12.72	11.60
LV	6.93	7.03	7.17	8.32	8.80	8.77	8.16	9.16	10.25	9.15	9.57
SCA	4.99	4.15	2.65	1.98	3.11	3.70	2.40	2.78	2.50	1.14	4.03

The maximum areas covered by bare soil, surface water bodies, dense vegetation, light vegetation and snow cover area were found in 2011, 2009, 2004, 2010 and 2002 respectively and the minimum areas covered by these classes were found in 2002, 2005, 2012, 2002 and 2011 respectively.



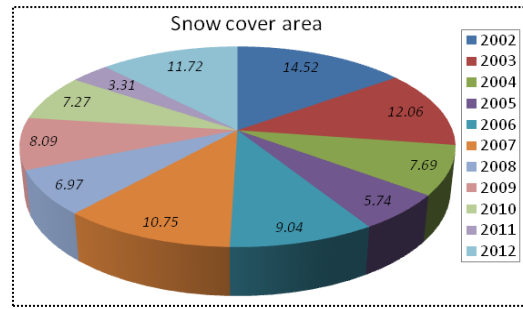
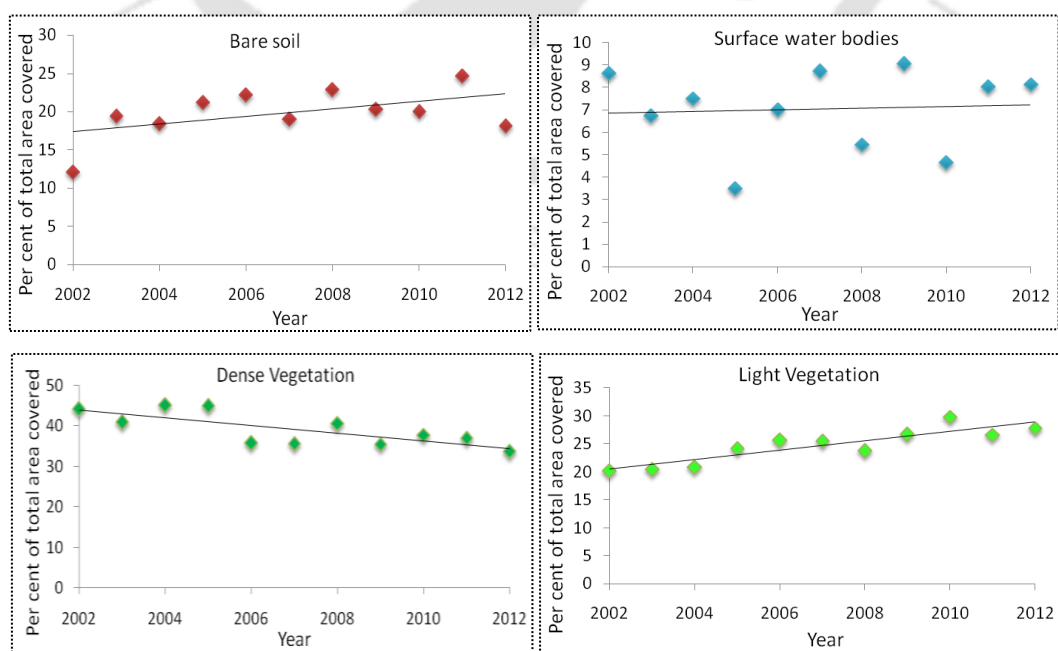


Fig. 5.20: Pie diagrams showing percent of total area covered by different LULC classes in the Subansiri River basin from 2002 to 2012 for the month of April

For the month of April from 2002 to 2012, the maximum area covered by bare soil, surface water bodies, dense vegetation, light vegetation and snow cover area were found in 2011, 2009, 2004, 2010 and 2002 respectively with values 24.64%, 9.08%, 45.14%, 29.81% and 14.52% of total area of the basin. During this period, the minimum area covered by bare soil, surface water bodies, dense vegetation, light vegetation and snow cover area were observed in 2002, 2005, 2012, 2002 and 2011 respectively. The percent of total area covered by these classes were found to be 12.13%, 3.47%, 33.74%, 20.14% and 3.31% respectively.

While analyzing the trends for the area covered by the different classes, it is clear from Fig. 5.21 that bare soil, surface water bodies and light vegetation show increasing trends and dense vegetation and snow cover area show decreasing trends. Deforestation might have led to increase in light vegetation and bare soil. Possible accumulation of snowmelt water in depressions, may be the reason of increase in surface water bodies.



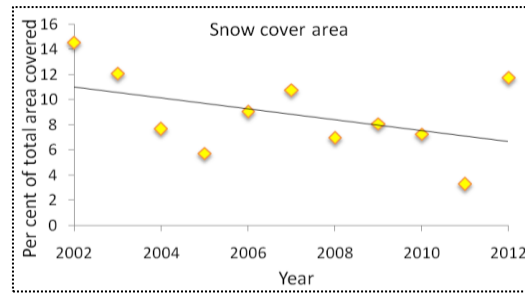


Fig. 5.21: Trends showing percent of total area covered by different LULC classes for the Subansiri River basin from 2002 to 2012 for the month of April

The LULC maps of the Subansiri basin prepared by the supervised classification method for the month of April are shown in Fig. 2.22 from the year 2002 to 2012.

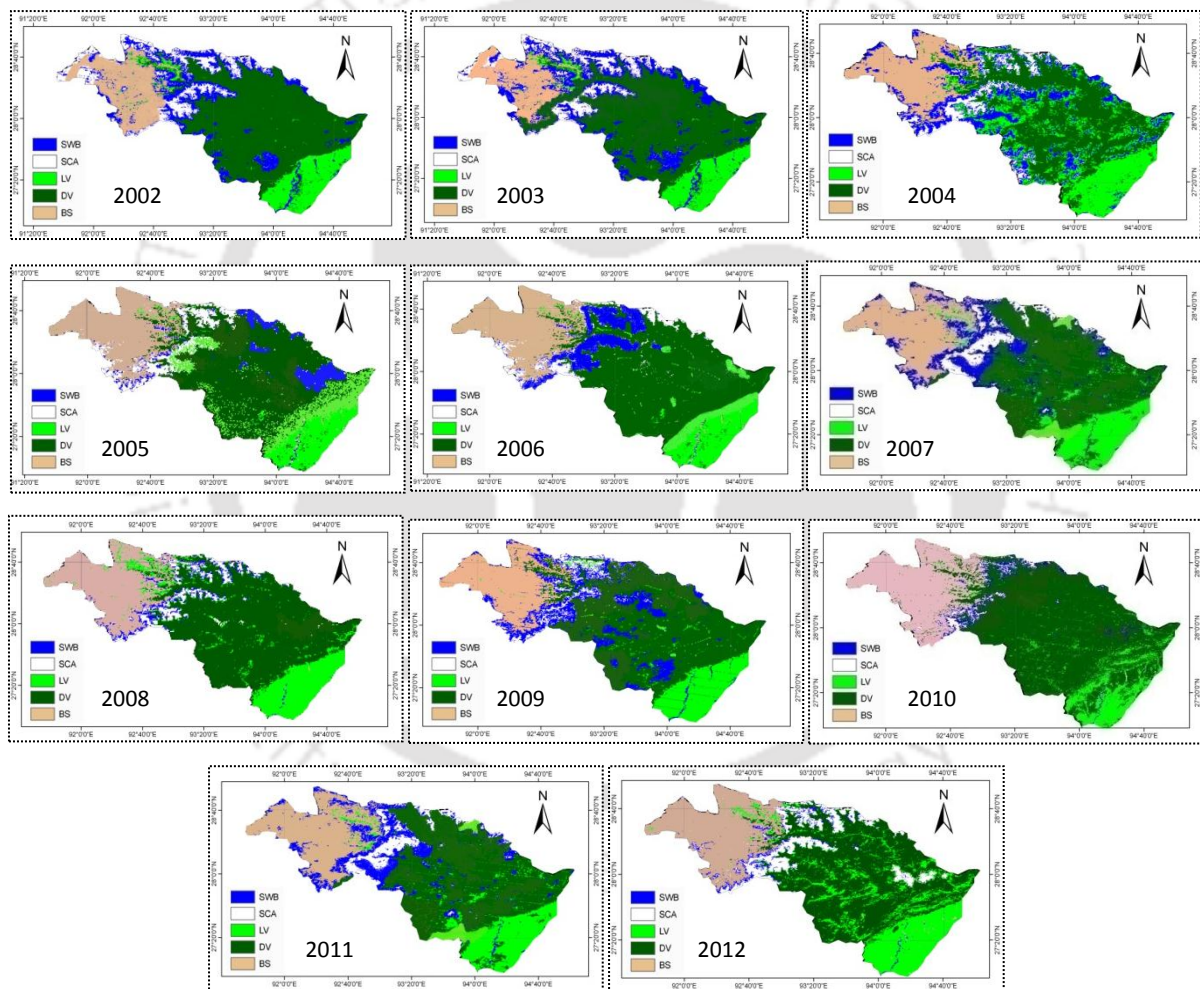


Fig.5.22:LULC maps of Subansiri River basin for the month of April from 2002 to 2012

The year wise changes for each LULC class from 2002 to 2012 are given in Table 5.14.

Table 5.14: Year wise Changes in Subansiri basin for different LULC classes from 2002 to 2012 for the month of April

Year	LULC Classes				
	BS(%)	SWB(%)	DV(%)	LV(%)	SCA(%)
2002-2003	7.23	-1.88	-3.21	0.31	-2.46
2003-2004	-0.99	0.78	4.19	0.38	-4.37
2004-2005	2.85	-4.04	-0.21	3.35	-1.95
2005-2006	0.92	3.53	-9.17	1.41	3.30
2006-2007	-3.12	1.72	-0.20	-0.11	1.71
2007-2008	3.88	-3.27	4.94	-1.78	-3.78
2008-2009	-2.65	3.60	-4.99	2.93	1.12
2009-2010	-0.22	-4.40	2.28	3.17	-0.82
2010-2011	4.61	3.37	-0.81	-3.21	-3.96
2011-2012	-6.50	0.12	-3.25	1.22	8.41

It is observed from the table that the maximum increase in bare soil, surface water bodies, dense vegetation, light vegetation and snow cover area had occurred during 2002-03 (7.23%), 2008-09 (3.60%), 2007-08 4.94%), 2004-05 (3.35%) and 2011-12 (8.41%) respectively. The maximum decrease for these classes have been observed during 2011-12 (6.50%), 2009-10 (4.40%), 2005-06 (9.17%), 2010-11 (3.21%) and 2003-04 (4.37%) respectively.

By taking the values of the two years i.e. 2002 and 2012, the overall changes that have taken place during the entire decade have been analyzed and the results are given in Table 5.15. The results are represented graphically in Fig. 5.23.

Table 5.15: Area and amount of change in different LULC categories in the Subansiri basin during 2002 to 2012 for the month of April

LULC Classes	Year				Change 2002-2012	
	2002		2012			
	Area(km ²)	%	Area(km ²)	%	Area(km ²)	%
Bare soil	4173	12.19	6242	18.23	2068	6.04
Surface water bodies	2963	8.65	2799	8.17	-164	-0.48
Dense vegetation	15188	44.35	11605	33.89	-3583	-10.46
Light vegetation	6928	20.23	9568	27.94	1107	7.71
Snow cover area	4993	14.58	4031	11.77	-962	-2.81

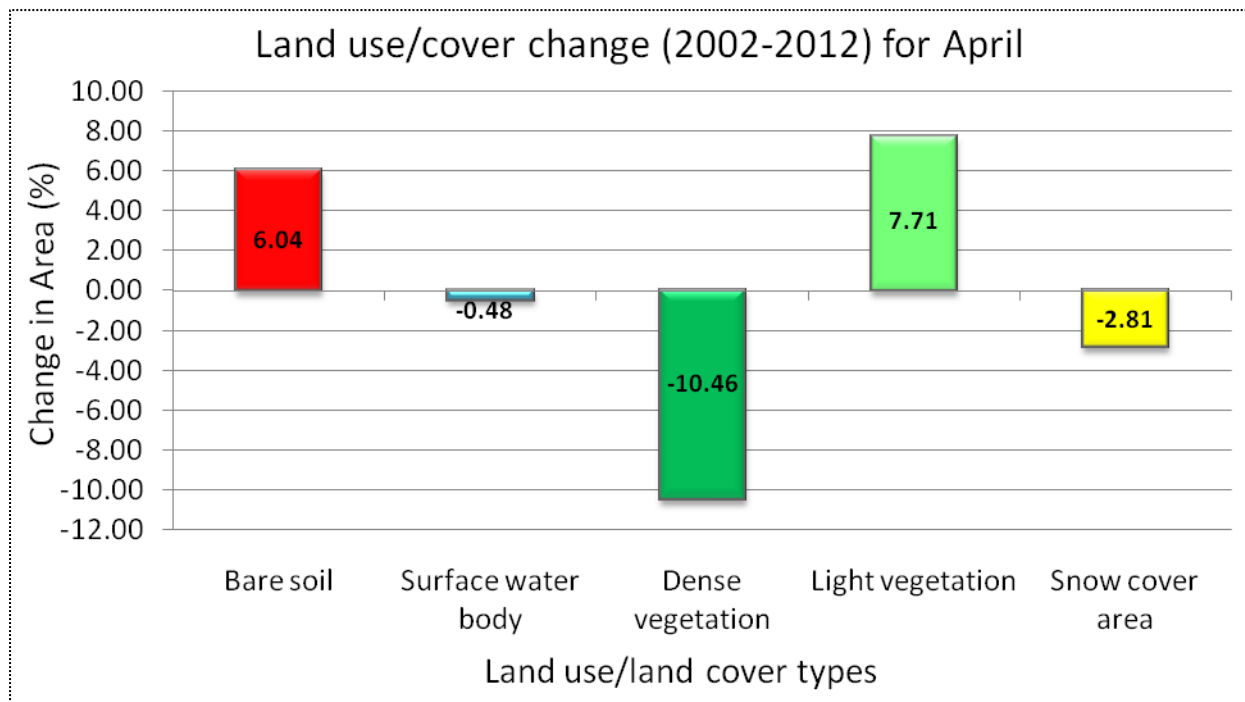


Fig. 5.23: LULC change in the Subansiri River basin during 2002 to 2012 for April

During the entire period from 2002 to 2012, for the month of April, bare soil has increased from 4173km² in 2002 to 6242km² in 2012 which accounts for 6.04%. The surface water body has decreased from 2963 km² in 2002 to 2799 km² in 2012 which accounts for 0.48% of the total study area. The dense vegetation has decreased from 15188km² in 2002 to 11605 km² in 2012 which accounts for 10.46%. Again, light vegetation has increased from 2002 (6928 km²) to 2012 (9568 km²) which accounts for 7.71%. The snow cover area has decreased from 4993km² in 2002 to 4031km² in 2012 which accounts for 2.81% of the total area of the basin. Thus, during this period, for the month of April, the maximum decrease has been observed in dense vegetation and the maximum increase has been observed in light vegetation.

5.3.2.3 Change detection analysis for the month of October

The areas covered by different land use/land cover types of Subansiri basin for the month of October are given in the Table 5.16. The pie diagrams for percent of total area covered by each class are shown in Fig. 5.24.

Table 5.16: Area covered by different LULC classes in Subansiri basin for the month of October from 2002 to 2012

LULC Classes	Year wise area covered ($\times 10^3 \text{km}^2$)										
	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
BS	5.81	8.77	7.38	5.30	8.97	8.13	9.31	9.46	6.35	8.95	9.05
SWB	3.20	4.07	3.72	3.65	2.01	2.30	1.34	1.89	1.54	2.02	2.40
DV	17.15	13.00	12.07	15.21	14.67	14.39	14.66	13.32	14.96	12.33	12.67
LV	6.57	7.51	7.25	8.93	7.77	8.32	7.93	8.69	9.60	10.21	9.07
SCA	1.50	0.90	3.82	1.16	0.83	1.11	1.01	0.90	1.80	0.74	1.05

For the month of October during 2002 to 2012, the maximum areas covered by bare soil, surface water bodies, dense vegetation, light vegetation and snow cover area have been observed in 2009, 2003, 2002, 2011 and 2004 respectively. The minimum areas covered by these classes were in 2005, 2008, 2004, 2002 and 2011 respectively.

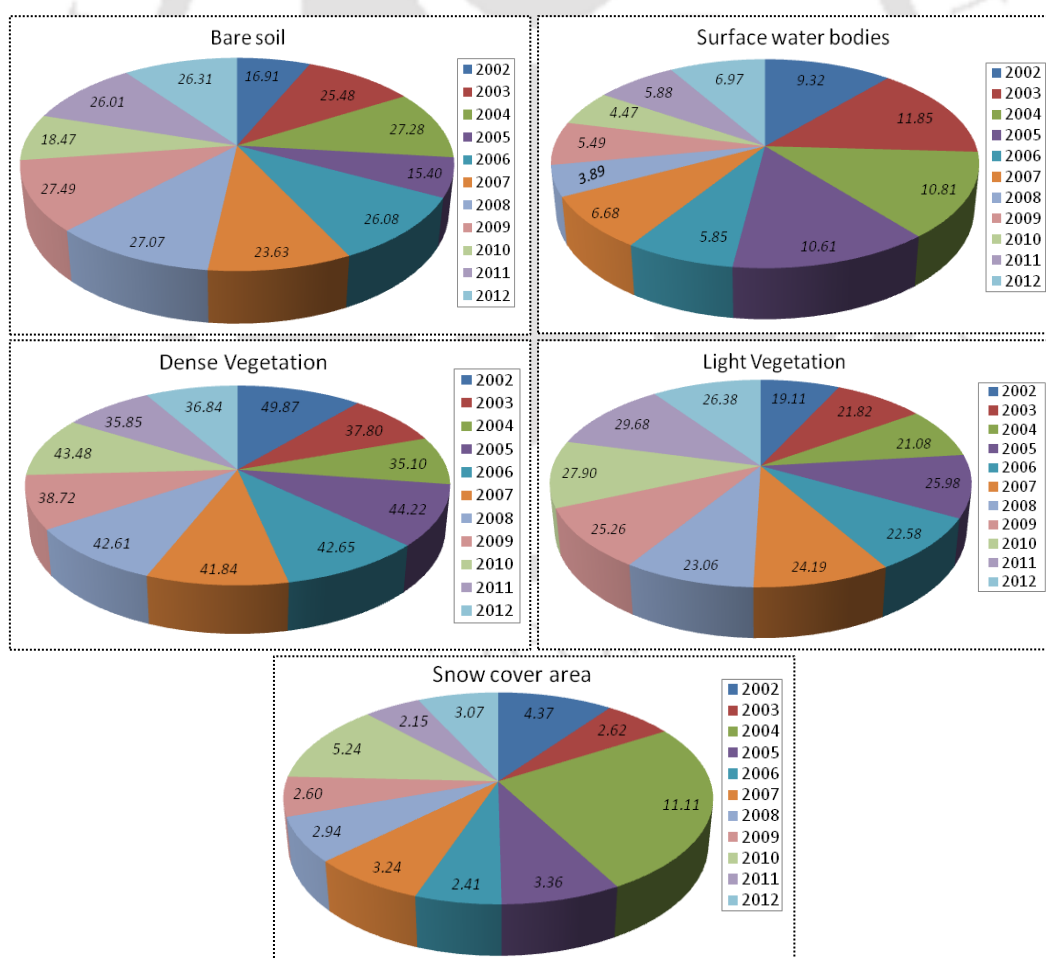


Fig. 5.24: Pie diagrams showing percent of total area covered by different LULC classes in the Subansiri River basin from 2002 to 2012 for the month of October

For the month of October, the area covered by bare soil was found to be the maximum in the year 2009 where 27.49% of the total area was covered by bare soil and the minimum was observed in the year 2005 with a value of 15.40% of total area. Area covered by surface water bodies and dense vegetation were found to be maximum in 2003 (11.85% of total area) and 2002 (49.87% of total area) respectively. For these two LULC classes, the area covered has been observed to be minimum in 2008 (3.89% of total area) and 2004 (35.25%) respectively. For the remaining two classes *i.e.* light vegetation and snow cover area, the maximum area covered were in 2011 (29.68% of total area) and 2004 (11.11% of total area) respectively while minimum areas covered by these classes have been observed in 2002 (19.11% of total area) and 2011 (2.15% of total area) respectively.

The trend analyses for different classes for the month of October are shown in Fig.5.25.

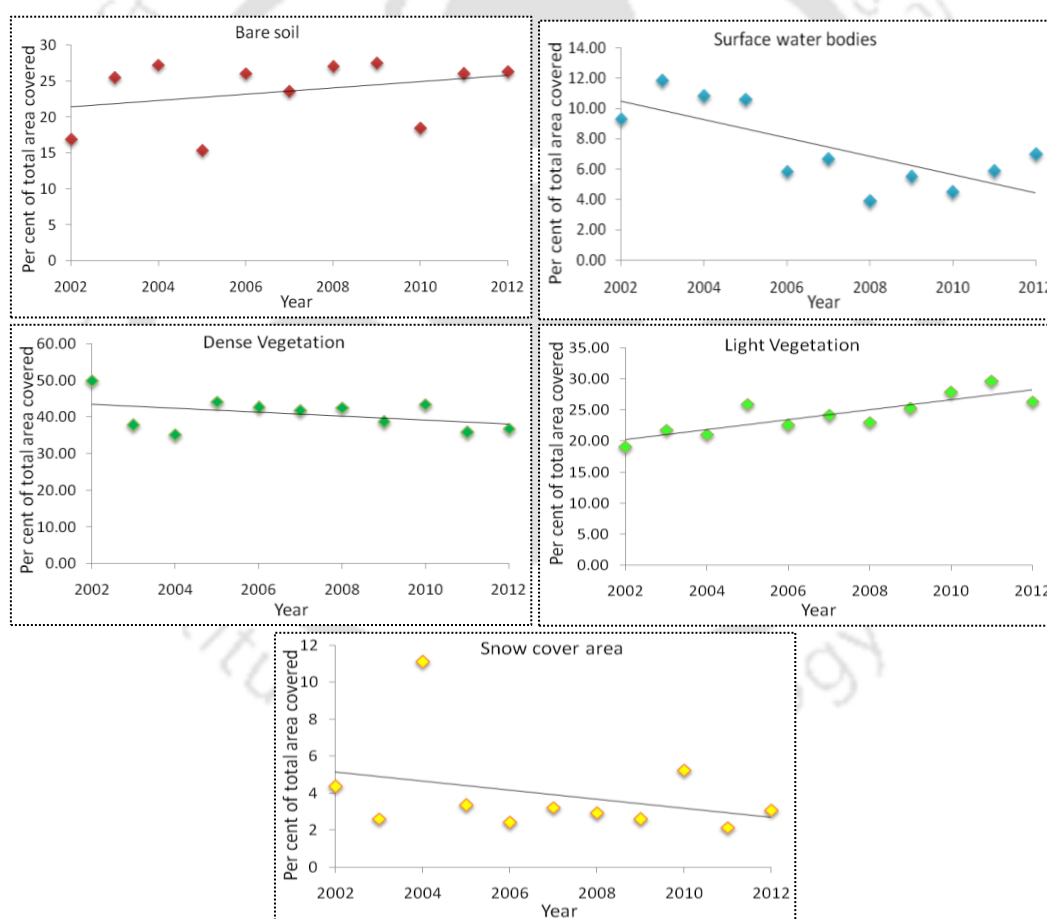


Fig. 5.25: Trends showing percent of total area covered by different LULC classes for the Subansiri River basin from 2002 to 2012 for the month of October

From Fig. 5.25, the area covered by dense vegetation, surface water bodies and snow cover area show decreasing trends while other three classes show increasing trends from 2002 to

2012. Increase in light vegetation may be the reason behind decrease in dense vegetation and increase in bare soil.

The land use/land cover maps of the Subansiri basin for the month of October from 2002 to 2012 are shown in Fig. 5.26.

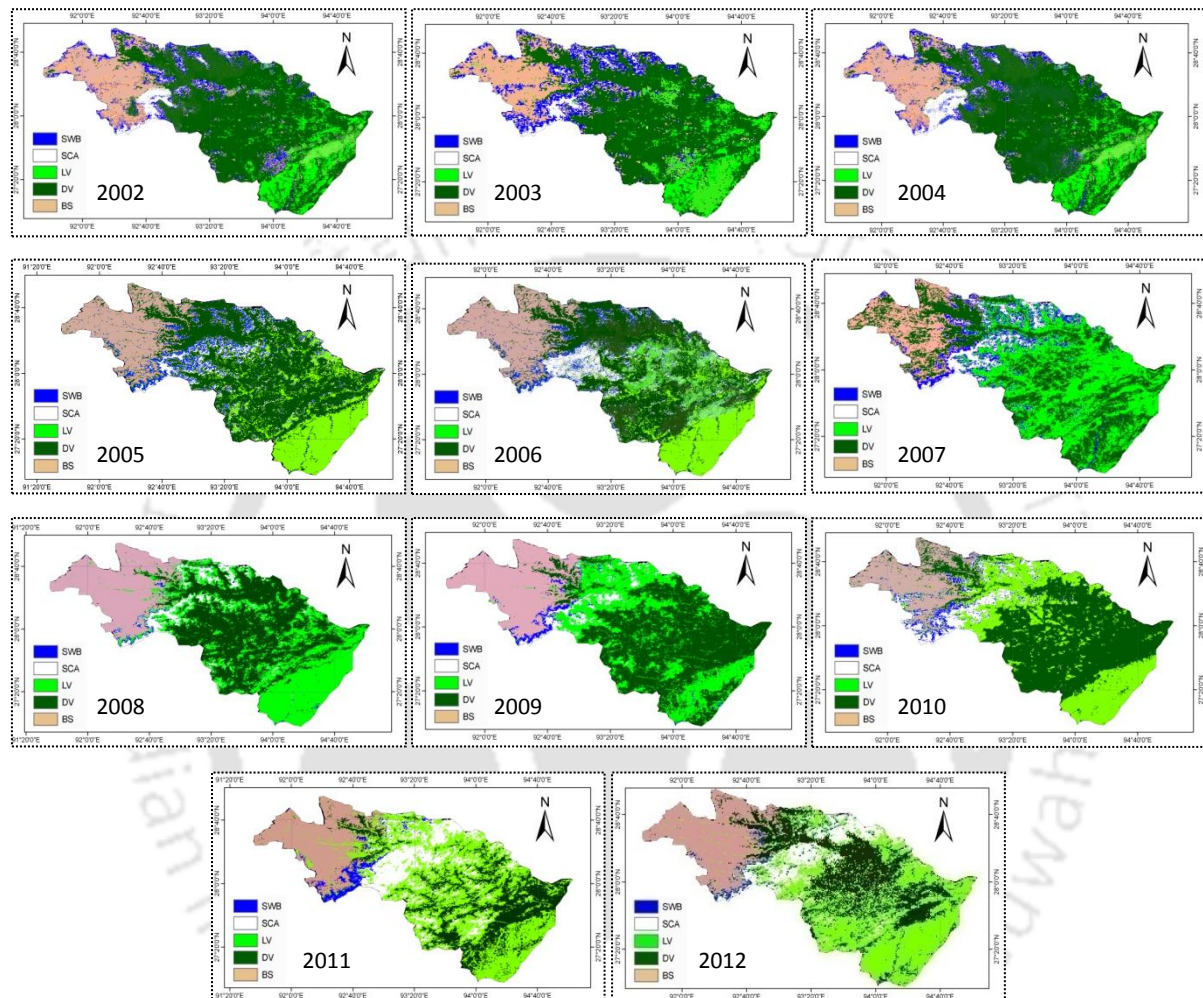


Fig.5.26:LULC maps of Subansiri River basin for the month of October from 2002 to 2012

The yearly changes taken place for each of the LULC classes from 2002 to 2012 are given in Table 5.17.

Table 5.17: Year wise Changes in Subansiri basin for different LULC classes from 2002 to 2012 for the month of October

Year	LULC Classes				
	BS(%)	SWB (%)	DV (%)	LV (%)	SCA (%)
2002-2003	8.58	2.53	-12.08	2.72	-1.75
2003-2004	-4.02	-1.04	-2.70	-0.74	8.50
2004-2005	-6.06	-0.20	9.12	4.89	-7.75
2005-2006	10.68	-4.76	-1.57	-3.40	-0.95
2006-2007	-2.46	0.83	-0.81	1.61	0.82
2007-2008	3.45	-2.79	0.77	-1.13	-0.30
2008-2009	0.42	1.60	-3.89	2.20	-0.33
2009-2010	-9.02	-1.02	4.77	2.64	2.64
2010-2011	7.54	1.41	-7.64	1.78	-3.10
2011-2012	0.30	1.08	1.00	-3.30	0.92

For bare soil, the maximum increase and decrease have been observed during 2005-06 and 2009-10 with percent increase and decrease values of 10.68% and 9.02% respectively. With percent increase and decrease values of 2.53% and 4.76%, the surface water bodies had the maximum increase and decrease during 2002-03 and 2005-06 respectively. For dense vegetation, light vegetation and surface water bodies, the maximum increases have been observed during 2004-05 (9.12%), 2004-05 (4.89%) and 2003-04 (8.50%). However, for these three classes the maximum decreases have been observed during 2002-03 (12.08%), 2005-06 (3.40%) and 2004-05 (7.75%) respectively.

The overall changes for each class from 2002 to 2012 have been analyzed and the results are given below in table 5.18. Fig.5.27 is the graphical representation of the changes for the entire decade.

Table 5.18: Area and amount of change in different LULC categories in the Subansiri basin during 2002 to 2012 for the month of October

LULC categories	Year				Change 2002-2012	
	2002		2012			
	Area(km ²)	%	Area(km ²)	%	Area(km ²)	%
Bare soil	5814	16.98	9049	26.42	3235	9.45
Surface water bodies	3204	9.36	2396	7.00	-808	-2.36
Dense vegetation	17154	50.09	12673	37.00	-4481	-13.09
Light vegetation	6572	19.19	9074	26.50	2502	7.31
Snow cover area	1501	4.38	1054	3.08	-447	-1.30

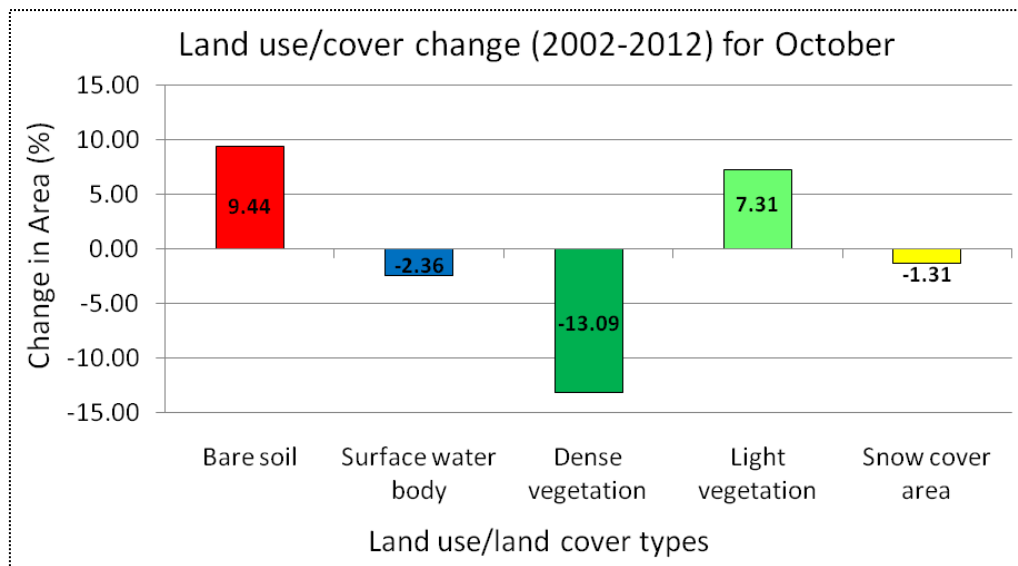


Fig. 5.27: LULC change in the Subansiri River basin during 2002 to 2012 for October

For the month of October, during the period from 2002 to 2012, bare soil has increased from 5814km² in 2002 to 9049km² in 2012 which accounts for 9.44%. The surface water body has decreased from 3204 km² in 2002 to 2396 km² in 2012 which accounts for 2.36% of the total study area. The dense vegetation has decreased from 17154km² in 2002 to 12673km² in 2012 which accounts for 13.09%. Light vegetation has increased from 2002 (6572km²) to 2012 (9074 km²) which accounts for 7.31%. The snow cover area has decreased from 1501km² in 2002 to 1054km² in 2012 which accounts for 1.31% of the total area of the basin. The maximum decrease has been observed for dense vegetation while the maximum increase has been observed for bare soil.

5.3.3 General Analysis

The above land use/land cover change detection study for both the Brahmaputra and the Subansiri River basins for the three different months, January, April and October reveal that both positive and negative changes occurred in the land use/land cover pattern of both the river basins during the time period from 2002 to 2012. However, from the current study it is evident that there is considerable decrease in the area covered by dense vegetation during the period of study for the basins. Light vegetation is showing increasing trends in both basins and thereby resulting to the inference that the population is playing an active role towards diminishing dense vegetation cover. In Brahmaputra basin, bare soil is decreasing in January and April and increasing in October. The expansion in light vegetation can be attributed to the increasing demand to feed the growing population as well as to the

increasing demand for residential place. In other words, the area covered by dense vegetation is declining due to its conversion to arable land. The reason behind decrease in area covered by surface water bodies may be encroachment of slum dwellers and land developers. Except for the month of January, for the other two months i.e. April and October, the snow cover area showed decreasing trends from 2002 to 2012. This may be attributed to the fact of increasing temperature which is the consequence of climate change. As described in chapter 3 & 4, the temperature data of HadCM3 GCM showed that in both Brahmaputra and Subansiri basins, temperature is gradually increasing. The rise in temperature in turn leads to the melting of snow. The snowmelt water when accumulates in the depressions, the area covered by surface water bodies get increased in January and April in Brahmaputra basin.

5.4 Conclusions

Here in this study, the land use/land cover change detections have been analyzed for both the Brahmaputra and the Subansiri River basins. Five LULC classes viz., bare soil, dense vegetation, light vegetation, surface water bodies and snow cover area have been considered for the analysis. It can be concluded that satellite remote sensing data plays an important role in understanding the nature of changes in LULC for a region in a particular period of time. Such information in turn is helpful for developing and preserving the natural resources and environment. Satellite remote sensing is a cost effective approach which gives the necessary information accurately. The study conducted here in the Brahmaputra and the Subansiri basins advocates that multi temporal satellite imagery plays a vital role in quantifying spatial and temporal phenomena which is otherwise not possible to attempt through conventional mapping.

For all the three months, overall decrease in dense vegetation and increase in light vegetation have been observed in both the basins. This can be attributed to the fact that increasing population is putting pressure on the land use/land cover of the basins. Also decrease in snow cover area in the basins attributed to the increase in temperature due to global warming. It is expected that the findings of this study will be useful for planners and local bodies to implement suitable land use plans in the watershed, thereby enabling the restoration of degraded land to the maximum possible extent.



CHAPTER 6

PREDICTION OF RAINFALL OVER THE SUBANSIRI RIVER BASIN USING STATISTICAL DOWNSCALING TECHNIQUES

6.1 Introduction

6.1.1 General Circulation Models and their downscaling

Climate models are the primary tool to evaluate the projected future response of the atmosphere-land-ocean system to changing atmospheric composition (MacCracken et al., 2003; Stocker et al., 2001), and they underpin most climate change impacts studies (Wilby and Harris, 2006). However, there is a mismatch between the grid resolution of current climate models (generally hundreds of kilometers), and the resolution needed by environmental impacts models (typically ten kilometers or less). Downscaling is the process of transforming information from climate models at coarse resolutions to a fine spatial resolution. Downscaling is necessary, as the underlying processes described by the environmental impact models are very sensitive to the nuances of local climate, and the drivers of local climate variations, such as topography, are not captured at coarse scales (Maurer and Hidalgo, 2008). As explained in the Review of literature chapter, there are two main methods of downscaling. These are dynamic downscaling and Statistical downscaling. Compared to statistical downscaling method, dynamic downscaling is computationally more intensive, making its use in impact studies limited, and essentially impossible for multi-decade simulations with different global climate models and/or multiple greenhouse gas emission scenarios. Thus, the most impacts studies rely on some form of statistical downscaling, where variables of interest can be downscaled using historical observations. Statistical downscaling involves deriving empirical relationships that transform large-scale features of the GCM (predictor) to regional-scale variables (predictand) such as precipitation, temperature and streamflow. Statistical downscaling is typically used to predict one variable at one site, though some techniques for simultaneous downscaling to multiple sites for precipitation have been developed (Harpham and Wilby, 2005; Wilks, 1999). However, for studies of some climate impacts such as river basin hydrology, it is important to downscale simultaneous values of multiple variables (such as precipitation and temperature) over large,

heterogeneous areas, while maintaining physically plausible spatial and temporal relationships, though few downscaling techniques have been developed to do this. Statistical downscaling models are based on statistical relationship and hence require less computational time. Regression method is one of the most widely used statistical techniques (Driver and Tasker, 1990; Saget, 1994; Mendelhall and Beaver, 1994). Multiple regression analysis is a multivariate statistical technique used to examine the relationship between a single dependent variable and a set of independent variables. The objective of the multiple regression analysis is to use independent variables whose values are known to predict the single dependent variable.

Another technique of downscaling which has gained wide recognition owing to its ability to capture non-linear relationships between predictor and predictand is the Artificial Neural Network (ANN) based downscaling techniques (Wilby et al., 1998; Sailor et al., 2000; Schoof and Pryor, 2001; Olsson et al., 2004.) The neural network is one of the tools used for methodological analysis of hydrological forecasting. It can be thought of as a computational pattern that involves searching and matching procedures, which permits forecasting without an intimate knowledge of the physical process. The neural network seeks the relationship between input and output data and then creates its own equations to match the pattern in an iterative manner.

The vulnerability of Indian subcontinent to the impact of changing climate is of vital importance because the major impact of climate change in this continent would be on the hydrology, affecting water resources and agricultural economy. The impact of climate change on hydrological cycle in river basins have been extensively analyzed in various parts of the world based on different emission scenarios and climate models. Devastating flood associated with intense rainfall in the upper catchments of the Subansiri River basin is a common phenomenon. In the present study, all the three techniques of downscaling *i.e.* both multiple linear and non linear based statistical downscaling techniques as well as Artificial Neural Network based downscaling technique have been applied to downscale the rainfall in Subansiri basin at 24 different APHRODITE's rainfall points by taking HadCM3 GCM climatic parameters as the predictors. The outcomes of these methods were compared to get the best method of downscaling. The best downscaling method was then used for prediction of rainfall and to determine its effect on future hydrology of the basin.

6.2 Materials and Methods

6.2.1 Data and software used

Rainfall data: APHRODITE's daily gridded rainfall data of spatial resolution $0.25^\circ \times 0.25^\circ$ from 1960 to 2007 have been used in this study. These daily rainfall data have then been converted into monthly rainfall for further analysis.

In recent years, there has been considerable interest in developing high resolution gridded data sets (New et al., 1999, Mitra et al., 2003, Rajeevan et al., 2006). The word APHRODITE stands for Asian Precipitation Highly Resolved Observational Data Integration towards Evaluation of Water Resources (APHRODITE's Water Resources). The APHRODITE's project develops state-of-the-art daily precipitation datasets with high resolution (0.5° and 0.25°) grids for Asia. APHRODITE's Water Resources project is executed by the research Institute for Humanity and Nature (RIHN) and the Meteorological Research Institute of Japan Meteorological Agency (MRI/JMA). The basic algorithm adopted by them is based on Xie et al., (2007). Details of the project and the data set are discussed in Yatagai et al., (2005). The datasets are created primarily with data obtained from in-situ-rain-gauge-observation network. Long-term high resolution daily precipitation data are useful for evaluating mesoscale models, driving river flow models and analyzing temporal and spatial variations of precipitation fields. In addition, gridded data make model evaluation and water budget analysis easier, when compared with point observation data (Kamiguchi et. al., 2010). The primary objective of the APHRODITE's project are to (1) release official state-of-the-art daily gridded precipitation data sets based on rain-gauge observations, (2) assess the projections of climate models by observing precipitation in the field, including extreme events and (3) to make suggestions to regional water resources managers in Asian countries.

In order to carry out spatial analysis, 24 APHRODITE's points were selected for the Subansiri River Basin (Fig.6.1). The coordinates of these 24 points are given in Table 6.1.

Table6.1: Geographical coordinates of the 24 APHRODITE's points

APHRODITE Points	Coordinates	APHRODITE Points	Coordinates
1	91.875°E, 28.625°N	13	93.375°E, 27.375°N
2	92.125°E, 28.375°N	14	93.375°E, 27.875°N
3	94.125°E, 27.625°N	15	93.625°E, 27.625°N
4	92.375°E, 27.875°N	16	93.875°E, 28.375°N
5	92.375°E, 28.125°N	17	94.125°E, 28.125°N

6	94.375°E, 27.375°N	18	94.375°E, 28.125°N
7	93.875°E, 27.875°N	19	94.625°E, 27.625°N
8	92.375°E, 28.875°N	20	94.875°E, 27.875°N
9	92.625°E, 28.625°N	21	92.625°E, 28.375°N
10	92.875°E, 28.625°N	22	93.125°E, 28.125°N
11	93.125°E, 27.875°N	23	93.375°E, 28.375°N
12	93.125°E, 28.625°N	24	93.625°E, 28.125°N

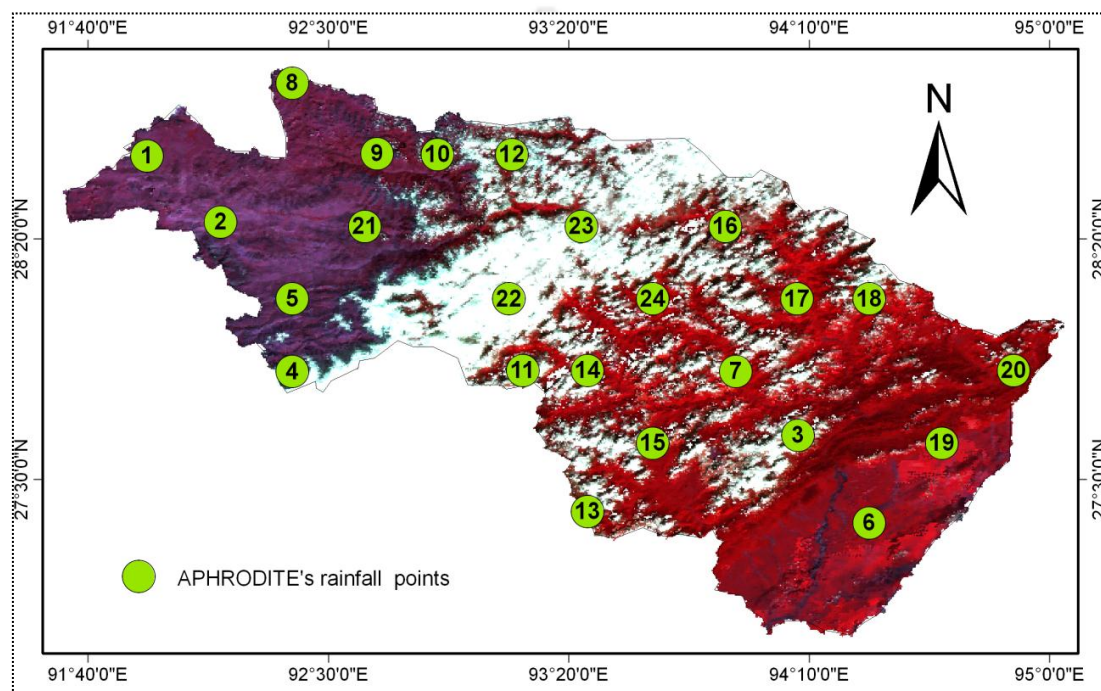


Fig.6.1: Map showing the APHRODITE's points over the Subansiri basin taken for the study

GCM parameters: Monthly climate parameters of HadCM3 GCM of A2 scenario available at a spatial resolution of $2.5^{\circ} \times 3.75^{\circ}$ (latitude by longitude) have been used as the predictors. The GCM data were downloaded from Intergovernmental Panel on Climate Change in two different assessments: fourth Assessment Report (AR4) and Third Assessment Report (AR3). Due to less availability of past data in AR4, HadCM3 model parameters were also downloaded from AR3. The time period of fourth Assessment is from 2001 to 2100 and the third assessment is 1890-2099. The raw data were downloaded from the website of IPCC Data Distribution Centre (http://www.ipcc-data.org/ar4/gcm_data.html). There is only one HadCM3 GCM point that falls inside the study area. Hence, three other HadCM3 points have also been selected that fall around the Subansiri Basin. The geographic coordinates of the GCM points are as given in Table 4.2 of chapter 4. The climatic parameters taken in this

study are, downward short-wave flux(dswf), near surface relative humidity (hurs), geopotential height at 200 hPa(zg200), geopotential height at 500 hPa (zg500), maximum temperature at near surface, minimum temperature at near surface, air temperature at 500 hPa (ta500), air pressure at sea level (mslp), soil moisture, precipitation rate, wind speed height above ground and relative humidity at 850 hPa (hur850).

The XLSTAT2014 has been used for the regression analysis. XLSTAT is a data analysis and statistical solution for Microsoft Excel. The XLSTAT statistical analysis add-in offers a wide variety of functions to enhance the analytical capabilities of Excel. XLSTAT relies on Excel for the input of data and the display of results, but the computations are done using autonomous software components. The use of Excel as an interface makes XLSTAT a user-friendly and highly efficient statistical and multivariate data analysis package. The ANN toolbox available in MATLAB is used to develop the ANN model.

6.2.2 Downscaling of Rainfall

Both multiple linear and non-linear based statistical downscaling methods have been applied to downscale the rainfall at 24 different APHRODITE's points.

In a regression analysis the relationship is studied, called the regression function, between one variable called the dependent variable, and several others, called the independent variables. If a regression function is linear in the parameters it is termed a linear regression model. Otherwise, the model is called non-linear. Regression models with more than one independent variable are referred to as multiple regression models, as opposed to simple regression models with one independent variable.

In Multiple Regression Analysis the basic steps are four namely,

- Specification: Here selection of predictor and model are done.
- Calibration: This is used to form a relation between the output and input.
- Validation: This is used to find the accuracy of the model.
- Forecasts: This uses the model from validation to predict the future variations.

6.2.2.1 Selection of Predictors

The predictor selection has been done using Pearson Correlation method. This method shows the linear relationship between two sets of data. The correlation coefficient ranges from -1 , a perfect negative relationship, through zero (no relationship), to $+1$, a perfect positive relationship. The correlation coefficients between rainfall and climatic parameters have been

determined at all the 24 APHRODITE's points separately using two approaches,(i) by taking the GCM point 93.75°E, 27.5°N which falls inside the study area and (ii) by taking weighted average of all the four GCM points. The weighted average has been determined by inverse distance method. Table 6.2 shows the distance in km from the rainfall points to each GCM point and Table 6.3 gives the weights calculated for each GCM point and APHRODITE's point.

Table 6.2: Distance in km from rainfall points to the GCM points

Sl. No.	Rainfall points	HadCM3 GCM points			
		90°E, 30°N	90°E, 27.5°N	93.75°E, 27.5°N	93.75°E, 30°N
1	91.875°E; 28.625°N	238.41	221.49	222.69	238.99
2	92.125°E; 28.375°N	275.62	228.68	187.59	243.29
3	94.125°E; 27.625°N	484.14	409.19	40.03	266.76
4	92.375°E; 27.875°N	331.12	237.85	141.62	270.54
5	92.375°E; 28.125°N	312.24	243.53	151.04	247.42
6	94.375°E; 27.375°N	518.00	432.98	63.62	296.63
7	93.875°E; 27.875°N	448.76	388.69	44.55	237.09
8	92.375°E; 28.875°N	261.74	277.41	201.91	184.03
9	92.625°E; 28.625°N	297.31	284.72	165.58	189.75
10	92.875°E; 28.625°N	317.52	308.71	151.35	173.17
11	93.125°E; 27.875°N	386.24	310.00	74.30	247.39
12	93.125°E; 28.625°N	340.42	330.19	139.43	167.71
13	93.375°E; 27.375°N	440.75	334.45	40.18	297.54
14	93.375°E; 27.875°N	404.47	333.26	54.50	239.39
15	93.625°E; 27.625°N	440.98	356.64	18.76	265.72
16	93.875°E; 28.375°N	417.92	392.11	97.21	180.57
17	94.125°E; 28.125°N	453.11	411.59	78.78	209.66
18	94.375°E; 28.125°N	473.19	434.97	91.03	217.91
19	94.625°E; 27.625°N	521.07	455.67	87.34	279.88
20	94.875°E; 27.875°N	527.93	481.56	119.43	258.39
21	92.625°E; 28.375°N	331.18	298.24	129.35	198.70
22	93.125°E; 28.125°N	368.53	313.47	93.95	220.36
23	93.375°E; 28.375°N	374.25	344.56	103.03	183.49
24	93.625°E; 28.125°N	408.26	362.51	72.72	202.63

Table 6.3: Weights calculated for APHRODITE and GCM points

Sl. No.	Rainfall Points	HadCM3 GCM points			
		90°E, 27.5°N	90°E, 30°N	93.75°E, 27.5°N	93.75°E, 30°N
1	91.875°; 28.625°	0.24	0.26	0.26	0.24
2	92.125°; 28.375°	0.21	0.25	0.31	0.24
3	94.125°; 27.625°	0.06	0.07	0.75	0.11
4	92.375°; 27.875°	0.17	0.23	0.39	0.21
5	92.375°; 28.125°	0.18	0.23	0.37	0.22
6	94.375°; 27.375°	0.08	0.10	0.67	0.14
7	93.875°; 27.875°	0.07	0.08	0.71	0.13
8	92.375°; 28.875°	0.21	0.20	0.28	0.31
9	92.625°; 28.625°	0.18	0.19	0.33	0.29
10	92.875°; 28.625°	0.17	0.17	0.35	0.31
11	93.125°; 27.875°	0.11	0.14	0.58	0.17
12	93.125°; 28.625°	0.15	0.16	0.38	0.31
13	93.375°; 27.375°	0.07	0.09	0.74	0.10
14	93.375°; 27.875°	0.09	0.11	0.66	0.15
15	93.625°; 27.625°	0.04	0.05	0.86	0.06
16	93.875°; 28.375°	0.12	0.12	0.50	0.27
17	94.125°; 28.125°	0.10	0.11	0.57	0.22
18	94.375°; 28.125°	0.11	0.12	0.55	0.23
19	94.625°; 27.625°	0.10	0.11	0.60	0.19
20	94.875°; 27.875°	0.12	0.13	0.52	0.24
21	93.125°; 28.125°	0.13	0.15	0.50	0.22
22	93.375°; 28.375°	0.13	0.14	0.47	0.26
23	92.625°; 28.375°	0.16	0.18	0.40	0.26
24	93.625°; 28.125°	0.10	0.12	0.58	0.21

6.2.2.2 Model calibration and validation for regression analysis

Calibration is a process of estimation of model parameters using known input and output information. Generally, a model is calibrated by minimizing the error between calculated and measured values of output. The most popular error function is least squared error. The use of a least squared errors approach infers constancy of error variance for all observations. Good match of calibration data does not guarantee that future predictions will be good. To increase confidence in prediction ability of a model, validation is performed. The validation is

concerned with determining whether the conceptual simulation model is an accurate representation of the system under study (Law and Kelton, 1991). To carry out calibration and validation properly, large datasets are required. In this study, the available data from 1960 to 2007 have been split into two parts i.e. data from 1960 to 1985 have been chosen for calibration and data from 1986 to 2007 have been chosen for the validation. The precipitation models have been developed for all the 24 APHRODITE's points and have been run for both the conditions i.e.

- i) For one GCM that falls inside the study region and
- ii) By taking the weighted average of all the four points.

6.2.2.3 Multiple Linear Regression Model

The objective of the multiple regression analysis is to use independent variables whose values are known to predict the single dependent variable. The effect of *independent variables* on the *response* can be expressed mathematically as:

$$y = f(x_1, x_2, \dots, x_n; \beta_1, \beta_2, \dots, \beta_n) \quad (6.1)$$

where, Y is the dependent variable i.e. the precipitation, $\beta_1, \beta_2, \dots, \beta_n$ are the regression parameters which are unknown and $x_1, x_2, \dots, x_n$ are the predictors. In this case the predictors are the HadCM3 GCM climatic parameters selected by Pearson Correlation method as shown in Table 6.5.

The regression model for the observed response variable can be written as:

$$z = y + \varepsilon = f(x_1, x_2, \dots, x_n; \beta_1, \beta_2, \dots, \beta_n) + \varepsilon \quad (6.2)$$

where ε is the error in observed value z .

To determine the unknown regression parameters, least squares method has been applied:

$$E(\beta_1, \beta_2, \dots, \beta_n) = \sum_{j=1}^n (z_j - y_j)^2 = \sum_{j=1}^n \{z_j - f(x_1, x_2, \dots, x_n; \beta_1, \beta_2, \dots, \beta_n)\}^2 \quad (6.3)$$

where $E(\beta_1, \beta_2, \dots, \beta_n)$ is the error function or sum of squares of the deviations. The primary goal is to determine the best set of parameters, such that the model predicts experimental values of the dependent variable as accurately as possible.

6.2.2.4 Multiple Non-linear Regression Model

The linear least squares method fits a straight line or an affine hyperplane to a bunch of data points. Sometimes the true relationships that are required to model may not be linear. For fitting a non-linear function, there is need to use non-linear regression method. Non-linear regression is a form of regression analysis in which observational data are modeled by a function which is a non-linear combination of the model parameters and depends on one or

more independent variables. Orthogonal polynomial non-linear regression model has been applied in this study with maximum polynomial degree in one variable as 3.

The equation for the non-linear regression developed in XLSTAT is as follows:

$$y = \alpha + p_1x_1 + p_2x_2 + \dots + p_nx_n + q_1x_1^2 + q_2x_2^2 + \dots + q_nx_n^2 + r_1x_1^3 + r_2x_2^3 + \dots + r_nx_n^3 \quad (6.4)$$

where y is the dependent variable i.e. the precipitation, $\alpha, p_1, p_2, \dots, p_n, q_1, q_2, \dots, q_n, r_1, r_2, \dots, r_n$ are the model parameters and $x_1, x_2, \dots, x_n$ are the predictors i.e. the HadCM3 GCM climatic parameters.

6.2.2.5 Downscaling using Artificial Neural Network

An Artificial neural network (ANN) is a massive parallel distributed information processing system that has certain performance characteristics resembling a biological neural network of the human brain. Typically, a neural network is characterized by its architecture that represents the pattern of connection between neurons, the method of determining the connections weights and the activation function used in a neuron. Fig. 6.2 shows the ANN with its functions. The ANN is an established technique with a flexible mathematical structure (Vu et. al., 2015). Over the years, the ANN based transfer functions have been used for downscaling large scale climatic variables (Fistikoglu and Okkan, 2011).

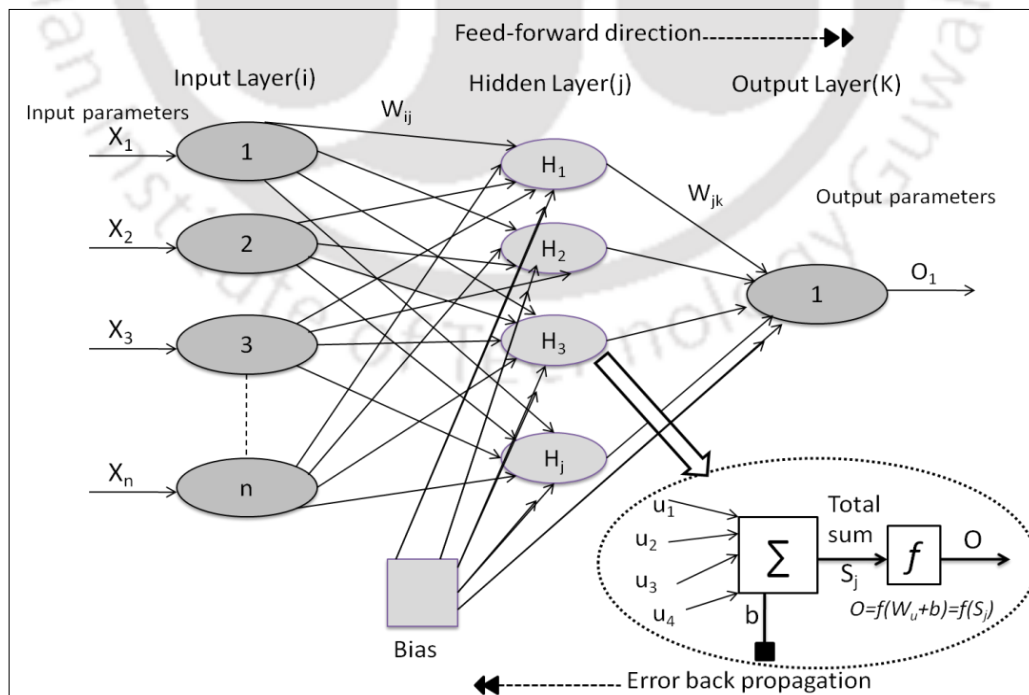


Fig.6.2: Artificial neuron showing its functions

The ANN forecasting has been followed in three separate stages. These are training phase, validation, and testing phase. In the training phase, the output is linked to as many of input nodes as desired and a pattern is defined. The network is adjusted according to this error. The validation dataset is used to ensure that the model was not over trained. In the testing phase, the model is tested using the dataset that was not used in the training. The most useful neural network in function approximation is multilayer perception (MLP) (Sharda and Patil, 1990). It consists of an input layer, hidden layer(s) and an output layer. This type of neural network is known as a supervised network as it requires the desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model then can be used to produce the output when the desired output is unknown. The inputs are fed into the input layer and get multiplied by the interconnection weights as they are passed from the input layer to the hidden layer. Within the hidden layer, they get summed then processed by a non linear function. Finally the data are multiplied by interconnection weights then processed one last time within the output layer to produce the neural network output. To perform any task, a set of experiments of an input output mapping is needed to train the neural network. These data are one of the most important factors to obtain reliable results from any trained ANN. Thus, the training sample data have to be fairly large to contain all the required information and must include a wide variety of data. During the training phase, the weights and biases of the network are optimized using an optimization algorithm. The most popular algorithm is the error back-propagation (BP) neural network (BPNN) model. It uses a gradient based optimization method to minimize the network error function. In fact, the name back propagation comes from the error term, which is propagated back through the network during learning and used to change the weights of the equation. The weights are changed using the following equation.

$$\Delta w_{ij} = -\eta \left(\delta E / \delta w_{ij} \right) + m \Delta w_{ij} (n - 1) \quad (6.5)$$

In this equation, η and m are known as learning rate and momentum coefficient respectively. While downscaling rainfall by ANN model, in this study, a multilayer perception neural network (MLP) with Back Propagation (BP) training algorithm is implemented. Back Propagation networks are the most widely used ANN models. Models with more number of neurons take more time for training. Also, very high number of neurons does not help in generalization of the model. Hence, the optimum number of neurons at which network performs at its best has to be determined. Selection of optimum number of neurons is essential part of ANN model development. In general, trial and error method has been applied

for achieving the same. In the case of present study, the number of neurons that performed the best were found to be 20. When the input variables are selected according to the best correlation, they are used as input parameters. Thus, input parameters vary from 8 to 10. The number of hidden layers is one. The transfer function used in the hidden layer is tan-sigmoid transfer function (tansig) and that used in the output layer is linear transfer function (purelin). The ANN structure developed during downscaling is shown in Fig. 6.3.

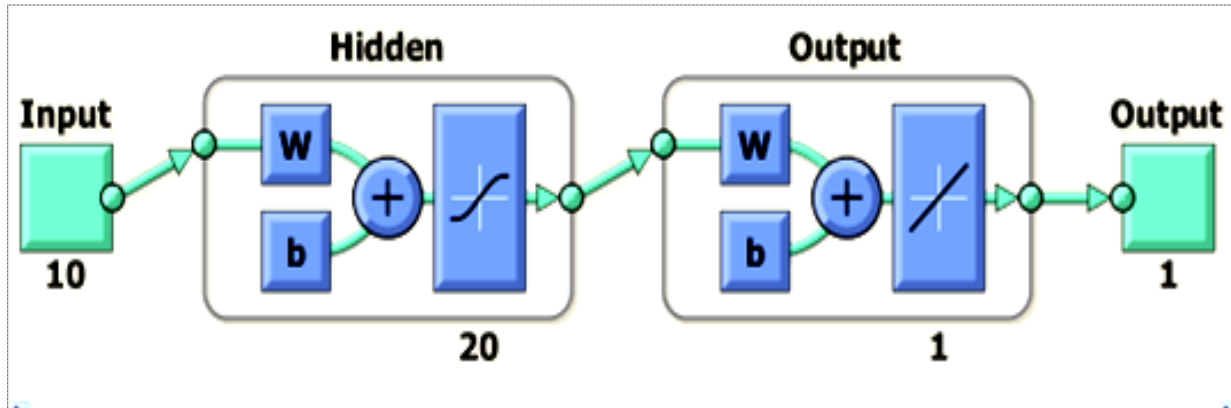


Fig. 6.3: ANN structure for downscaling of rainfall

Using the values of observed and simulated rainfall, the Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Coefficient of determination (R^2) were determined for both the regression analyses and the Artificial Neural Network method at each of the 24 APHRODITE's rainfall points and were compared to get the best method of downscaling.

6.2.3 Prediction of Rainfall

The best downscaling method has been used to predict the future monthly rainfall at all the 24 APHRODITE's points from 2020 up to the year 2099. For this, the entire period from 2020 to 2099 has been divided into four different time steps viz., 2020 to 2039, 2040 to 2059, 2060 to 2079 and 2080 to 2099. The monthly rainfall has then been predicted for these four time steps by taking 1960 to 2007 as the base period for which historical rainfall data are available.

6.3 Results and Discussions

6.3.1 Determination of correlation coefficient and selection of predictors

In the present study, the techniques applied for modeling and forecasting the monthly rainfall of Subansiri catchment area are, both linear and non-linear regression based statistical downscaling techniques and downscaling by Artificial Neural Network technique. The HadCM3 GCM climatic parameters have been used as the predictors and the appropriate

predictors have been selected by Pearson correlation method for all the 24 APHRODITE's points. Table 6.4(a) and 6.4(b) give the correlation coefficient values between the predictors and predictand at all the 24 APHRODITE's points when the climatic parameters of one GCM point that falls inside the Subansiri basin has been considered. The predictors selected for the APHRODITE's points are shown in Table 6.5. Again, Table 6.6(a) and 6.6(b) show the correlation coefficient values between predictors and predictand calculated by taking weighted average values of the parameters of the four GCM points and Table 6.7 shows the predictors selected for the APHRODITE's points by this method. The predictors selected in each case, show either a good positive correlation or a good negative correlation. The parameters for which the correlation coefficient values were found to be greater than 0.5 or less than -0.5 have been chosen as the predictors.

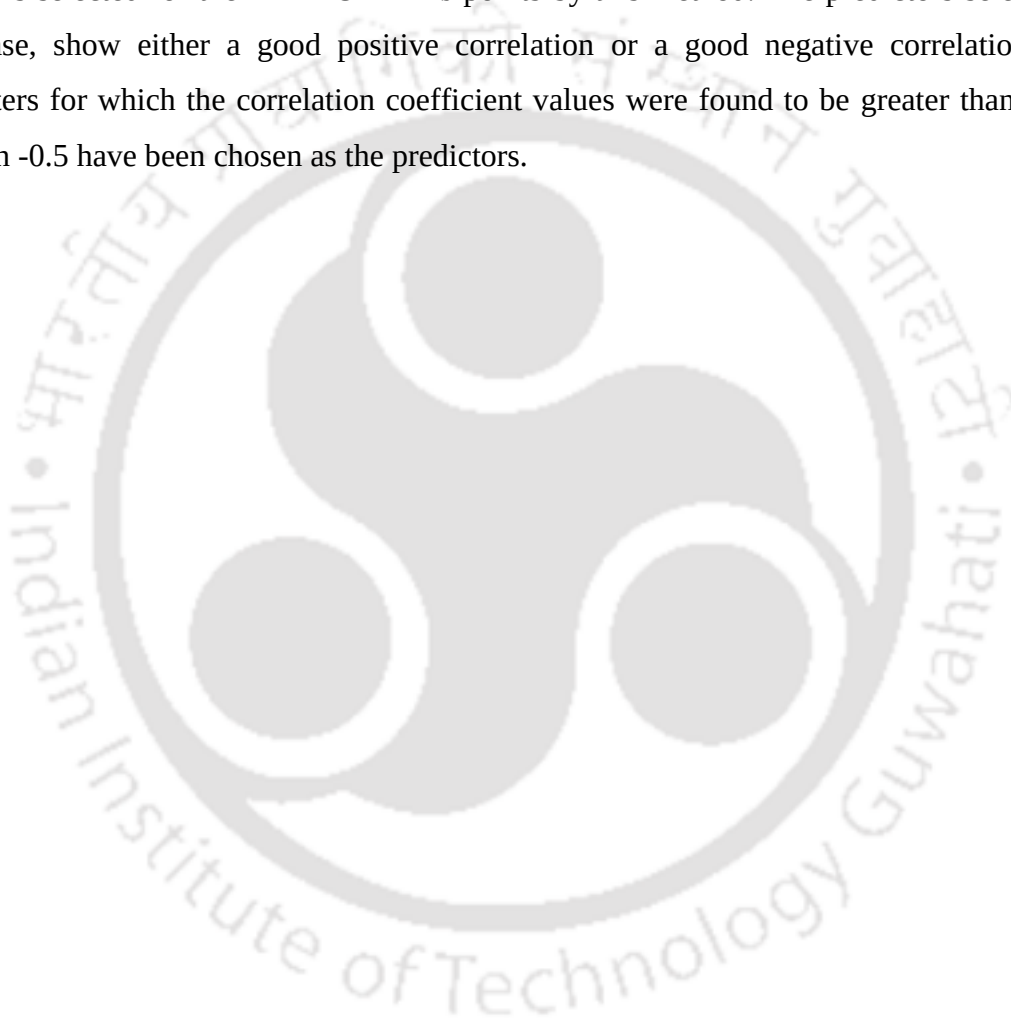


Table 6.4(a): Correlation coefficient values between predictors and predictand when climatic parameters of one GCM point are taken (from SI. No. 1 to 12 APHRODITE's points)

Predictors	APHRODITE's Points											
	1	2	3	4	5	6	7	8	9	10	11	12
dwsf	0.053	0.080	0.029	0.054	0.079	0.049	0.006	-0.099	0.004	0.009	0.038	0.053
Near surface relative humidity	0.506	0.501	0.522	0.508	0.505	0.516	0.527	0.512	0.518	0.535	0.530	0.506
Geopotential ht at 500hPa	0.726	0.725	0.736	0.718	0.723	0.732	0.730	0.689	0.721	0.750	0.746	0.726
Maximum temperature	0.764	0.776	0.761	0.763	0.775	0.768	0.747	0.672	0.732	0.760	0.782	0.764
Minimum temperature	0.827	0.835	0.829	0.826	0.836	0.833	0.818	0.744	0.803	0.832	0.849	0.827
Geopotential ht at 200 hPa	0.804	0.795	0.815	0.799	0.793	0.805	0.812	0.804	0.797	0.823	0.826	0.804
air temperature at 850 hPa	0.784	0.794	0.782	0.782	0.793	0.787	0.768	0.690	0.753	0.781	0.801	0.784
air temperature at 500 hPa	0.806	0.803	0.814	0.803	0.802	0.809	0.809	0.779	0.794	0.820	0.830	0.806
air temperature	0.801	0.811	0.800	0.798	0.811	0.805	0.786	0.705	0.771	0.800	0.819	0.801
mslp	-0.829	-0.839	-0.825	-0.832	-0.839	-0.830	-0.812	-0.733	-0.792	-0.818	-0.848	-0.829
soil moisture	0.674	0.678	0.679	0.690	0.684	0.677	0.674	0.616	0.649	0.674	0.699	0.674
precipitation rate	0.619	0.654	0.609	0.649	0.669	0.633	0.592	0.425	0.577	0.599	0.638	0.619
Ice thickness ht	-0.459	-0.460	-0.466	-0.461	-0.465	-0.466	-0.464	-0.416	-0.457	-0.471	-0.476	-0.459
Wind speed ht above ground	-0.588	-0.576	-0.604	-0.583	-0.573	-0.592	-0.608	-0.634	-0.598	-0.618	-0.610	-0.588
Relative humidity at 850hPa	0.533	0.528	0.548	0.533	0.531	0.541	0.550	0.530	0.542	0.561	0.556	0.533

Table 6.4(b): Correlation coefficient values between predictors and predictand when climatic parameters of one GCM point are taken (from SI. No. 13 to 24 APHRODITE's points)

Predictors	APHRODITE's Points											
	13	14	15	16	17	18	19	20	21	22	23	24
dwsf	0.000	0.042	0.029	0.048	0.048	0.045	0.047	0.059	0.044	0.040	0.033	0.034
Near surface relative humidity	0.536	0.532	0.534	0.541	0.541	0.538	0.537	0.518	0.528	0.532	0.539	0.521
Geopotential ht at 500hPa	0.744	0.748	0.750	0.767	-0.765	0.763	0.767	-0.767	0.758	0.751	0.761	0.734
Maximum temperature	0.769	0.787	0.785	0.800	0.767	0.799	0.802	0.750	0.795	0.784	0.789	0.761
Minimum temperature	0.840	0.855	0.854	0.869	0.800	0.866	0.868	0.795	0.861	0.851	0.859	0.828
Geopotential ht at 200 hPa	0.838	0.828	0.834	0.835	0.869	0.834	0.836	0.858	0.834	0.827	0.837	0.807
air temperature at 850 hPa	0.790	0.806	0.805	0.820	0.835	0.817	0.821	0.823	0.815	0.803	0.810	0.780
air temperature at 500 hPa	0.835	0.833	0.837	0.841	0.820	0.840	0.841	0.813	0.837	0.830	0.840	0.809
air temperature	0.807	0.824	0.823	0.839	0.841	0.836	0.840	0.829	0.833	0.821	0.828	0.799
mslp	-0.839	-0.854	-0.853	-0.861	0.839	-0.858	-0.859	0.830	-0.856	-0.847	-0.853	-0.822
soil moisture	0.694	0.700	0.698	0.692	-0.861	0.688	0.682	-0.854	0.674	0.691	0.694	0.670
precipitation rate	0.582	0.640	0.624	0.634	0.692	0.623	0.620	0.676	0.605	0.635	0.629	0.618
Ice thickness ht	-0.462	-0.477	-0.474	-0.482	0.634	-0.473	-0.472	0.622	-0.463	-0.477	-0.479	-0.468
Wind speed ht above ground	-0.630	-0.611	-0.617	-0.619	-0.482	-0.619	-0.620	-0.460	-0.617	-0.612	-0.624	-0.598
Relative humidity at 850hPa	0.559	0.558	0.560	0.568	-0.619	0.564	0.563	-0.602	0.554	0.558	0.565	0.546

Table 6.5: Predictors selected for the APHRODITE's points

APHRODITE's Points	Predictand	Predictors
1,2 ,4, 5, 6, 21	Rainfall	Maximum temperature Minimum temperature Geopotential ht at 200 hPa Air temperature at 500 hPa mslp Soil moisture Precipitation rate
3, 7, 8, 11, 12, 14, 15, 16, 17, 18, 19, 20, 22, 23, 24	Rainfall	Maximum temperature Minimum temperature Geopotential ht at 200 hPa Air temperature at 500 hPa mslp Soil moisture Precipitation rate Wind speed ht above ground
9	Rainfall	Maximum temperature Minimum temperature Geopotential ht at 200 hPa Air temperature at 500 hPa mslp Soil moisture
10, 13	Rainfall	Maximum temperature Minimum temperature Geopotential ht at 200 hPa Air temperature at 500 hPa mslp Soil moisture Wind speed ht above ground

Table 6.6(a): Correlation coefficient calculated by taking weighted average of the four GCM points for APHRODITE's points 1-12.

Predictors	APHRODITE's Points											
	1	2	3	4	5	6	7	8	9	10	11	12
dwsf	-0.072	-0.032	-0.104	-0.055	-0.019	-0.071	-0.131	-0.323	-0.132	-0.123	-0.048	-0.097
Near surface relative humidity	0.517	0.503	0.541	0.531	0.505	0.528	0.555	0.634	0.546	0.554	0.563	0.545
Geopotential ht at 200 hPa	0.813	0.804	0.823	0.806	0.801	0.814	0.820	0.813	0.805	0.831	0.832	0.840
Geopotential ht at 500 hPa	0.742	0.741	0.751	0.732	0.739	0.747	0.745	0.704	0.735	0.764	0.757	0.780
Maximum temperature	0.792	0.804	0.792	0.790	0.807	0.799	0.779	0.685	0.766	0.798	0.812	0.820
Minimum temperature	0.829	0.833	0.838	0.832	0.835	0.838	0.831	0.781	0.816	0.844	0.859	0.859
Air temperature at 500 hPa	0.822	0.821	0.830	0.816	0.818	0.825	0.824	0.785	0.809	0.837	0.841	0.849
mslp	-0.854	-0.857	-0.858	-0.857	-0.858	-0.857	-0.850	-0.804	-0.831	-0.856	-0.875	-0.868
soil moisture	0.620	0.629	0.660	0.658	0.648	0.665	0.678	0.683	0.679	0.713	0.716	0.727
precipitation rate	0.759	0.767	0.761	0.762	0.771	0.762	0.752	0.686	0.729	0.746	0.735	0.751
Wind speed ht above ground	-0.588	-0.576	-0.604	-0.583	-0.573	-0.592	-0.608	-0.634	-0.598	-0.618	-0.610	-0.619
Relative humidity at 850 hPa	0.580	0.566	0.607	0.586	0.567	0.593	0.621	0.688	0.613	0.628	0.615	0.625

Table 6.6(b): Correlation coefficient calculated by taking weighted average of the four GCM points for APHRODITE's points 13-24

Predictors	APHRODITE's Points											
	13	14	15	16	17	18	19	20	21	22	23	24
dwsf	-0.142	-0.028	-0.002	-0.052	-0.046	-0.049	-0.022	-0.061	-0.081	-0.059	-0.078	-0.006
Near surface relative humidity	0.577	0.571	0.561	0.549	0.562	0.560	0.547	0.558	0.537	0.556	0.558	0.535
Geopotential ht at 200 hPa	0.847	0.833	0.837	0.844	0.842	0.844	0.830	0.842	0.815	0.834	0.845	0.828
Geopotential ht at 500 hPa	0.760	0.756	0.754	0.780	0.774	0.779	0.760	0.771	0.748	0.763	0.774	0.764
Maximum temperature	0.805	0.809	0.799	0.839	0.831	0.835	0.824	0.827	0.797	0.818	0.827	0.835
Minimum temperature	0.852	0.865	0.861	0.874	0.873	0.875	0.863	0.867	0.837	0.861	0.868	0.868
Air temperature at 500 hPa	0.850	0.841	0.842	0.858	0.853	0.856	0.841	0.851	0.825	0.844	0.855	0.845
mslp	-0.880	-0.877	-0.866	-0.887	-0.884	-0.885	-0.877	-0.883	-0.853	-0.876	-0.884	-0.885
soil moisture	0.727	0.711	0.713	0.738	0.730	0.729	0.705	0.716	0.691	0.714	0.731	0.718
precipitation rate	0.746	0.715	0.658	0.746	0.723	0.726	0.714	0.722	0.744	0.746	0.751	0.742
Wind speed ht above ground	-0.630	-0.611	-0.617	-0.619	-0.619	-0.620	-0.602	-0.617	-0.598	-0.612	-0.624	-0.603
Relative humidity at 850 hPa	0.648	0.612	0.592	0.622	0.623	0.624	0.602	0.621	0.604	0.616	0.628	0.597

Table 6.7: Predictors selected for the APHRODITE's points

APHRODITE's Points	Predictand	Selected Predictors
1, 2, 4, 5, 6	Rainfall	Geopotential ht at 200 hPa Geopotential ht at 500 hPa Maximum temperature Minimum temperature Air temperature at 500 hPa Mslp Soil moisture precipitation rate
9, 21	Rainfall	Geopotential ht at 200 hPa Geopotential ht at 500 hPa Maximum temperature Minimum temperature Air temperature at 500 hPa Mslp soil moisture precipitation rate Wind speed ht above ground
15, 24	Rainfall	Geopotential ht at 200 hPa Geopotential ht at 500 hPa Maximum temperature Minimum temperature Air temperature at 500 hPa Mslp soil moisture precipitation rate Relative humidity at 850 hPa
3, 7, 8, 10, 11, 12, 13, 14, 16, 17, 18, 19, 20, 22, 23	Rainfall	Geopotential ht at 200 hPa Geopotential ht at 500 hPa Maximum temperature Minimum temperature Air temperature at 500 hPa Mslp soil moisture precipitation rate Wind speed ht above ground Relative humidity at 850 hPa

6.3.2 Comparison of Regression Based Statistical Downscaling Method and Downscaling using Artificial Neural Network Model

Calibration and Validation have been performed at all the 24 APHRODITE's rainfall points for both the multiple linear and multiple non-linear regression methods. Fig.6.4 shows the calibration and validation graphs for (a) multiple linear regression and (b) multiple non-linear regression at the APHRODITE's point (91.875°E, 28.625°N) for the one GCM point that falls inside the study area. The calibration and validation graphs obtained while considering the climatic parameters of one HadCM3 GCM point for all the 24 APHRODITE's points are shown in Annexure 1 (multiple linear regression) and Annexure 2 (multiple non-linear regression) respectively.

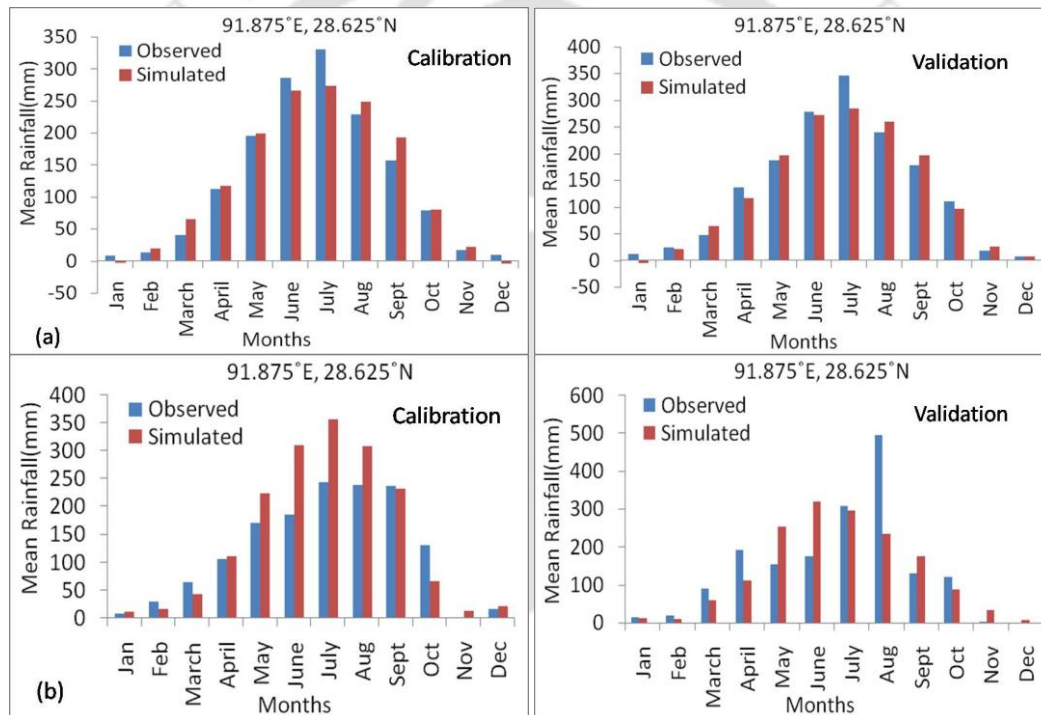


Fig. 6.4: Calibration and validation graphs for (a) multiple linear regression and (b) multiple non-linear regression at the APHRODITE point 91.875°E; 28.625°N for the GCM that falls inside the study area

It is observed that from Fig. 6.4 (a) that during calibration, the simulated rainfalls are less than the observed rainfalls for January, June, July and December, while for rest of the months the simulated values are more than the observed values. For the validation part, it is observed that up to July, the simulated rainfalls are less than observed rainfall including the month of October, while for the other months simulated rainfall values are more than the observed values.

From Fig. 6.4(b), during calibration, the simulated rainfall values are more than the observed rainfall values for May, June, July, August and December and less for the rest of the months. While validating, it has been observed that for May, June, September, October, November and December, the simulated rainfalls are more than observed rainfall. For the rest of the months, the observed values are more than the simulated ones. The highest difference has been observed in the month of August.

The calibration and validation graphs for (a) multiple linear regression and (b) multiple non-linear regression performed by taking weighted average of all the four GCM points at the APHRODITE's point (91.875°E, 28.625°N) are shown in Fig.6.5. The graphs for the rest of the rainfall points for multiple linear and non-linear regression analysis are given in Annexure 3 and Annexure 4 respectively.

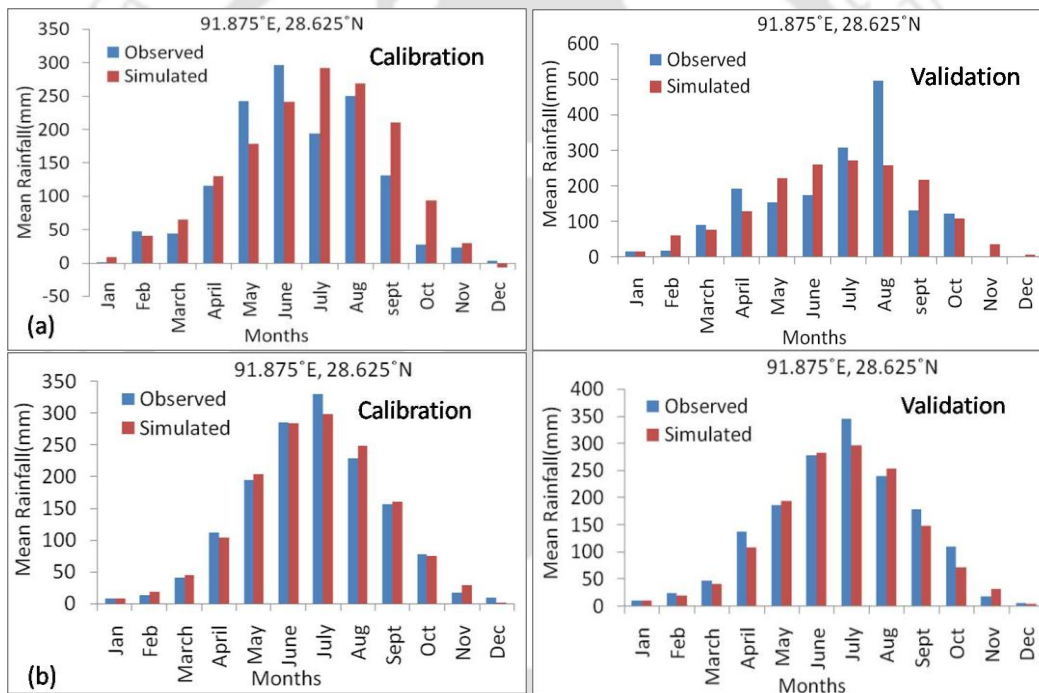


Fig.6.5: Calibration and Validation graphs for (a) multiple linear regression and (b) multiple non linear regression at the APHRODITE point 91.875°E; 28.625°N for the weighted average of all the GCMs

From Fig.6.5(a), during calibration simulated values are more than the observed values for January, March, April, July, August, September, October and November and are less than the observed values for the rest of the months. During validation, for the month of August, the observed and simulated rainfall values show the maximum difference. For other months the difference is not that significant. From Fig. 6.5(b), during calibration and validation, the correlation between observed and simulated rainfall are better than the other methods.

The performance of ANN model at point (91.875°E, 28.625°N) can be evaluated from Fig. 6.6 where the scatter plots for training, validation and testing are shown. The regression plots for all the 24 APHRODITE's points are given in Annexure 5.

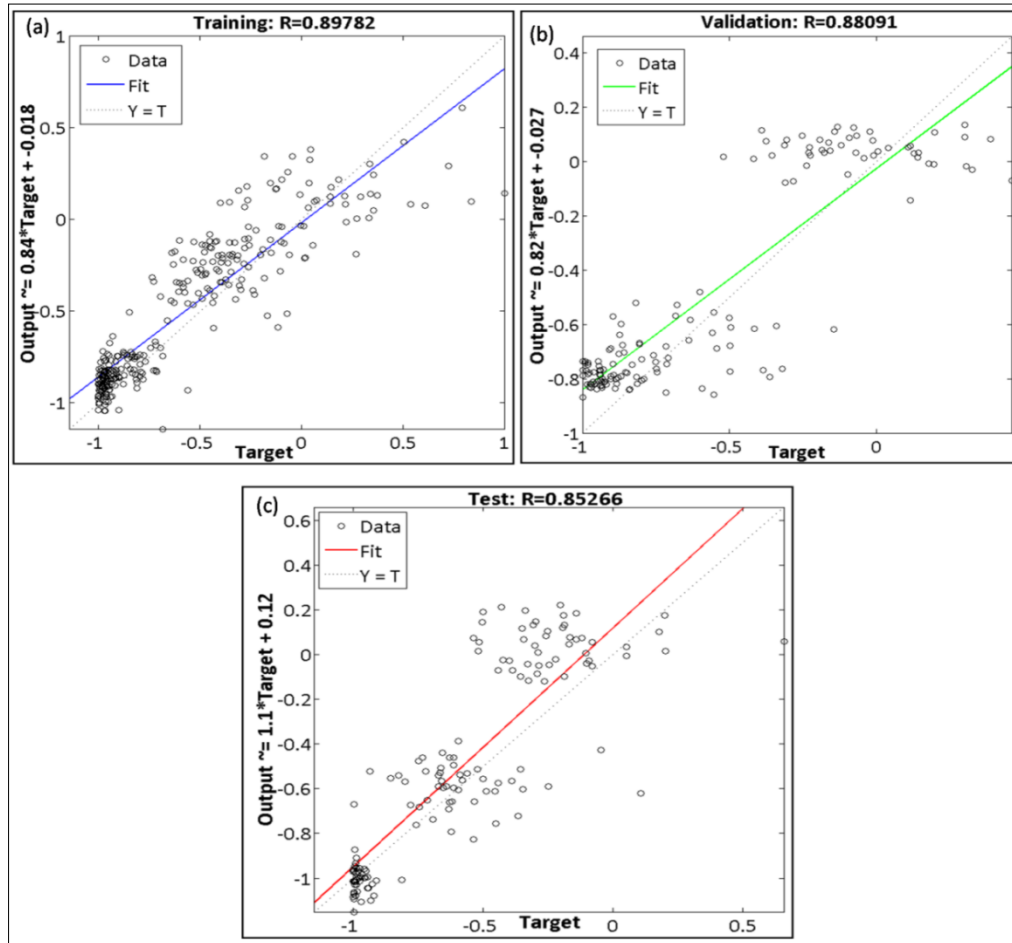


Fig.6.6: Regression plots for (a)Training, Validation and Testing for the ANN model at the APHRODITE's point 91.875°E; 28.625°N

The R value observed at this point is 0.85 which is acceptable for further analysis using ANN.

The coefficient of correlation (R^2) values obtained from the methods have been compared at all the 24 points. It has been found that for the multiple non-linear regression method, the R^2 values at all the rainfall points are better compared to multiple linear based regression method and ANN method. The R^2 values obtained for these methods are given in table 6.8.

Table 6.8: R² values determined for regression and ANN methods

APHRODITE points Sl. No.	Linear Regression		Non-linear Regression		ANN
	At point 93.75°E; 27.5°N	Weighted Average	At point 93.75°E; 27.5°N	Weighted Average	
1	0.774	0.769	0.817	0.818	0.733
2	0.766	0.759	0.809	0.808	0.760
3	0.769	0.774	0.809	0.817	0.778
4	0.771	0.768	0.820	0.820	0.780
5	0.770	0.765	0.815	0.816	0.774
6	0.755	0.754	0.796	0.797	0.769
7	0.742	0.750	0.783	0.791	0.769
8	0.745	0.795	0.815	0.842	0.810
9	0.687	0.699	0.724	0.733	0.741
10	0.759	0.769	0.790	0.798	0.775
11	0.808	0.817	0.851	0.857	0.814
12	0.780	0.808	0.828	0.833	0.792
13	0.806	0.822	0.848	0.855	0.817
14	0.782	0.819	0.854	0.861	0.796
15	0.814	0.821	0.855	0.861	0.824
16	0.828	0.835	0.859	0.865	0.828
17	0.814	0.832	0.854	0.864	0.819
18	0.808	0.836	0.856	0.867	0.815
19	0.802	0.814	0.838	0.848	0.806
20	0.801	0.831	0.853	0.865	0.808
21	0.742	0.751	0.780	0.790	0.773
22	0.797	0.816	0.845	0.854	0.801
23	0.826	0.833	0.857	0.865	0.828
24	0.813	0.817	0.850	0.855	0.832

This shows certainly a better forecasting ability of multiple non-linear regression based statistical downscaling technique when performed by taking the weighted average values of the parameters of all the four GCM points.

By applying above three techniques, the rainfalls have been simulated at the 24 APHRODITE's precipitation points. The observed and simulated rainfalls were then used to determine the Mean Absolute Error (MAE), Mean Square Error (MSE) and Root Mean Square Error (RMSE) which are given in table 6.9, 6.10 and 6.11 respectively. Based on these three errors, the forecasting abilities of the models have been assessed.

Table 6.9: MAE for each APHRODITE's point for linear regression, non-linear regression and ANN

APHRODITE Points Sl. No	Regression taking 1 GCM		Regression taking weighted average		ANN
	Non-linear	Linear	Non-linear	Linear	
1	39.09	43.68	38.02	42.92	49.32
2	34.04	37.69	32.55	37.04	36.3
3	35.82	39.73	35.6	38.04	37.96
4	49.03	55.16	47.58	54.52	50.97
5	41.93	46.59	40.74	46.26	45.7
6	37.11	41.5	35.46	40.4	37.07
7	38.98	43.26	37.88	40.88	36.95
8	39.93	43.01	39.29	41.29	39.41
9	39.78	44.35	38.64	42.25	39.52
10	41.04	45.47	39.85	42.44	40.54
11	34.97	38.36	34.21	36.23	35.74
12	49.95	56.38	48.33	54.48	49.41
13	44.34	49.76	42.95	47.92	46.88
14	32.16	35.11	31.28	33.32	32.66
15	30.74	35.34	29.2	33.33	31.54
16	50.91	57.15	49.56	55.26	63.31
17	36.39	40.51	35.15	38.69	37.81
18	49.47	56.28	48.34	54.22	51.35
19	40.83	44.99	38.96	43.81	38.66
20	33.58	37.1	32.06	35.22	33.47
21	37.97	42.22	35.96	40.07	38.37
22	38.06	42.21	35.97	39.86	39.31
23	47.74	53.71	46.59	51.35	50.84
24	42.59	47.34	40.92	45.23	51.03

The Mean Absolute Error for multiple non-linear regression performed by taking one GCM point varies between 30.74 and 50.91 with an average value of 40.27.

For multiple linear regression performed by taking one GCM, the MAE varies between 35.11 and 57.15 with an average MAE of 44.87.

For the multiple non-linear and multiple linear regression performed by taking the weighted average of the four GCMs, the MAE vary between 29.20 and 49.56; and 33.32 and 55.26 respectively. The average error values are 38.96 and 43.13 respectively.

The MAE for ANN model varies between 31.54 and 63.31 with an average error value of 42.23.

Table 6.10: MSE for each APHRODITE's point for linear regression, non-linear regression and ANN

APHRODITE Points Sl.No	Regression taking 1 GCM		Regression taking weighted average		ANN
	Non-linear	Linear	Non-linear	Linear	
1	3330	3590	3300	4850	3610
2	2480	2630	2410	2670	2670
3	2780	2960	2690	2920	2880
4	5440	5890	5520	6060	5620
5	3770	4010	3740	4120	4240
6	3000	3180	2850	3140	3060
7	3370	3560	3150	3400	3320
8	3235	3332	3217	3270	3222
9	3460	3640	3280	3520	3370
10	4020	4190	3730	3970	3930
11	2620	2730	2540	2660	2660
12	5060	5540	4920	5330	5070
13	4010	4330	3850	4160	4150
14	2130	2240	2110	2170	2130
15	1880	2140	1690	1950	1980
16	5040	5570	4890	6890	5310
17	2620	2890	2540	2800	2740
18	4700	5320	4570	5090	4870
19	3190	3430	2990	3330	3010
20	2230	2330	2070	2210	2190
21	2820	3020	2620	2860	2850
22	2820	3040	2610	2940	2870
23	4610	5090	4450	4900	4980
24	3540	3890	3290	4740	3720

The minimum and maximum MSE for the multiple non-linear regression done by taking one GCM are 1880 and 5440 respectively with an average value of 3423.13. Again, the minimum and maximum MSE for the multiple linear regression done by taking one GCM are 2140 and 5890 respectively with an average value of 3689.25.

The MSE for multiple non-linear regression performed by taking the weighted average of the four GCMs varies between 1690 and 5520 with an average value of 3292.79. For multiple

linear regression performed by taking the weighted average of the four GCMs, the MSE varies between 1950 and 6890 with an average value of 3747.92.

For the ANN model, the minimum and maximum MSE are 1980 and 5620 respectively with and the average MSE is 3518.83.

Table 6.11: RMSE for each APHRODITE's point for linear regression, non-linear regression and ANN

APHRODITE Points Sl. No.	Regression taking 1 GCM		Regression taking weighted average		ANN
	Non-linear	Linear	Non-linear	Linear	
1	57.73	59.92	57.46	69.64	60.09
2	49.81	51.29	49.12	51.74	51.68
3	52.71	54.4	51.96	53.72	54.01
4	73.75	76.77	74.3	77.85	74.96
5	61.43	63.35	61.15	64.09	65.13
6	54.81	56.41	53.44	56.04	55.33
7	58.11	59.69	56.2	58.35	57.56
8	55.34	58.23	54.74	56.45	54.92
9	58.85	60.39	57.27	59.33	58.1
10	63.44	64.76	61.09	63.07	62.69
11	51.22	52.65	50.37	51.57	51.6
12	71.15	74.45	70.19	73.03	71.27
13	63.36	65.8	62.03	64.54	64.44
14	46.21	47.36	45.85	46.64	46.25
15	43.38	46.28	41.12	44.24	44.52
16	70.98	74.63	69.98	83.04	72.88
17	51.19	53.76	50.37	52.34	52.97
18	68.56	72.94	67.58	71.38	69.76
19	56.56	58.56	54.72	57.7	54.88
20	47.18	48.25	45.54	47.05	46.87
21	53.12	54.94	51.16	53.45	53.41
22	53.15	55.14	51.12	53.66	54.28
23	67.87	71.39	66.75	70.02	70.62
24	59.54	62.35	57.41	61.01	59.77

The RMSE were also determined at the rainfall points. The minimum and maximum RMSE for the multiple non-linear regression method performed by taking the climatic parameters of one GCM are, 43.38 and 73.75 respectively and the average RMSE is 57.89. The RMSE for

the multiple regression method done by taking parameters of one GCM varies between 46.28 and 76.77 with an average value of 60.15.

For the multiple non-linear regression performed by taking the weighted average of the climatic parameters of the four GCM, the RMSE varies between 41.12 and 74.20 with an average value of 56.71. The minimum and maximum RMSE for multiple linear regression done by taking the weighted average of climatic parameters of the four GCMs are 44.24 and 83.04 respectively and the average RMSE is 59.98.

The RMSE for the ANN model varies between 44.52 and 74.96 with an average value of 58.67.

The average values of MAE, MSE and RMSE for the two methods are given in Table 6.12.

Table 6.12: Average values of MSE, MAE and RMSE

Downscaling Methods		Average Error Values		
		MSE	MAE	RMSE
Linear Regression	Taking one GCM	3689.25	44.87	60.15
	Taking weighted average	3747.92	43.13	59.98
Non-linear Regression	Taking one GCM	3423.12	40.27	57.89
	Taking weighted average	3292.79	38.96	56.70
Artificial Neural Network		3518.83	42.23	58.67

It is observed from the above table that all the three errors were the minimums in the case of multiple non-linear regression analysis done by taking the weighted average values of the four HadCM3 GCM points. For this particular method, the average MSE, MAE and RMSE are 3292.79, 38.96 and 56.70 respectively. The ANN model was found to be better than (i) multiple linear and non-linear regression methods done by taking climatic parameters of one GCM and (ii) multiple linear regression method done by taking the weighted average values of the climatic parameters of the four GCMs. The MSE, MAE and RMSE for ANN model were found to be 3518.83, 42.23 and 58.67 respectively. The MSE, MAE and RMSE were found to be the maximum for multiple linear regression analysis performed by taking the climatic parameters of one GCM that falls inside the study area with values 3689.25, 44.87 and 60.15 respectively.

This results imply that multiple non-linear regression based method outperformed the linear regression as well as the ANN model. Hence this method can efficiently be used for future prediction of rainfall in the Subansiri River basin.

6.3.3 Prediction of future Rainfall

6.3.3.1 Future Rainfall Analysis at all the APHRODITE rainfall points

Future four sets of rainfall data have been predicted viz. 2020 to 2039, 2040 to 2059, 2060 to 2079 and 2080 to 2099 by taking 1960 to 2007 precipitations as the base. The month wise analysis of rainfall at all the 24 APHRODITE's points are explained below.

It is observed that rainfall first decreases for the period 2020-39 compared to the base period for the months January, February, April, June, July, August, September and October. On the other hand, for March, May, November and December, the rainfall increases for 2020-39 compared to the base period from 1960-2007.

While analyzing the trend from 2020-39 to 2080-99, it has been observed that for January, February and March, the rainfall gradually increases from 2020-39 to 2080-99 except at the rainfall points (93.375°E, 27.375°N), (93.875°E, 28.375°N), (94.125°E, 28.125°N), (94.375°E, 28.125°N), (93.125°E, 28.125°N), (93.375°E, 28.375°N) and (93.625°E, 28.125°N). At these points, for the month of March, rainfall decreases for the period 2080-2099.

For the month of April and December, rainfall first increases from 2020-39 to 2060-79 and then decreases for the period 2080-99. However, at the rainfall points (92.375°E, 28.625°N), (92.375°E, 28.875°N), (92.625°E, 28.625°N), (92.875°E, 28.625°N) and (93.625°E, 27.625°N) rainfall increases continuously from 2020-39 to 2080-99 for the month of April. For the month of December, at the rainfall points (93.125°E, 28.625°N) and (94.125°E, 28.125°N) the rainfall increases from 2020-39 to 2080-99 for the month of December.

Different points show different rainfall patterns for the month of May. At points (91.875°E, 28.625°N), (92.125°E, 28.375°N), (92.375°E, 27.875°N), (94.375°E, 27.375°N) rainfall decreases from 2020-39 to 2080-99. However, increase in rainfall during 2040-59 compared to 2020-39 is observed at points (93.375°E, 27.375°N), (93.375°E, 27.875°N), (93.625°E, 27.625°N), (93.875°E, 28.375°N), (94.125°E, 28.125°N), (93.125°E, 28.125°N), (93.375°E, 28.375°N), (93.625°E, 28.125°N), (94.375°E, 28.125°N), (94.625°E, 27.625°N), (94.875°E, 27.875°N) and (93.125°E, 27.875°N) where the rainfall then again decreases for 2060-79 and 2080-99. At points (94.125°E, 27.625°N), (92.375°E, 28.625°N) and (92.625°E, 28.375°N) rainfall increases continuously from 2020-39 to 2060-79 and then decreases again for 2080-

99. A continuous increase of rainfall from 2020-39 to 2080-99 is observed at points (92.375°E, 28.875°N), (92.625°E, 28.625°N) and (92.875°E, 28.625°N).

For July, August and October most of the rainfall points show similar trends where rainfall decreases from the period 2020-39 to 2080-99 with few exceptions. For example, at the point (92.375°E, 28.875°N), for all these three months, rainfall increases from 2020-39 to 2080-99. Again, for the month of October, at (92.375°E, 27.875°N) and (93.375°E, 27.375°N), rainfall first decreases from 2020-39 to 2060-79 and then increases again during 2080-99. Reverse is the case for points (92.625°E, 28.625°N) and (92.875°E, 28.625°N) where rainfall first increases from 2020-39 to 2060-79 and decreases during 2080-99.

Rainfall first increases for 2040-59 compared to 2020-39 and then again start decreasing for the rest of the periods up to 2099 for June and September. Exceptions are points (92.375°E, 28.125°N), (93.375°E, 27.375°N), (94.125°E, 28.125°N), (94.625°E, 27.625°N) and (93.625°E, 28.125°N) where rainfall show a decreasing trend from 2020-39 to 2080-99 for both the months. In addition to these points, (92.125°E, 28.375°N), (92.375°E, 27.875°N), (92.375°E, 28.125°N) and (92.625°E, 28.375°N) show a decreasing trend of rainfall for the month of September. On the other hand, for both the months, at point (92.375°E, 28.875°N) the rainfall increases from 2020-39 to 2080-99.

For the month of November, different points show different rainfall trends. For all the points rainfall increases for 2020-39 compared to the base period 1960-2007. At few points, rainfall first increases from 2020-39 to 2060-79 and then decreases for 2080-99. At few other points, compared to 2020-39, rainfall decreases gradually from 2040-59 to 2080-99. At some points, on the other hand rainfall shows alternate changes from 2040-59 to 2080-99.

The graphical representation of the future predicted rainfall at points (91.875°E; 28.625°N), (92.125°E; 28.375°N), (94.125°E, 27.625°N) and (92.375°E; 27.875°N) are shown in Fig.6.7 while at all APHRODITE rainfall points are shown in Annexure 6.

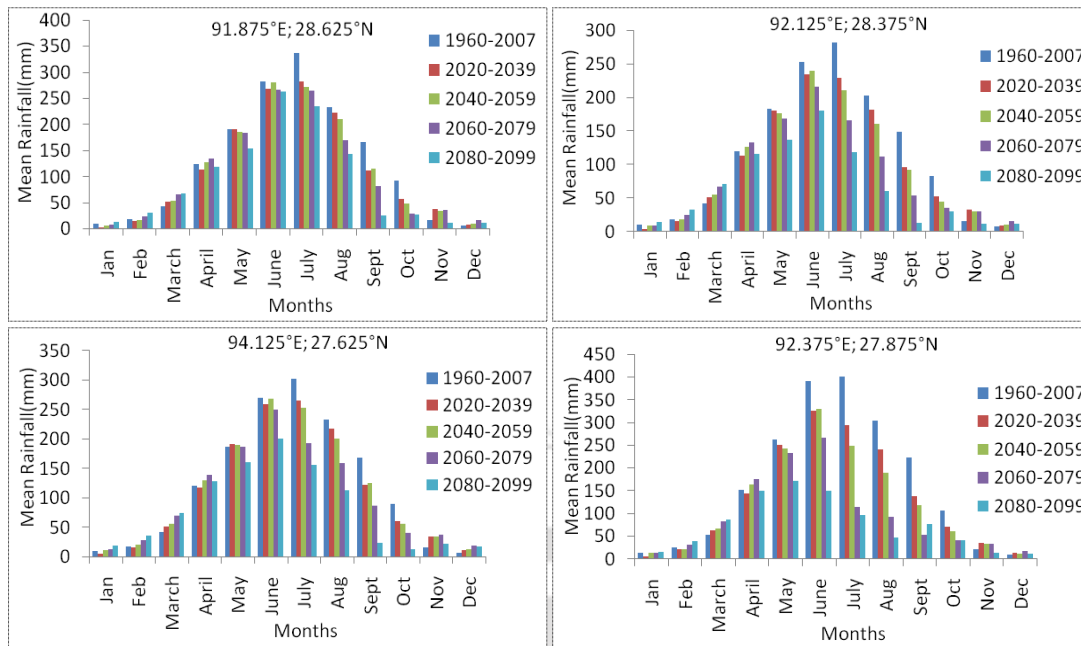


Fig.6.7: Historical and future rainfall at four different APHRODITE points

6.3.3.2 Future average rainfall analysis over the Subansiri basin

The average rainfall of all the 24 APHRODITE points have been calculated and analyzed the future trends of rainfall over the Subansiri river basin for the four different future time steps. Fig. 6.8 shows the trends of rainfall for (a) 2020-39, (b) 2040-59, (c) 2060-79 and (d) 2080-99.

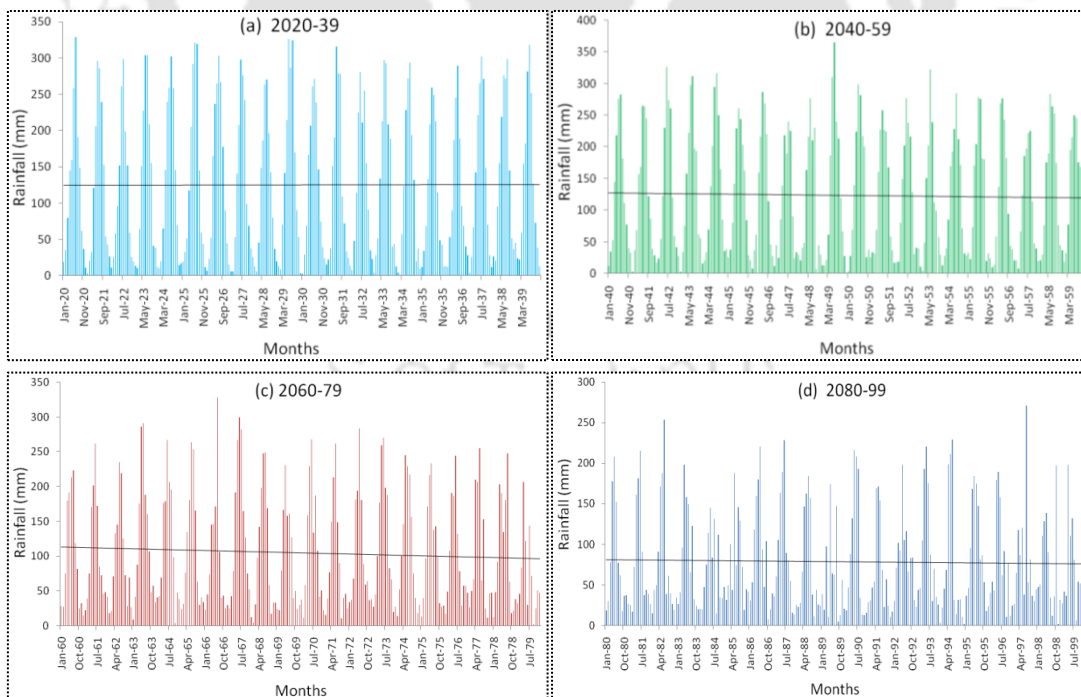


Fig. 6.8: Trends showing change in average rainfall over Subansiri catchment for different time steps

It is seen from the graphs that when the average rainfall values of all the APHRODITE's points are considered, the rainfall during the period 2020-39 remains almost the same. The linear trend lines for other three time steps indicate that there will be decreasing trends of rainfall for 2040-59, 2060-79 and 2080-99. There is a possibility that the period 2060-79 will experience the highest decrease in rainfall over the Subansiri River basin.

6.3.3.3 Spatial variation of rainfall over the Subansiri river basin

The total annual rainfall at each APHRODITE point has been used to study the spatial variation of rainfall for the different time steps. Fig. 6.9 shows the spatial variation maps prepared in GIS by taking the total annual rainfall values at all the 24 APHRODITE points for the five different time steps.

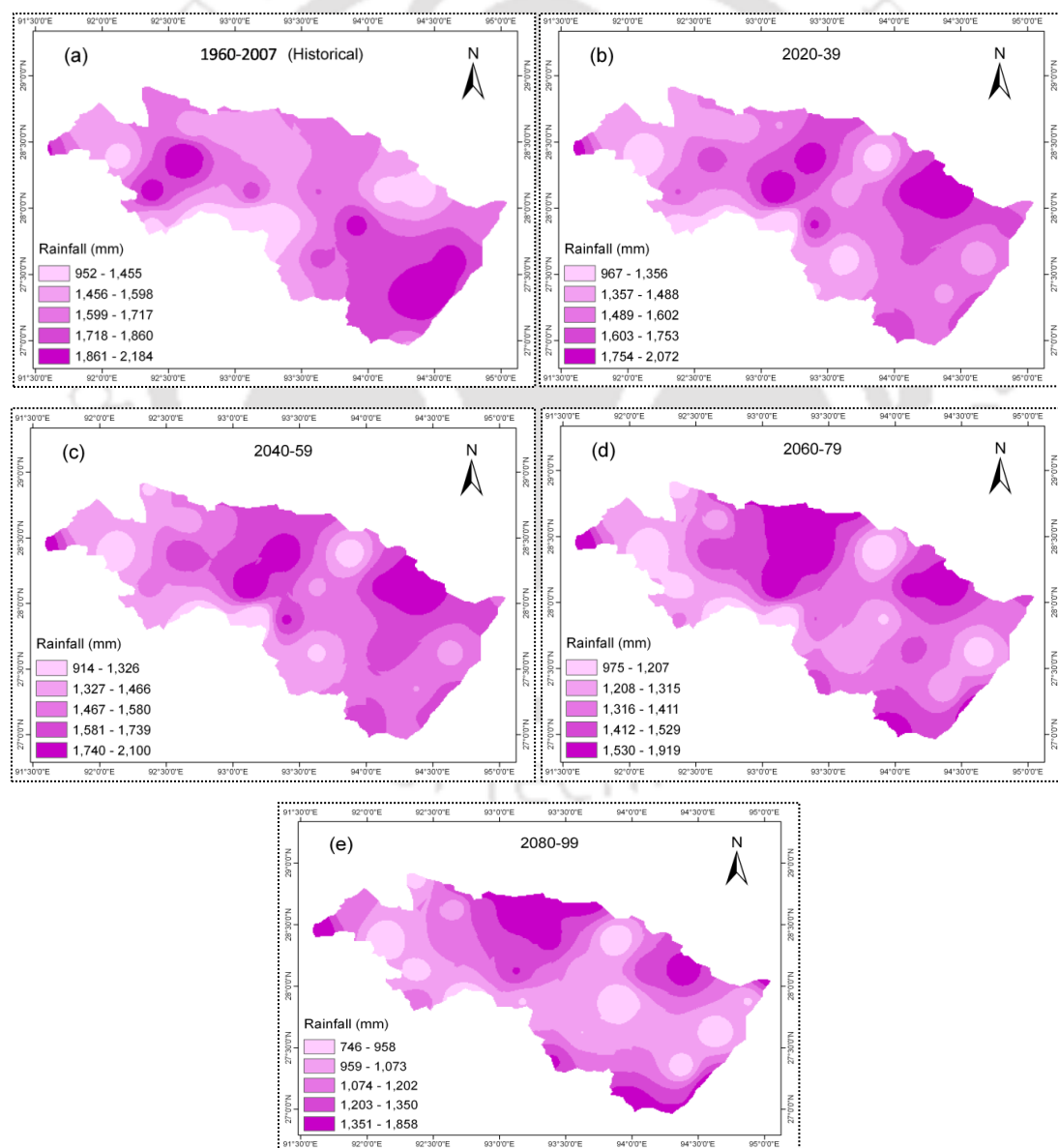


Fig. 6.9: Spatial variation of total rainfall for different time steps over the Subansiri basin

It is observed from the maps that during 1960-2007, the basin experienced heavy rainfall at the downstream which gradually decreases for the later periods. During 2020-39, most parts of the basin will receive rainfall between 1489-1602mm. It is also observed that the maximum rainfall for 2020-39, 2040-59 and 2060-79 will occur at the middle part of the catchment which shifts slightly upward during 2080-99. During 2040-59, 1327-1580mm of rainfall will be experienced by most of the area in the catchment. During 2060-79, 1208-1529 mm of rainfall will be experienced by most parts of the basin. Again, during 2080-99, maximum area will receive rainfall in the range of 956-1073mm. The minimum rainfalls for 1960-2007, 2020-39, 2040-59, 2060-79 and 2080-99 are 952mm, 967mm, 914mm, 975mm and 746mm respectively. The maximum rainfalls for these periods are predicted to be 2184mm, 2072mm, 2100mm, 1919mm and 1858mm respectively. It is clear that the basin will receive less rainfall during 2080-99 compared to the other time periods. These changes in rainfall are the indications of climate change that would occur in the Subansiri basin in the near future.

6.3.3.4 Future Rainfall Analysis over the Subansiri basin on the basis of wet months, dry months and months with moderate rainfall

While analyzing the historical rainfall data from 1960-2007 at all the 24 APHRODITE's points, heavy rainfall were observed for the months May, June, July and August. Together these four months accounted for 64-70% of the total annual rainfall. These four months hence are considered as the wet months. Unlike the wet months, for the months of November, December, January and February, the observed rainfalls were the minimum (2-5% of the total annual rainfall) and are considered as the dry months. In between these two, the remaining four months *i.e.* March, April, September and October experienced moderate rainfall and together they accounted for 28-31% of the annual total rainfall. The spatial variations of rainfall in these three different kinds of months have been analyzed in this study.

6.3.3.4.1 Spatial variation of rainfall for the wet months

Fig. 6.10 shows the average rainfall experienced by the basin during (a) 1960-2007 and future possibility for the periods (b) 2020-39, (c) 2040-59, (d) 2060-79 and (e) 2080-99 for the wet months.

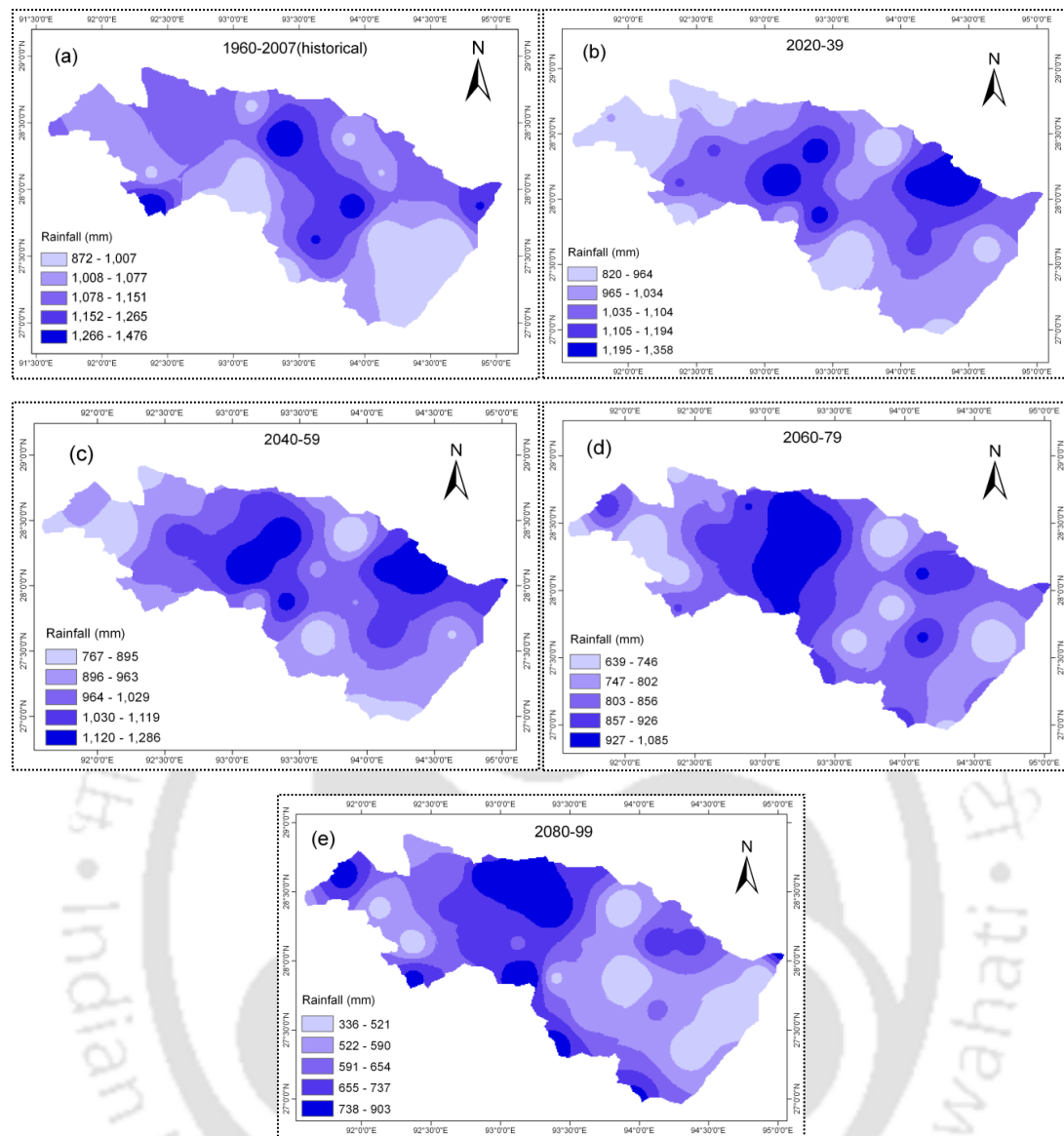


Fig.6.10: Spatial variation of rainfall over the Subansiri basin during the wet months for different time steps

It is observed from the figure that during 1960-2007, the basin experienced the minimum rainfall of 872-1007mm mostly at the downstream. Some areas of the middle part of the catchment experienced the maximum rainfall of 1266-1476mm. Most part of the catchment during this period had rainfall of 1078-1151 mm.

The upstream rainfall decreases and the downstream rainfall increases for the period 2020-39 compared to the rainfall during 1960-2007. The upstream is indicated to experience the minimum rainfall of 820-984 mm. Rainfall of 1035-1104mm is indicated in the middle part of the basin during this period.

Not much change is observed during 2040-59 compared to that of 2020-39. However, rainfall slightly increases at the upstream. Maximum rainfall is 1120 to 1266 which is indicated in the

middle and in some areas at the downstream. The minimum rainfall predicted for this period is 767-895mm. Most parts would have rainfall of 954-1029mm.

For 2060-79, the upstream rainfall increases more compared to 2040-59 and the rainfall is indicated to be the maximum in the middle part of the catchment with rainfall amount of 927-1085mm. A small portion at the upstream is also indicated to experience the maximum rainfall.

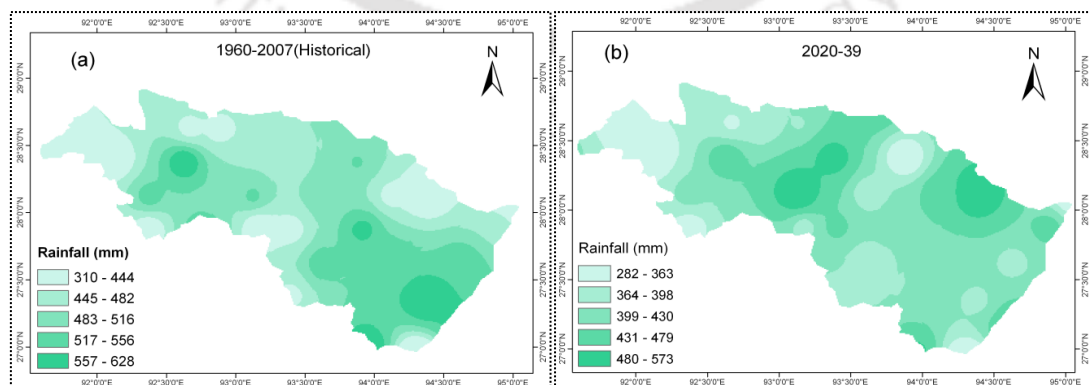
During 2080-99, rainfall significantly decreases at the downstream of the basin. The minimum rainfall of 335-521mm is predicted at the downstream as well as at some areas in the middle portion. Maximum rainfall is indicated to be shifted towards upstream. The maximum rainfall during this period could be 738-903mm.

Thus it is seen that at the downstream, the rainfall gradually decreases from 2020-39 and becomes the minimum during 2080-99. Again, the maximum rainfall decreases gradually from 1960-2007 to 2080-99 with values 1266-1476mm, 1195-1358mm, 1120-1286mm, 927-1085mm and 738-903mm for the periods 1960-2007, 2020-2039, 2040-2059, 2060-2079 and 2080-2099 respectively. Similarly, the minimum rainfall also decreases from 1960-2007 to 2080-2099. The ranges of the minimum rainfall values for the periods 1960-2007, 2020-39, 2040-59, 2060-79 and 2080-99 are 872-1007mm, 820-984 mm, 767-895mm, 639-746mm and 336-521mm respectively.

Hence, the basin would experience less rainfall compared to the historical rainfall during the wet months i.e. during May, June, July and August.

6.3.3.4.2 Spatial variation of rainfall for the months with moderate rainfall

The spatial variation maps prepared in GIS for the months with moderate rainfall for each time step are shown in Fig. 6.11.



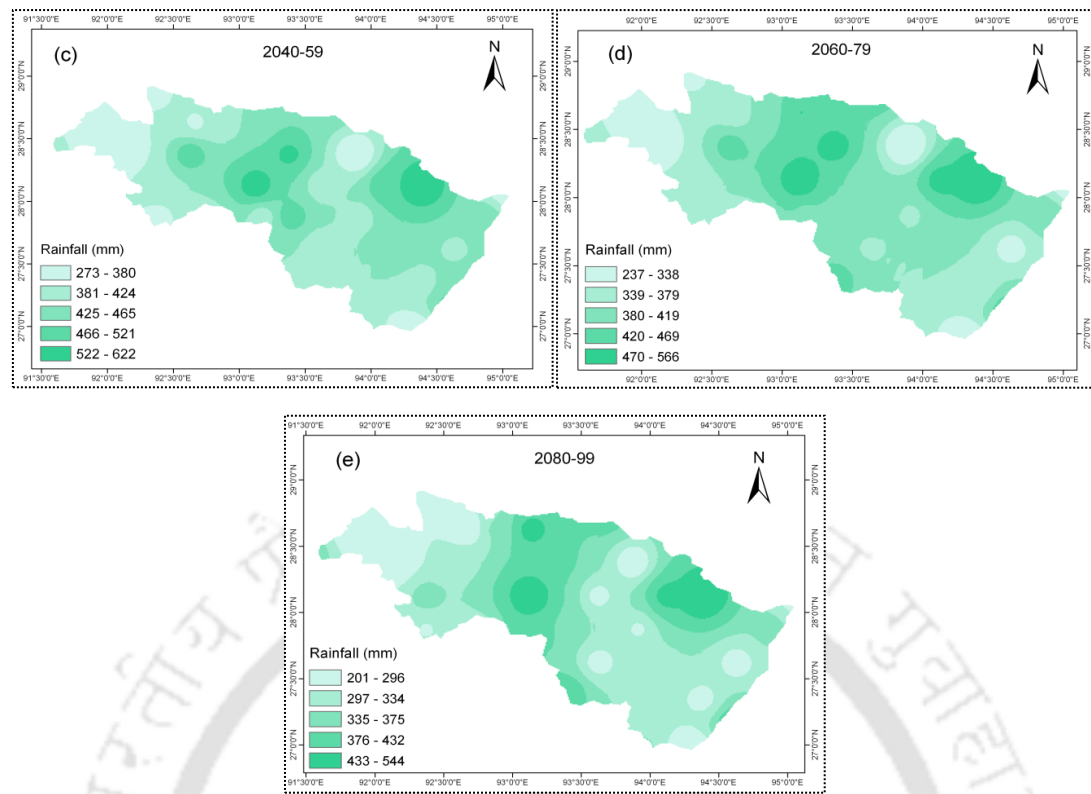


Fig.6.11 Spatial variation of rainfall over the Subansiri basin during the months with moderate rainfall for different time steps

While analyzing the rainfall distribution over the Subansiri basin during the past and future time periods, it is observed that at the downstream, the rainfall decreases gradually for every time period compared to the historical period.

For all these periods, the upstream of the basin is observed to experience less rainfall than at the middle part except during 2040-59 where a part of the middle catchment also experiences similar rainfall at that at the upstream with rainfall between 381-424mm. During 2020-39, most part of the catchment will receive rainfall amount between 339-430mm. During 2060-79, 380-419mm rainfall will be experienced by most part of the basin. For the period 2080-99, 297-334mm would be the rainfall in most part of the basin. The minimum rainfall for 1960-2007, 2020-39, 2040-59, 2060-79 and 2080-99 would be 310mm, 282mm, 273mm, 237mm and 207mm respectively. The maximum rainfalls for these periods would be 628mm, 573mm, 622mm, 566mm and 544mm respectively. It is seen that minimum rainfall decreases gradually from 1960-2007 to 2080-99. The maximum rainfall on the other hand first decreases from 1960-2007 to 2020-39 and then increases again for the next time period i.e. 2040-59. It again starts decreasing from 2060-79 to 2080-99. Overall, for the months with

moderate rainfall also, the basin would experience lesser rainfall compared to the historical period.

6.3.3.4.3 Spatial variation of rainfall for the dry months

The spatial variation of rainfall that would occur over the Subansiri basin during the dry months has been analyzed for the different time steps. Fig. 6.12 shows the spatial variation maps for each different time period.

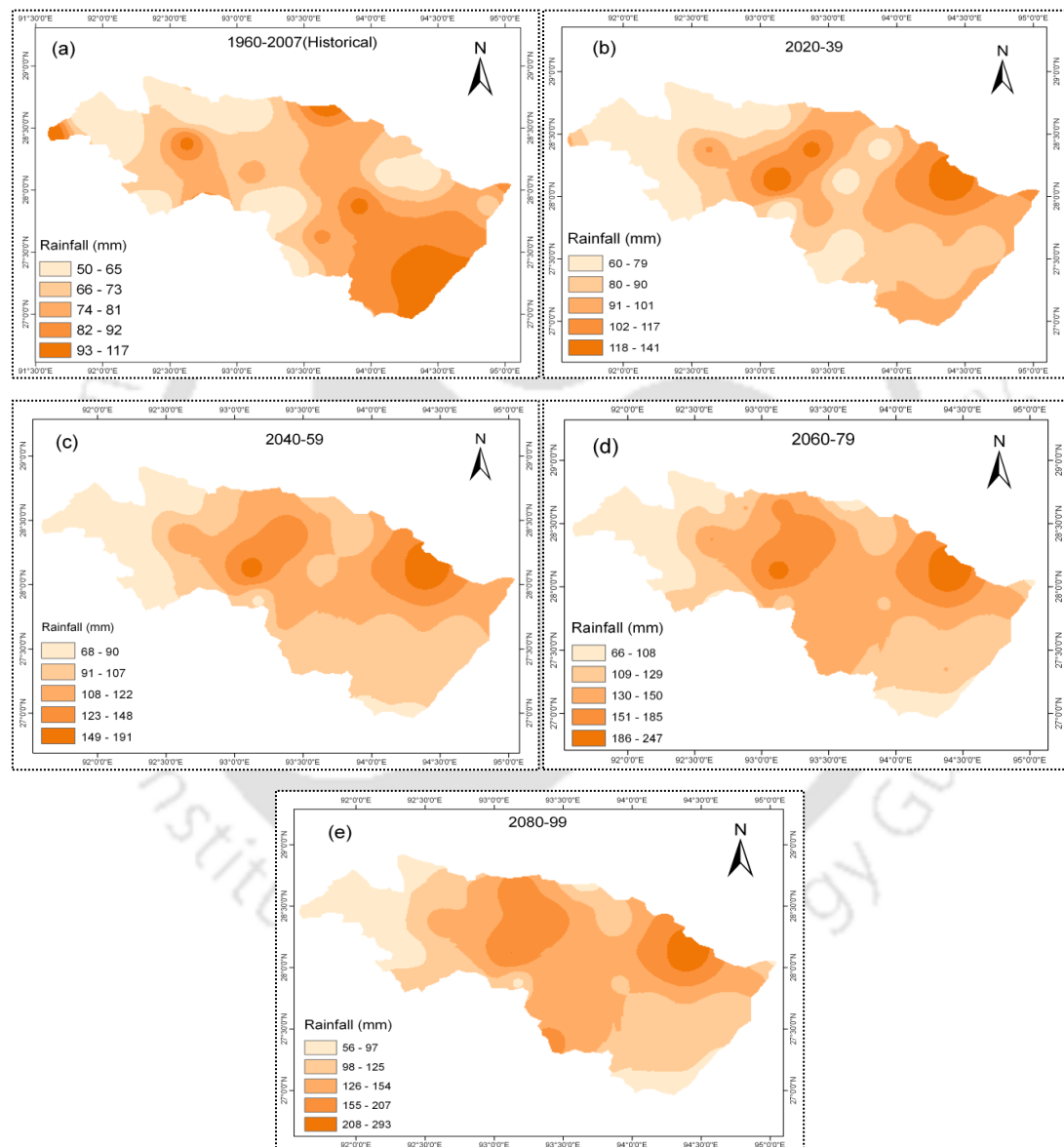


Fig.6.12: Spatial variation of rainfall over the Subansiri basin during the dry months for different time steps

For dry months, it is observed from the figure that, for all the time steps, the upstream catchment experiences the minimum rainfall. Like in case with the other months, here also the rainfall at downstream gradually decreases compared to the historical rainfall. Even

during 1960-2007, the extreme downstream had the maximum rainfall (93-117mm). During 2020-39, most parts of the catchment seem to experience 80-90mm of rainfall with some areas experiencing maximum rainfall (118-141mm). During 2040-59, 91-122mm would be the rainfall range that will be experienced by most parts of the basin. During the period 2060-79, a large portion of the area is likely to experience rainfall between 130-150mm. For 2080-99, it is seen that 126-154mm rainfall will be experienced by most parts of the basin.

The minimum rainfalls as predicted for 1960-2007, 2020-39, 2040-59, 2060-79 and 2080-99 are 50mm, 60mm, 68mm, 66mm and 56mm respectively. The maximum rainfalls for these periods would be 117mm, 141mm, 191mm, 247mm and 293mm respectively. Thus it is seen that the minimum rainfall first increases from 1960-2007 to 2040-59 and then decreases again for the next two time periods. The maximum rainfall on the other hand gradually increases from 1960-2007 to 2080-99. Therefore, it can be said that during the dry months, there is a possibility that the basin will experience more rainfall in future compared to the historical period.

6.4 Conclusions

In this study, three techniques have been used to downscale the rainfall at Subansiri river basin. These are, multiple linear and non-linear regression-based statistical downscaling techniques and downscaling by Artificial Neural Network. These methods have been applied at 24 different selected APHRODITE's rainfall points in the catchment of Subansiri river basin. The APHRODITE's rainfall has been used as the predictand and HadCM3 GCM climatic parameters as the predictors and the appropriate predictors have been selected using Pearson correlation method. Two cases were considered while performing the regression analysis. First, the climatic parameter of one HadCM3 GCM point that falls inside the study area has been considered as the predictors. Second, the weighted average values of the climatic parameters of the four HadCM3 GCM points have been considered. Both multiple linear and non-linear regression analyses were carried out for these two conditions. The forecasting ability of these models has been accessed on the basis of MAE, MSE and RMSE. It has been found that multiple non-linear regression based statistical downscaling method done by taking the weighted average values of the climatic parameters of the four GCMs outperformed linear regression based downscaling method and Artificial Neural Network model in forecasting.

Using this multiple non-linear based statistical downscaling technique, the future rainfall has been predicted up to the year 2099 for four different time steps viz. 2020-39, 2040-59, 2060-

79 and 2080-99. The average rainfall of all the APHRODITE points has been considered to study the future variation of rainfall for the different time steps. No significant change has been observed for the period 2020-39, while for the other three time steps, the rainfall show decreasing trends. The spatial variation of total rainfall over the basin has also been analyzed. It has been observed that the basin will receive less rainfall during 2080-99 compared to the other time periods.

Depending upon the amount of rainfall received by the Subansiri basin, the months were divided into wet months, months with moderate rainfall and dry months. The spatial change in rainfall pattern for all these three types of months has also been analyzed over the basin. Potential decrease of rainfall in the wet months and months with moderate rainfall and increase of rainfall in the dry months are indicated for the future rainfall pattern of the Subansiri basin.





CHAPTER 7

RUNOFF SIMULATION OF THE SUBANSIRI RIVER USING ANN MODEL AND ANN-SCS BASED HYBRID MODEL

7.1 Introduction

Runoff calculation of a river is essential owing to its effect on flood and erosion at the downstream. The actual physical processes that convert rainfall to runoff are both complex and highly variable. As such, these processes cannot be replicated mathematically with exact certainty. However, through the use of simplifying assumptions and empirical data, there are several mathematical models and equations that can simulate these processes and predict resultant runoff volumes and rates with acceptable accuracy. An empirical model is a representation of data and has no theoretical basis. A physically based model is one that has a theoretical basis and whose parameters and variables are measurable in the field (Beven, 1983). In reality, many empirical relationships are used for parameter estimation by the “physically based” models (Wilcox et al., 1990). In general, all runoff computation methods are, to some degree, mathematical expressions of the hydrologic cycle. However, most transform its cyclical character to a linear one, treating rainfall as an input and producing runoff as an output. During this transformation, each method uses mathematical approximations of the real rainfall-runoff processes to produce its estimates of runoff volume and/or rate. Each method has its own complexity, data needs, accuracy, and range of results.

It is a common problem in hydrological studies to estimate runoff from a watershed for which only precipitation records are available. An approach to solution of this problem is to compare runoff characteristics with those of watershed characteristics (Jabari et al., 2009). Watershed characteristics which may be most readily compared to estimating the volume of runoff that will result from a given amount of rainfall are soil type and cover, which includes land use.

Subansiri, being the major tributary of the river Brahmaputra has major contribution towards discharge at its confluence with the Brahmaputra. The contribution of Subansiri River is estimated to be about 10 percent of the total discharge of the river Brahmaputra at Pandu near Guwahati. The river has maximum and minimum observed discharge record of 12,024 cumec

and 188 cumec at Gerukmukh respectively. At Chauldhuwaghat, the maximum discharge is 21,230 cumec (GSI, 1977). It has an average annual runoff of 57,296 mm (Rao, 1979).

In this study, the runoff of the river Subansiri has been simulated up to the year 2099 for four different time steps viz., 2020-39, 2040-59, 2060-79 and 2080-99. Two models have been developed to simulate the runoff of Subansiri. These are,

(i) An ANN based rainfall runoff model

In this model, average rainfalls of different sub-catchments of the basin are considered as the inputs. However, rainfall alone cannot explain the runoff variance efficiently as it does not consider the effect of soil type and change in land use/land cover.

(ii) An ANN-SCS based hybrid model.

To overcome the limitations of the ANN based rainfall runoff model, an ANN-SCS based hybrid model has been developed where the SCS-CN model has been used to determine the runoffs at different sub-catchments of the Subansiri basin. The land use/land cover is an important parameter input to the SCS-CN model. The CN is estimated based on the hydrologic soil group (HSG), land use/land cover and hydrologic conditions. Thus, this hybrid model can be used for better simulation of runoff of Subasnsiri River.

7.2 Materials and Method

7.2.1 Data used

Rainfall data: The rainfall data as simulated by multiple non-linear regression based statistical downscaling method from 1990 to 2099 have been used to study its impact on runoff of Subansiri River.

Discharge data: Daily discharge data from 1990 to 2014 at Khabulighat gauge station of the river Subansiri have been collected from the Assam State Water Resources Department.

Land use/land cover data: Land use land cover maps prepared by supervised classification method from 2002 to 2012 as described in Chapter 5 have been used in the SCS model.

Soil map: The USDA National Resource Conservation Service (NRCS) soils have been used in this study. The raw soil map has been processed in Erdas Imagine and ArcGIS software for georeferencing and digitization (Fig.7.1). The entire study area has been divided into five soil types as given in Table 7.1.

Table 7.1: Soil types as per USDA NRCS and their description

Soil Type	Description
1. Alfisols	Soil high in silt size and larger particles
2. Entisols	Loamy and clayey soil
3. Vertisols	Soil with high clay content
4. Inceptisols	Very fine sand and loamy fine sand
5. Histosols	Highly porous soil

These soil types are divided into four Hydrologic Soil Groups as given in Table 7.2.

Table 7.2: Division of soil types according to Hydrologic Soil Group

Soil types	Hydrologic Soil Group
Inceptisols and Histosols	Group A
Alfisols	Group B
Vertisols	Group C
Entisols	Group D

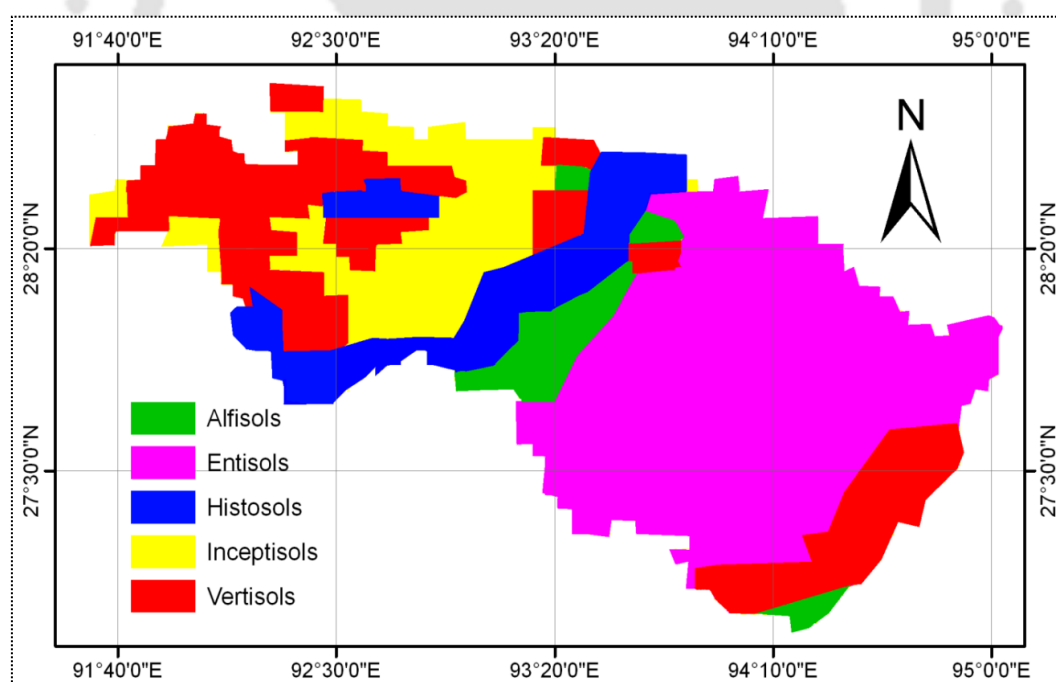


Fig.7.1: Soil map for the Subansiri River basin

7.2.2 Runoff Simulation of the Subansiri River

In this study, the runoff of Subansiri River has been simulated using two different methods:

- By developing an Artificial Neural Network based rainfall-runoff model where rainfall has been considered as the only input
- By developing an ANN-SCS based Hybrid Model

The runoff has been simulated up to the year 2099 for both the models and their efficiency has been compared on the basis of coefficient of correlation (R) values obtained while running the ANN models.

To perform the analysis, the entire Subansiri catchment has first been divided into eleven sub-catchments. The delineation of sub-catchments has been done in ILWIS software. These eleven sub-catchments have different geomorphological properties. The details of these properties are shown in Table 7.3. Fig. 7.2 shows the eleven different sub-catchments of the Subansiri basin along with the APHRODITE's rainfall points that fall in each sub-catchment. As discussed in chapter 6, the rainfall of Subansiri basin has been simulated at 24 different APHRODITE's points up to the year 2099 by non-linear regression based statistical downscaling technique. The average rainfall at each sub-catchment has been determined by considering the rainfall of the APHRODITE's points that fall in each sub-catchment. The rainfall at each sub-catchment has been analyzed for future four time steps viz., 2020-39, 2040-59, 2060-79 and 2080-99.

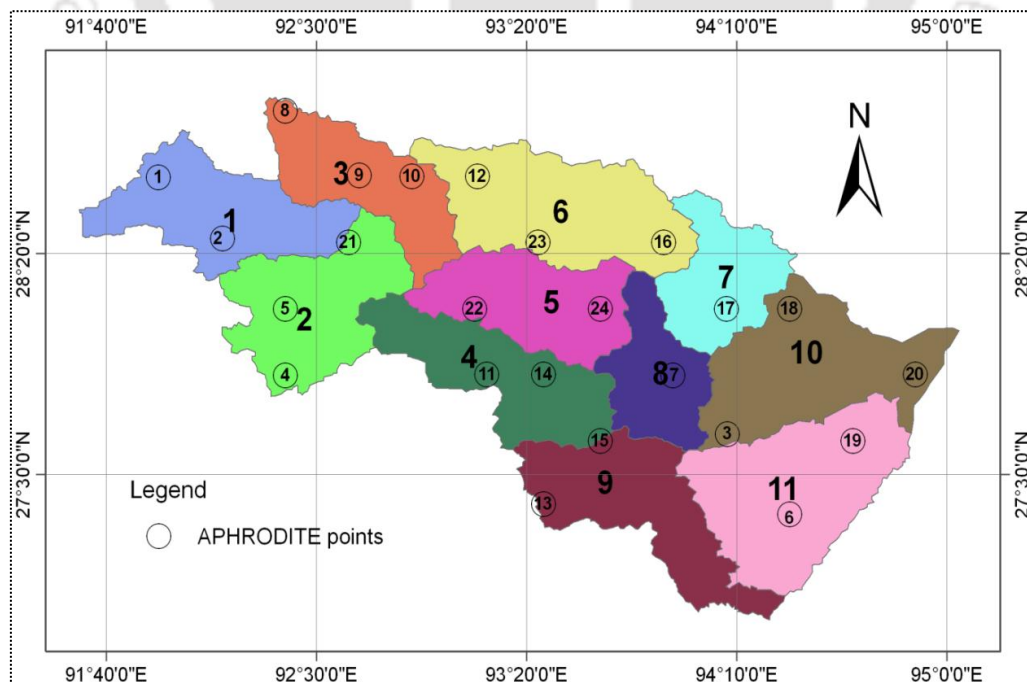


Fig.7.2: The eleven sub-catchments of the Subansiri basin delineated in ILWIS software

Table 7.3: Properties of the eleven sub-catchments of the Subansiri Basin

Sub-Catchments	Perimeter (km)	Area (km ²)	Drainage density(km/km ²)	Longest flow path length(km)
1	380.73	3123.87	0.24	134.82
2	352.83	3202.02	0.28	122.43
3	322.22	2799.04	0.27	138.94
4	368.66	2937.14	0.29	135.08
5	316.18	2734.97	0.25	115.12
6	390.47	3815.74	0.39	157.25
7	271.69	3116.62	0.38	83.33
8	267.01	2874.23	0.28	74.91
9	466.65	3240.40	0.26	166.34
10	343.40	3124.43	0.33	105.89
11	423.45	3277.73	0.24	147.75

7.2.2.1 Development of the Artificial Neural Network based rainfall-runoff model

An Artificial Neural Network Model was developed to simulate the runoff of Subansiri River at its outlet at Khabulighat. The average rainfall of the respective sub-catchments have been put as the input to the ANN model. The ANN model was run using the time series analysis and this was carried out in MATLAB. The method selected in the present study is the Non-linear Autoregressive with External (Exogenous) Input (NARX) which predicts series $y(t)$ given d past values of $y(t)$ and another series $x(t)$ (Fig.7.3). The NARX is a recurrent dynamic network, with feedback connections enclosing several layers of the network. The NARX model is based on the linear ARX model, which is commonly used in time-series modeling. NARX networks can learn to predict one time series given past values of the same time series, the feedback input, and another time series, called the external or exogenous time series.

The standard NARX network is a three-layer feedforward network, with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. This network also uses tapped delay lines to store previous values of the $x(t)$ and $y(t)$ sequences. In the present study, $y(t)$ is the runoff at the final outlet (Khabulighat) of the Subansiri catchment and $x(t)$ are the average rainfall at each sub-catchment. Mathematically, it can be defined as,

$$y(t) = f(x(t-1), \dots, x(t-d), y(t-1), \dots, y(t-d)) \quad (7.1)$$

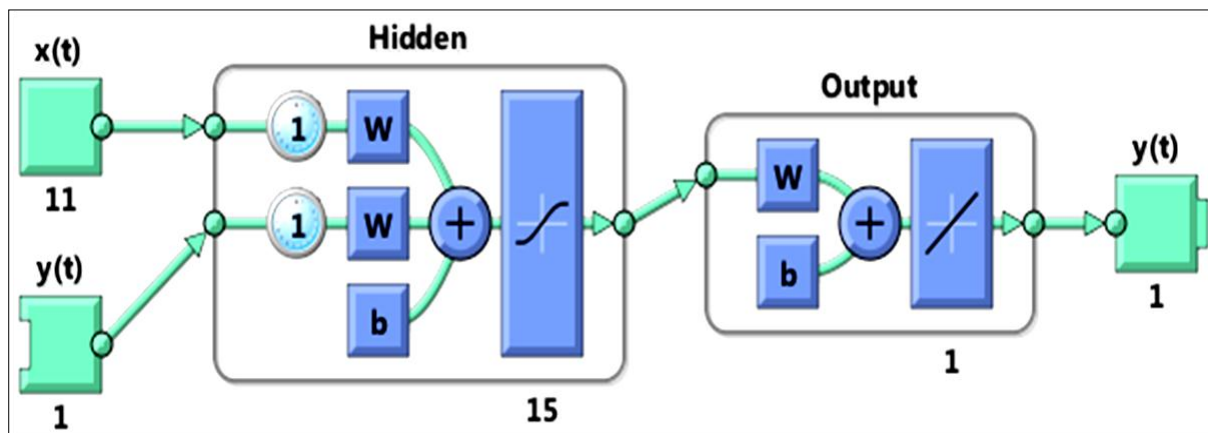


Fig. 7.3: ANN structure for rainfall-runoff model (open loop)

Prediction is a kind of dynamic filtering, in which past values of one or more time series are used to predict future values. Dynamic neural networks, which include tapped delay lines are used for non-linear filtering and prediction. There are three kinds of target time-steps: (i) Training time steps which are presented to the network during training, and the network is adjusted according to its error, (ii) Validation time steps which are used to measure network generalization, and to halt training when generalization stops improving and (iii) Testing time steps that have no effect on training and so provide an independent measure of network performance during and after training. In the present study, testing, training and validation were performed for the period 1990 to 2014 (up to which the observed discharge data are available). Out of the total data, 70% were selected for training and 15% each for validation and testing. The number of hidden neurons selected was 15 and the number of delays selected was 1. The network was created and trained in open loop form. Open loop (single-step) is more efficient than closed loop (multi-step) training. Open loop allows to supply the network with correct past outputs as it is trained to produce the correct current outputs. After training, the network was converted to closed loop form for multi-step prediction up to 2099. Close loop converts neural network open-loop feedback to closed loop. Fig.7.4 shows the NARX neural structure for closed loop. The *preparets* function available in MATLAB is used to prepare the input and target time series data for network simulation or training. This function simplifies the normally complex and error prone task of reformatting input and target time series. It automatically shifts input and target time series in as many steps as are needed to fill the initial input and layer delay states.

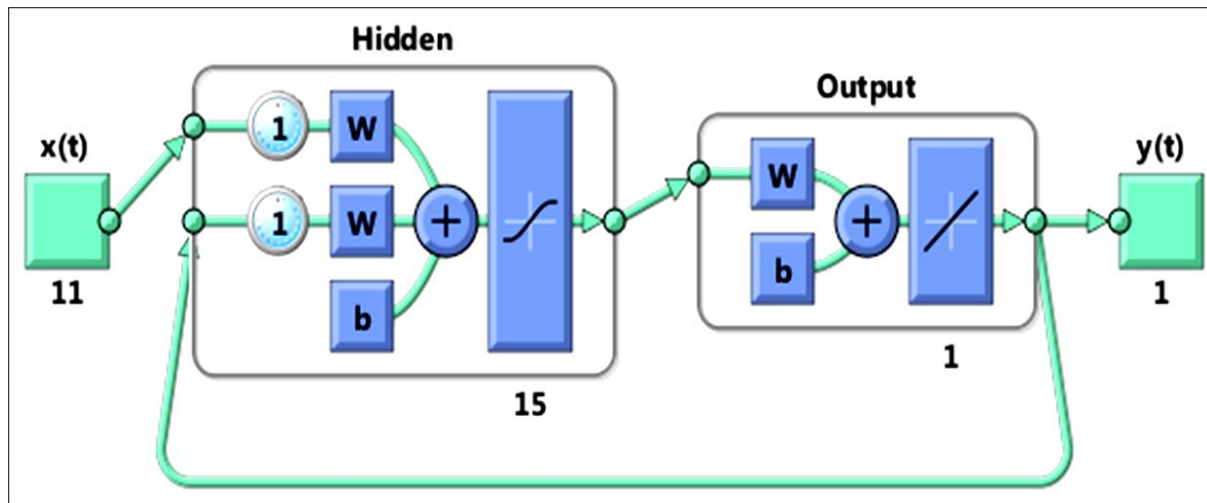


Fig. 7.4: NARX neural network (closed loop)

Here, in this study, the monthly future runoff has been predicted for four different time steps viz., 2020-2039, 2040-2059, 2060-2079 and 2080-2099 by taking 1990-2014 runoff as the base period.

7.2.2.3 Development of an ANN-SCS based Hybrid Model

In the ANN based rainfall-runoff model described above, the only input considered was the average rainfall over each sub-catchment of the Subansiri basin. In order to increase the efficiency of the model and to make the simulated runoff more accurate, an attempt has been made to develop a hybrid model. This hybrid model is based on Artificial Neural Network model and SCS-CN model. The SCS approach involves the use of simple empirical formulae and readily available tables and curves. The empirical equation requires rainfall and a watershed coefficient as inputs. The watershed coefficient is called the curve number (CN), which is an index that represents the combination of hydrologic soil group and land use and land treatment classes. The model involves relationships between land cover, hydrologic soil group and curve number.

The advances in Remote Sensing (RS) and Geographical Information System (GIS) Technologies have led to their widespread use in studies based on the improvement of hydrology and water resources. Nowadays, different land uses and land covers can be determined with the help of satellite images and the data derived can be easily used in hydrological studies focusing on runoff calculations and thus these provide useful input support for SCS model.

In this study, runoff curve numbers were determined using remote sensing and GIS technique. SCS-CN model in ILWIS GIS platform has been applied to estimate variations in

runoff during significant rainfall events for each sub-catchment of the Subansiri River basin starting from 1990 to 2099. These runoffs of the eleven sub-catchments were then used as the input to the ANN model and the runoff of the Subansiri at final outlet has been simulated.

7.2.2.3.1 Soil Conservation Service Curve Number Model

Amongst the various models, ranging from complex to simple, Soil Conservation Services (SCS) Model is widely used for estimating runoff on small to medium sized ungauged drainage basins which has now been named as NRCS-CN (Natural Resources Conservation Service-CN) method. The runoff curve number method for the estimation of direct runoff from storm rainfall is well established in hydrologic engineering and environmental impact analysis (Ponce and Hawkins, 1996). The method was developed in 1954 by the USDA Soil Conservation Service (Rallison, 1980) and is described in the Soil Conservation Service (SCS) National Engineering Handbook section 4: Hydrology (NEH 4) (SCS, 1985). The CN method continues to be updated and amended with increasing data and research (Mishra and Singh, 1999; Jain et al., 2006), as well as innovative applications such as water quality modeling (Mishra and Singh, 2003) and continuous simulations (Williams and LaSeur 1976; Arnold et al., 1993). Many researchers have demonstrated from rainfall and runoff data that its key parameter CN has variable components and is not a constant for a watershed and varies with rainfall (McCuen, 2002; Hjelmfelt et al., 1982). Ponce and Hawkins (1996) pointed out the main advantages of the SCS-CN model. These are, (i) its simplicity; (ii) its predictability; (iii) its stability; (iv) its reliance on only one parameter; and (v) its responsiveness to major runoff-producing watershed properties. The main drawbacks of SCS-CN method as described by some researchers (Michel et al., 2005; Hawkins, 1993; McCuen, 2002) include (i) it does not consider the impact of rainfall intensity; (ii) it does not address the effects of spatial scale, (iii) it is highly sensitive to changes in values of its single parameter CN and (iv) it is ambiguous considering the effect of antecedent moisture conditions.

7.2.2.3.1.1 Theory of SCS Model

The SCS-CN method is based on the principle of water balance and the following two hypotheses:

- i) The ratio of direct runoff to potential maximum runoff is equal to the ratio of infiltration to potential maximum retention.
- ii) The initial abstraction is proportional to the potential maximum retention.

The water balance equation and the two hypotheses are expressed mathematically respectively as:

$$P = I_a + F + Q \quad (7.2)$$

$$\frac{Q}{P - I_a} = \frac{F}{S} \quad (7.3)$$

$$I_a = \lambda S \quad (7.4)$$

where, P is the total precipitation (mm), I_a is the initial abstraction before runoff (mm), F is the cumulative infiltration after runoff begins (mm), Q is direct runoff (mm), S is the potential maximum retention (mm), and λ is the initial abstraction (ratio) coefficient.

The general runoff equation is the combination of Equation (7.2) and Equation (7.3) by taking $\lambda=0.2$ is shown in Equation (7.5):

$$Q = \frac{(P - I_a)^2}{\{(P - I_a) + S\}} \text{ for } P > 0.2S \quad (7.5)$$

= 0, otherwise.

The potential maximum retention, S (mm) can vary between 0 to ∞ and is directly linked to CN (Curve Number).

$$S = \frac{25400}{CN} - 254 \quad (7.6)$$

The CN depends on land use, hydrologic soil group, hydrologic condition, antecedent moisture condition (AMC) and it can vary from 0 to 100. CN equals to 100 represents a condition of zero potential retention ($S=0$), that is an impermeable watershed and CN equals to 0 a theoretical upper bound to the potential retention ($S=\infty$), which is an infinitely abstracting watershed. While it is theoretically possible for the curve numbers to span the range 0-100, practical design values validated by experience are more likely to be in the range 40-98, with few exceptions (Van Mullem, 1989). This is a significant advantage, because it restricts the method's only parameter to a relatively narrow range.

Antecedent Moisture Condition (AMC) is an indicator of watershed wetness and availability of soil moisture storage prior to a storm, and can have a significant effect on runoff volume. Recognizing its significance, SCS developed a guideline for adjusting CN according to AMC based on total rainfall in the 5-day period preceding a storm. Three levels of AMC are used in the CN method: AMC-I for dry, AMC-II for normal and AMC-III for wet conditions (Table 7.4).

Table 7.4: Classification of Antecedent Moisture Conditions

AMC	AMC(Dormant) (mm)	AMC(Growing) (mm)	Condition
I	<12.5	<35	Dry soil but not the wilting point.
II	12.5-27.5	35-52.5	Average conditions
III	>27.5	>52.5	Saturated soils

Higher amount of antecedent moisture and CN value would indicate high runoff and vice versa. Apart from the AMC condition, much of the variability of CN has been attributed to soils in a way that soils that are wetter have a higher curve number, creating more runoff for a given amount of precipitation, than soils that are drier (Streenhuis et al., 1995; Soulis et al., 2009; Huang et al., 2007).

Hydrologically soils are assigned into four groups on the basis of intake of water on bare soil when thoroughly wetted (Table 7.5). The Hydrologic Soil Group classification can be based on texture of distributed soil.

Table 7.5: Hydrologic Soil Group

Hydrologic Soil Group	Infiltration Rate (mm/hr)		Soil Texture
A	High	>25	Sand, Loamy Sand, or Sandy Loam
B	Moderate	12.5-25	Silt Loam or Loam
C	Low	2.5-12.5	Sandy Clay Loam
D	Very low	<2.5	Clay Loam, Silty Clay, Sandy Clay, Silty Clay or Clay

The CN values corresponding to the catchment soil types, land cover and land management conditions can be selected from NEH-4 tables. The CN value of AMCI(CNI) was provided by the SCS CN manual and the CN value of AMC II (CNII) and CN value of AMC III (CNIII) can be calculated by applying the following equations (USDA, 1985):

$$CNI = \frac{(4.2 \times CNII)}{\{10 - (0.058 \times CNII)\}} \quad (7.7)$$

$$CNIII = \frac{(23 \times CNII)}{\{10 + (0.13 \times CNII)\}} \quad (7.8)$$

The flowchart for detailed methodology of SCS-CN method is shown in Fig. 7.5.

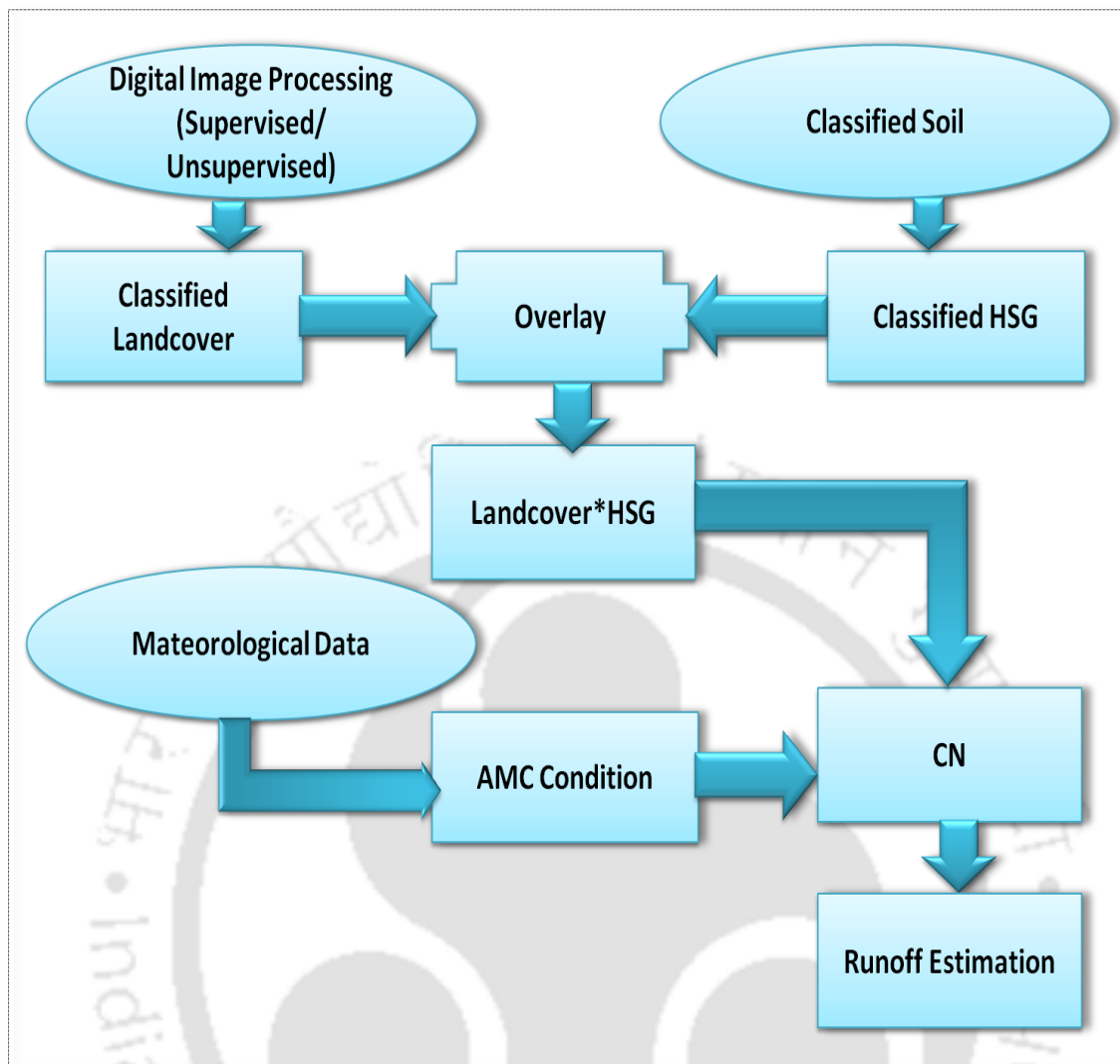


Fig.7.5: Methodology for surface runoff estimation (SCS Model)

The various input parameters required for SCS model for runoff estimation have been derived in GIS environment in raster module. The land use/land cover map and the Hydrologic Soil Group maps are combined using the curve number table into a curve number map. By integrating all the GIS layers with the meteorological data, runoff has been computed for each sub-catchment of the Subansiri basin.

7.2.2.3.2 Calculation of Curve Numbers

The key component of the NRCS runoff equation is the NRCS Curve Number (CN), which is based on soil permeability, surface cover, hydrologic condition, and antecedent moisture. As discussed in Chapter 5, the land use/land cover (LULC) maps for the Subansiri River basin have been prepared from 2002 to 2012 by supervised classification method. The average Curve Numbers (CN) for these eleven years were calculated on the basis of land use/cover type and hydrologic soil class for each sub-catchment. Appropriate CN values corresponding

to AMC-II have been assigned to each polygon obtained from cross map between land use and soil maps in ILWIS GIS software. The average CN number of the watershed obtained from the histogram of CNMAP was considered as the CN-II for the entire watershed. The CN-I and CN-III have then been calculated using equations (7.7) and (7.8) respectively. S1, S2 and S3 values were calculated using Eq. (7.6). By applying the AMC conditions, the curve numbers have been calculated for each sub-catchment. CN-I was obtained for January, February, March, November and December, CN-II was obtained for the months of April, September and October while CN-III was obtained for May, June, July and August.

7.2.2.3.3 Creation of different land use/land cover scenarios

The parameter defined by land use allows the user to experiment with alternative forms of land development and management and to assess the impact of the proposed changes. The change of land use has had a considerable impact on the runoff characteristics and related hydrological processes.

To assess the effect of change in land use/land cover on the flow scenario of the river Subansiri, three different land use/land cover scenarios have been created for the Subansiri basin. As discussed in Chapter 5, the dense vegetation and snow cover area over the basin had decreased during 2002 to 2012. On the other hand light vegetation and bare soil had increased during this period. On the basis of these changes, further changes on the LULC categories have been incorporated to create the following LULC scenarios.

Scenario 1

Under this scenario, it has been assumed that the land use/land cover conditions of the year 2012 will not change in the future and will remain constant up to the year 2099. In other words, the CNII value of 2012 has been assumed to be constant in the future and runoff for each sub-catchment has been calculated accordingly.

Scenario 2

Under this scenario, four different sub-scenarios have been created to determine the future runoff. These four sub-scenarios were for four different time steps viz. 2020-2039, 2040-2059, 2060-2079 and 2080-2099.

Sub-scenario 1: Bare land over clayey soil, dense vegetation over very fine sand and snow cover area over fine sand is reduced which was assumed to be covered by light vegetation and surface water bodies for the period 2020-2039.

Sub-scenario2: Under this scenario, further reductions have been made in bare land, dense vegetation and snow cover area over soil with high clay and silt content for the period 2040-2059. These were then assumed to be covered by light vegetation and surface water bodies.

Sub-scenario3: Under this scenario, it is assumed that area covered by light vegetation over very fine sand is reduced resulting in the formation of bare land for the period 2060-2079.

Sub-scenario4: For the period 2080-99, in addition to the assumptions made in the previous sub-scenarios, it was assumed that due to melting of snow, which is the result of global warming, the snow cover area over the region would be reduced more which in turn will result in the increase in surface water bodies.

Scenario3

Under this scenario too four different sub-scenarios have been created. The LULC conditions applied are same as those for the sub-scenarios of the Scenario 2. The difference is that in Scenario 2, each sub-scenario was for the different time periods, and here in Scenario 3 it has been assumed that these four different LULC conditions would remain constants for the period 2020-99.

The runoff from each of the eleven sub-catchments were determined using SCS- Curve Number method for each of the aforementioned land use/land cover scenarios up to the year 2099. These calculated eleven different runoffs were put in the ANN model as the inputs. Observed runoff data at Khabulighat is available from 1990 to 2014, which has been used as the output to the ANN model. The CNII value obtained for the year 2002 has been considered to be constant from 1990 to 2002 and accordingly the runoff was determined for this period. Future four sets of runoff values have been predicted viz. 2020-2039, 2040-2059, 2060-2079 and 2080-2099. The assumed different land use/land cover scenarios are tabulated in table 7.6.

Table7.6: Different land use/land cover scenarios created

Scenario1	Scenario2				Scenario3			
	S ₂₁	S ₂₂	S ₂₃	S ₂₄	S ₃₁	S ₃₂	S ₃₃	S ₃₄
No change in land use/land cover has been assumed from 2012 to 2099.	2020-39	2040-59	2060-79	2080-99	S ₂₁ conditions are kept constant from 2020-2099.	S ₂₂ conditions are kept constant from 2020-2099.	S ₂₃ conditions are kept constant from 2020-2099.	S ₂₄ conditions are kept constant from 2020-2099.
	Area covered by BS, DV, SCA is reduced and filled up with LV and SWB.	In addition to S ₂₁ , BS, DV and SCA is reduced more and were assumed to be covered by LV and SWB	In addition to condition S ₂₂ , the LV is reduced and was assumed to be covered by BS.	SCA is reduced more and SWB has been increased				

BS: Bare soil; DV: Dense vegetation; LV: Light vegetation; SWB: Surface water body; SCA: Snow cover area

S₂₁, S₂₂, S₂₃, S₂₄: Sub-scenarios 1, 2, 3 and 4 respectively under scenario2

S₃₁, S₃₂, S₃₃, S₃₄: Sub-scenarios 1, 2, 3 and 4 respectively under scenario3

As described in section 7.2.2.2, in this hybrid model also, the ANN model was run using the time series analysis and the method selected is the Non-linear Autoregressive with External (Exogenous) Input (NARX). NARX predicts series $y(t)$ given d past values of $y(t)$ and another series $x(t)$. In this case, $y(t)$ represents the runoff of Subansiri at final outlet while $x(t)$ represents the runoffs at each of the eleven sub-catchments of the Subansiri basin. The overall methodology to simulate future runoff at Khabulighat by the two different models is shown in Fig.7.6 below.

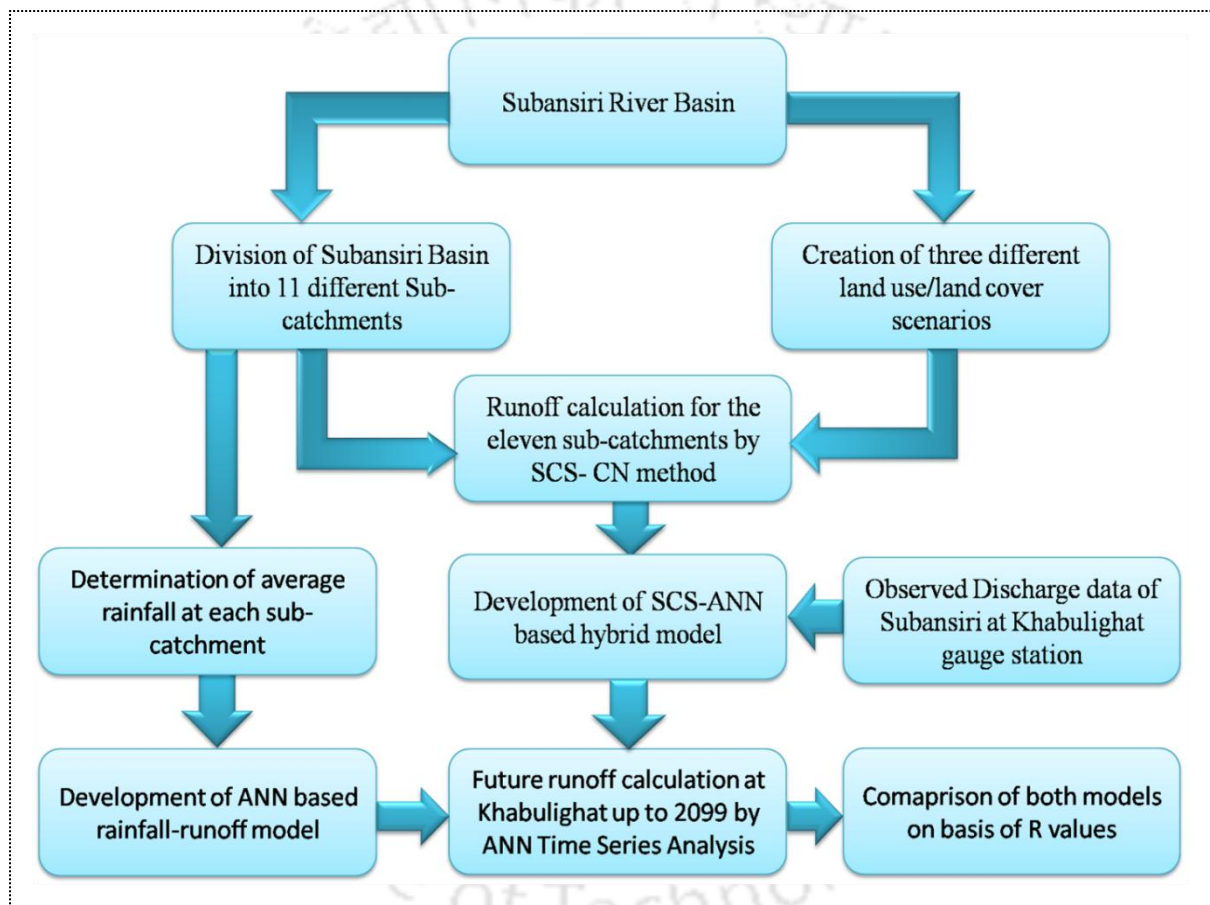


Fig.7.6: Flowchart showing the methodology adopted to simulate future runoff

7.3 Results and Discussions

7.3.1 Sub-catchment wise rainfall analysis for each time step

The changes in rainfall in each sub-catchment for the different time steps have been analyzed. The future trends obtained for different sub-catchments for the period 2020-39 are shown in Fig. 7.7.

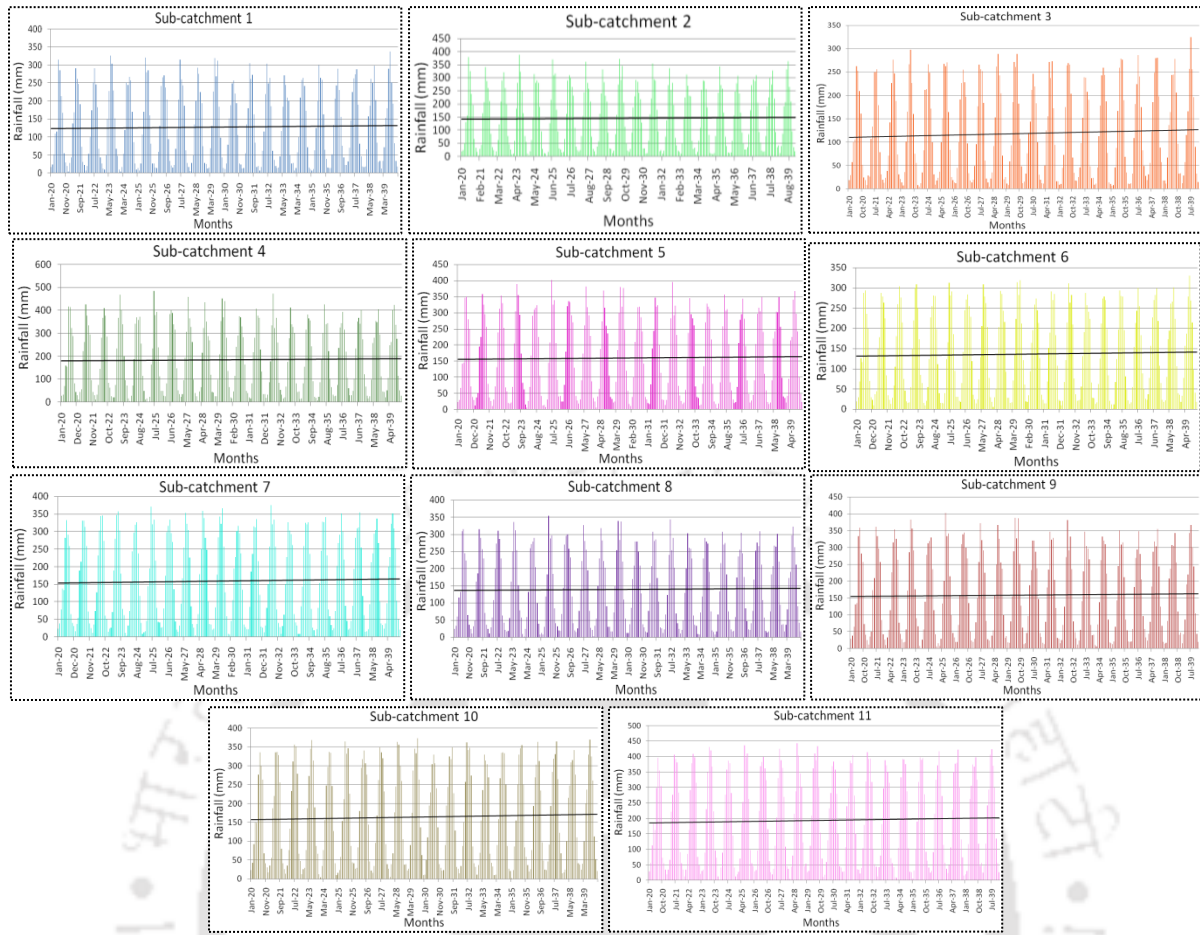
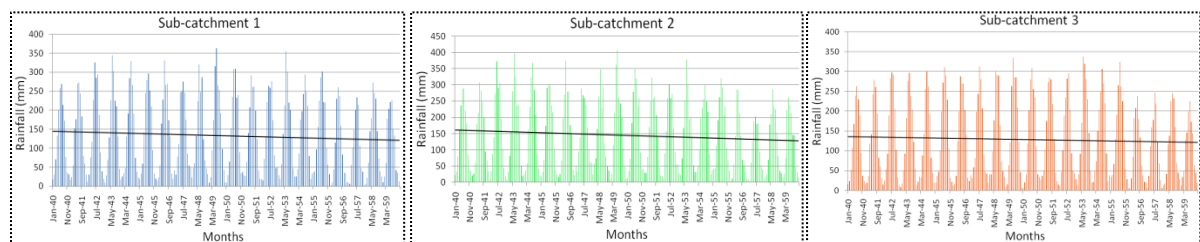


Fig. 7.7: Sub-catchment wise changes in rainfall trends for the period 2020-39

It is observed from the Fig. 7.7 that during 2020-39, there is either an increasing trend of rainfall or the rainfall remains almost the same for the different sub-catchments. For the sub-catchments 1, 4 and 9, the rainfall will remain the same, whereas for the other sub-catchments there is a possibility that rainfall will slightly increase during this time period.

The future trends obtained for different sub-catchments for the period 2040-59 are shown in Fig. 7.8. Unlike the period 2020-39, the rainfall shows decreasing trend for each of the sub-catchments during the period 2040-59. However, for the sub-catchments 3, 6 and 11, the decrease in rainfall is almost negligible.



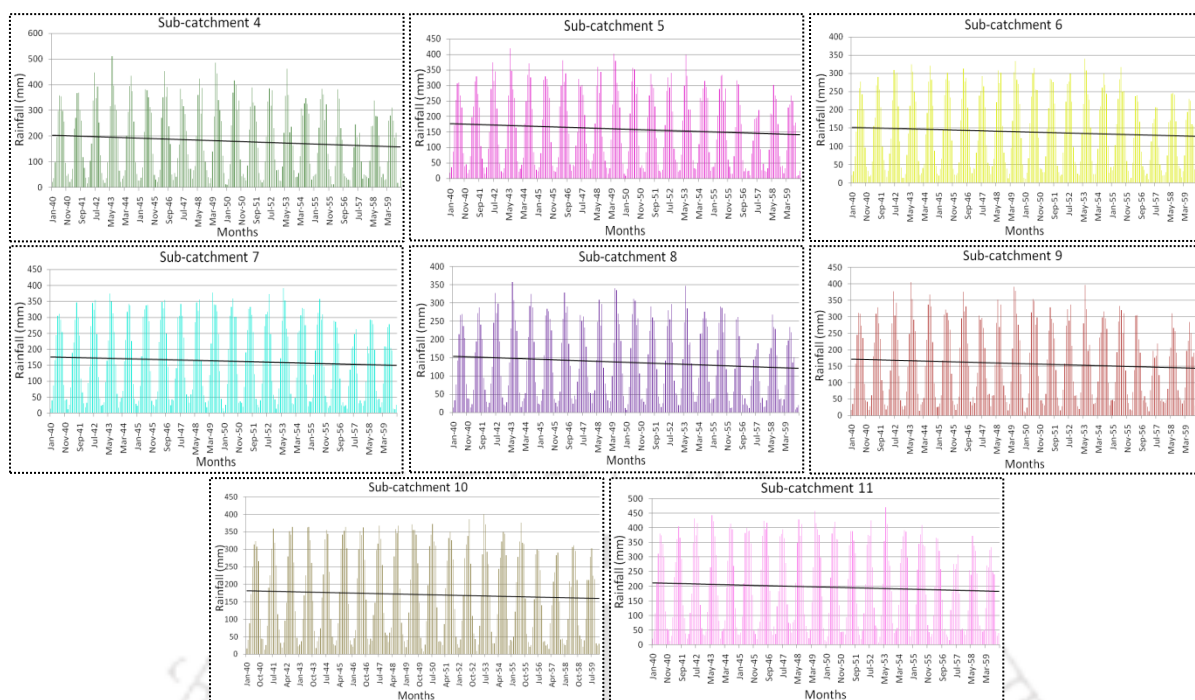
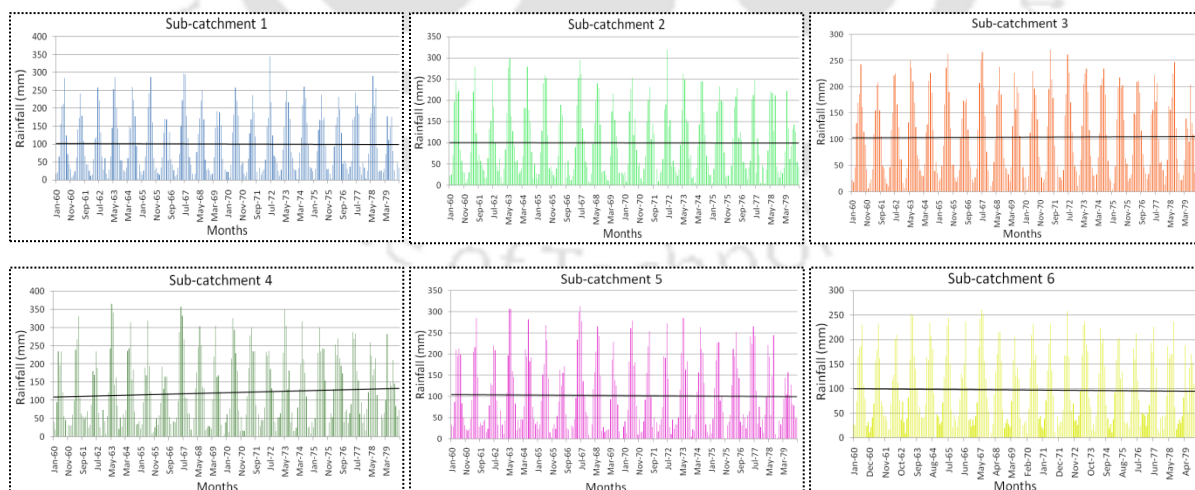


Fig. 7.8: Sub-catchment wise changes in rainfall trends for the period 2040-59

The future trends obtained for different sub-catchments for the period 2060-79 are shown in Fig. 7.9. Both increasing and decreasing trends of rainfall are observed during the period 2060-79 for the different sub-catchments. For the sub-catchments 1, 2, 3, 5, 6, 9 and 11, the rainfall does not show any significant variation. Increasing trends of rainfall are observed in sub-catchments 4 and 8, whereas, rainfall shows decreasing trends for the sub-catchments 7 and 10.



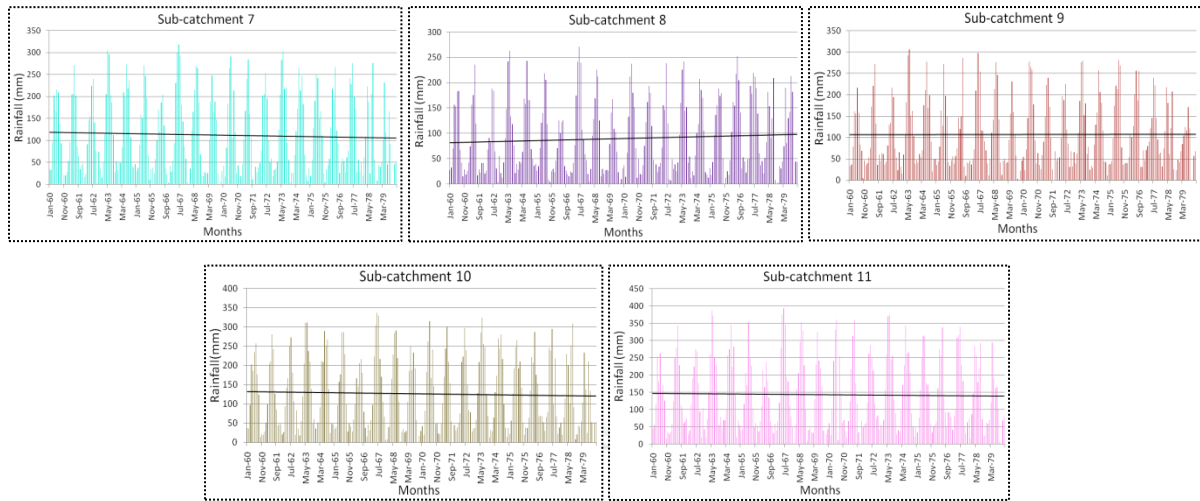


Fig. 7.9: Sub-catchment wise changes in rainfall trends for the period 2060-79

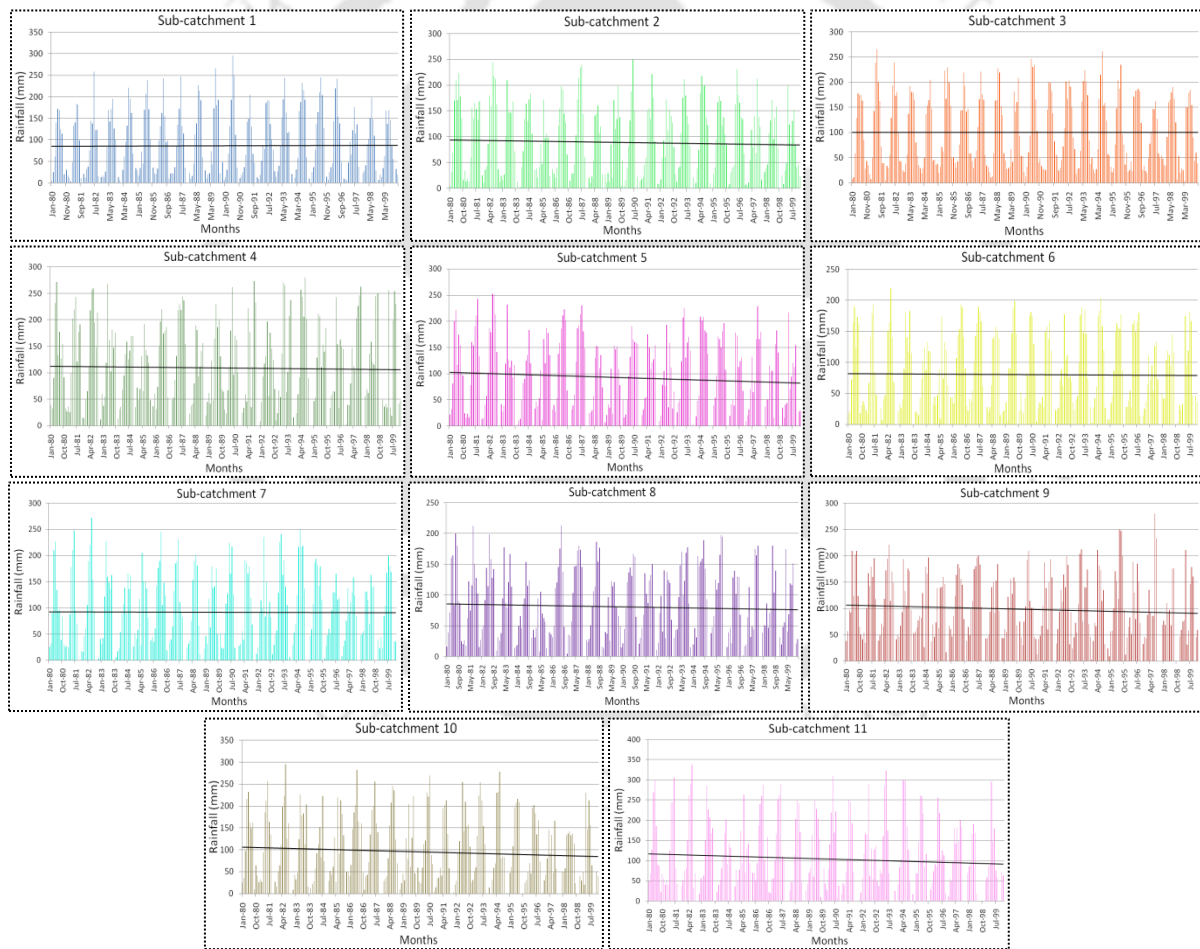


Fig. 7.10: Sub-catchment wise changes in rainfall trends for the period 2080-99

While analyzing the rainfall trends for the time period 2080-99, it has been observed that the rainfall during this period, either remains unchanged or decreases for the different sub-

catchments. No significant change of rainfall is observed for the sub-catchments 1, 3 and 7. For rest of the sub-catchments the rainfall shows decreasing trends during 2080-99.

The future trends of rainfall for each sub-catchment have also been analyzed for the entire period from 2020-99 for each sub-catchment. Fig. 7.11 shows the future trends of Subansiri basin at the eleven sub-catchments for 2020-99.

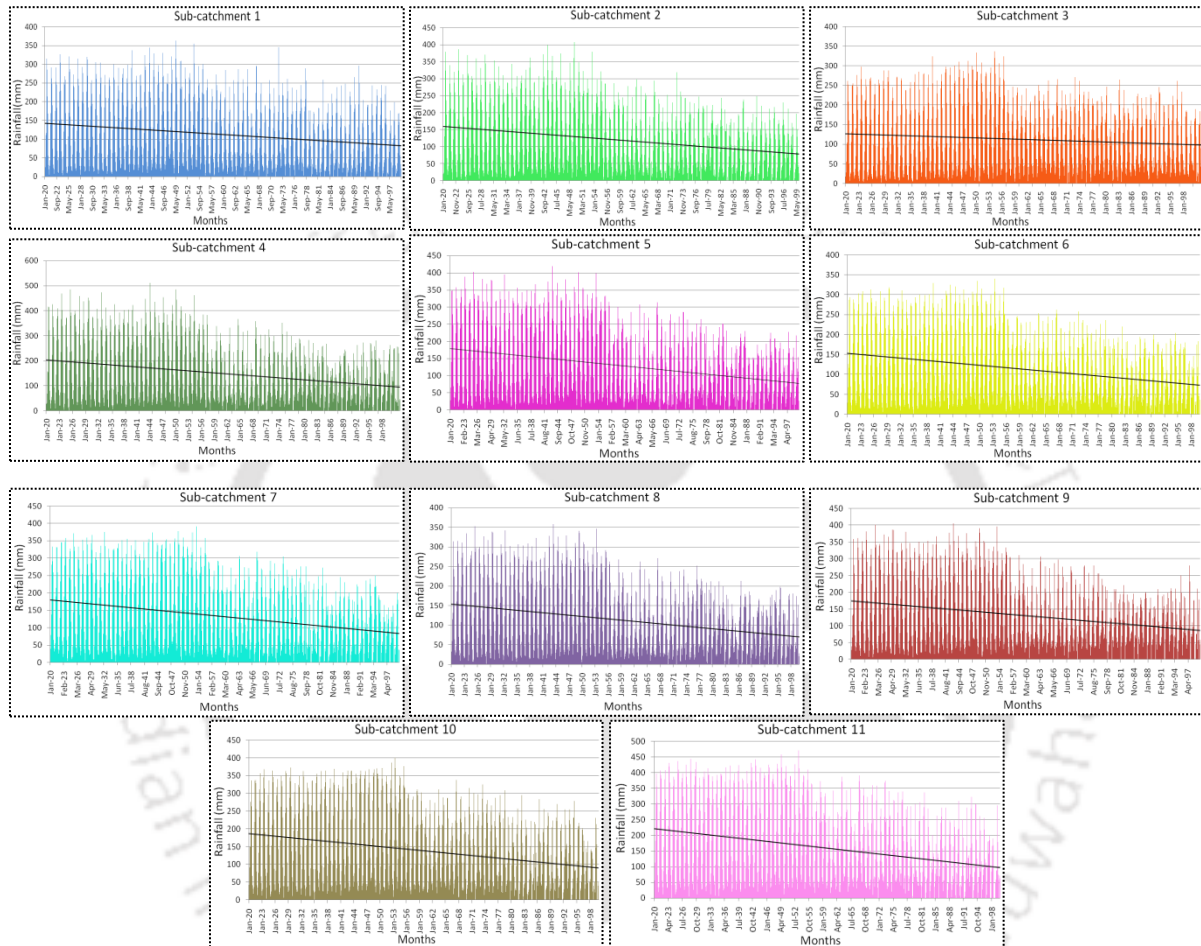


Fig. 7.11 Trends showing future rainfall from 2020-99 at different sub-catchments of the Subansiri basin

The linear trend plotted for each sub-catchment reveals that there will be a decrease in rainfall at each of the eleven sub-catchments of the Subansiri basin from 2020 to 2099. However, it is seen that for the sub-catchment 3, the decrease in rainfall during this period is not significant. As a whole, the entire Subansiri catchment thus will experience less rainfall from 2020 to 2099 which is mainly due to change in climate.

7.3.2 Runoff analysis for ANN based rainfall-runoff model

The ANN model run by considering the average rainfall at each sub-catchment as the input has been analyzed for future four different time steps viz., 2020-39, 2040-59, 2060-79 and 2080-99. Fig.7.8 gives the regression plot for the study.

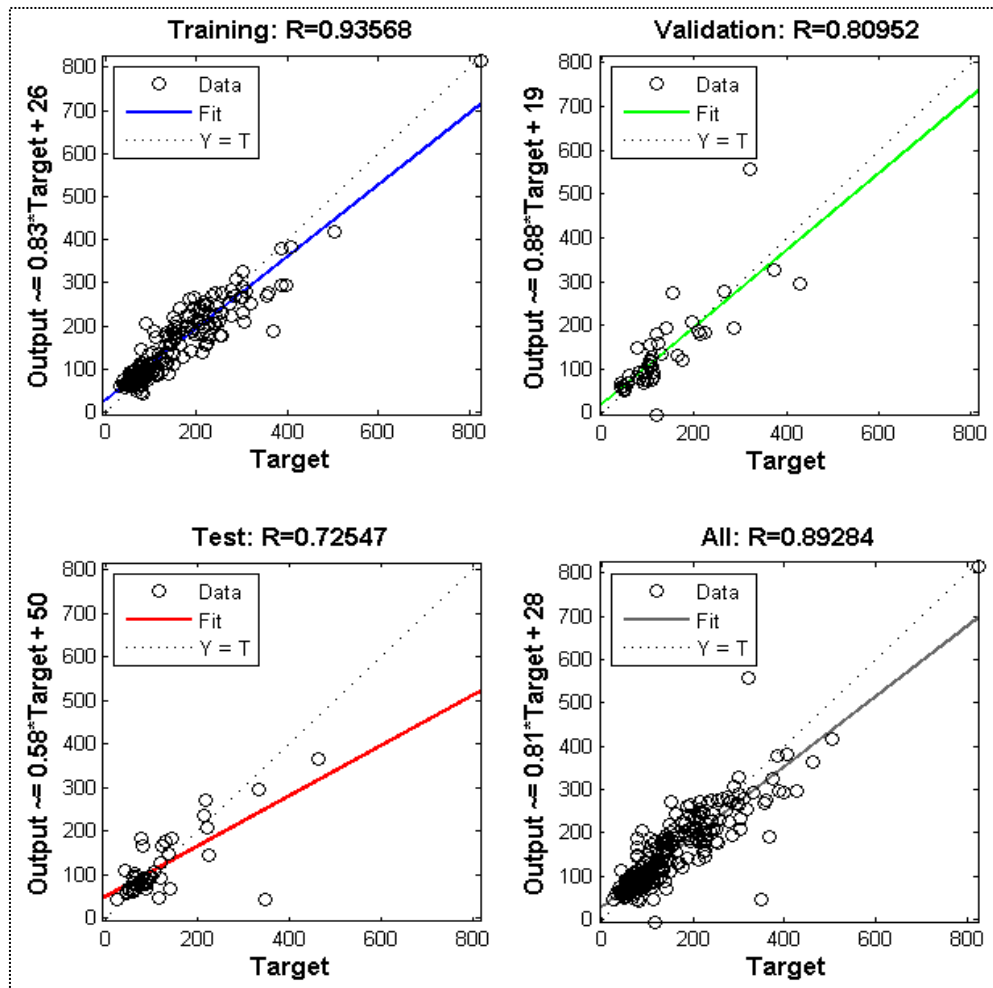


Fig.7.12: Regression plot for ANN based rainfall-runoff model

The coefficient of correlation (R) values obtained are 0.94, 0.81 and 0.73 respectively for training, validation and testing phase. Though the 0.73 value of R for testing phase is not satisfactory, yet the overall R value obtained as 0.89 shows a good correlation between observed and the simulated data. This depicts that the model can be used efficiently for runoff simulation.

The future runoff predicted from this model is shown in bar diagram in Fig.7.13.

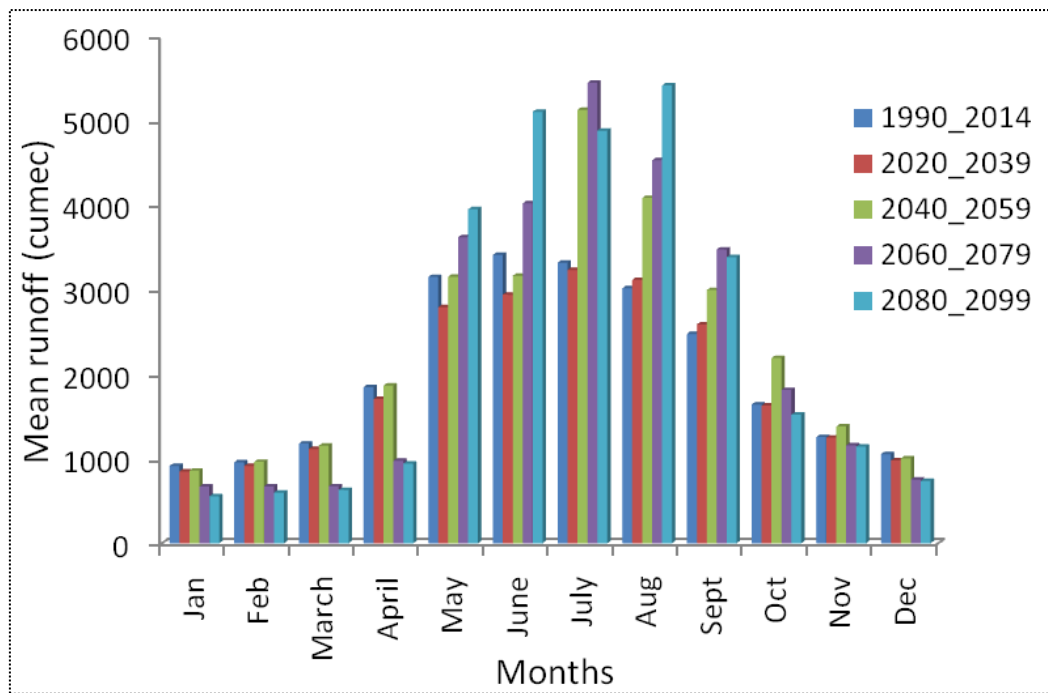
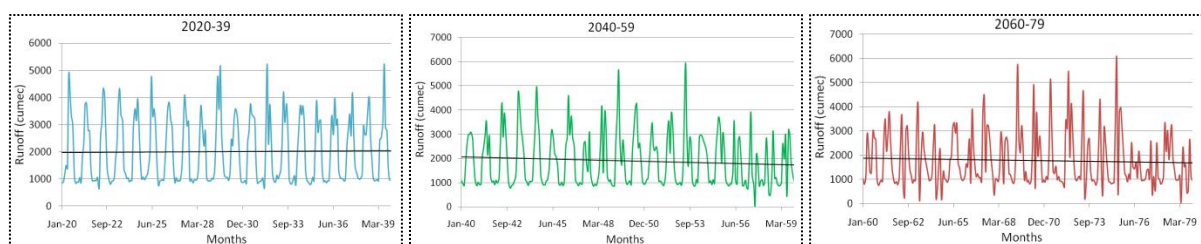


Fig.7.13: Bar diagrams representing the runoff of Subansiri river for different time steps as obtained from ANN based rainfall-runoff model

It has been observed from the result that except for August and September, for the other ten months, the runoff for the time step 2020-39 decreases compared to the runoff for the period 1990-2014. Again, compared to 2020-39, the runoff first increases for 2040-59 and then decreases from 2060 to 2099 for the months of January, February, March, April, October, November and December. On the other hand, for May, June and August it has been observed that runoff continuously increases from 2020-39 to 2080-99. For September, rainfall first increases from 2020-39 to 2060-79 and then decreases for 2080-99. There are possibility of occurrence of 5000-6000 cumec of runoff during 2060-79 and 2080-99 for June, July and August.

The linear trends of future runoff have been analyzed for the four different time periods and for the entire period from 2020-99. The trends are shown in Fig. 7.14.



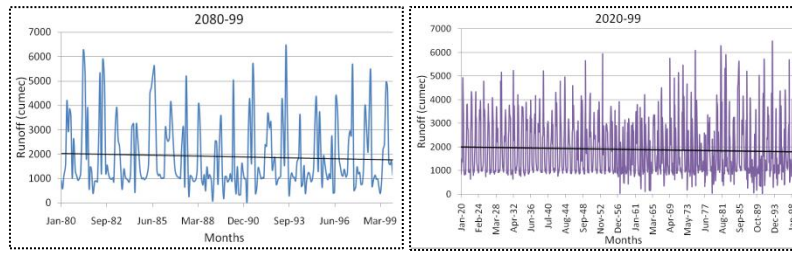


Fig. 7.14: Trends showing future runoff simulated by ANN based rainfall-runoff model for different time periods

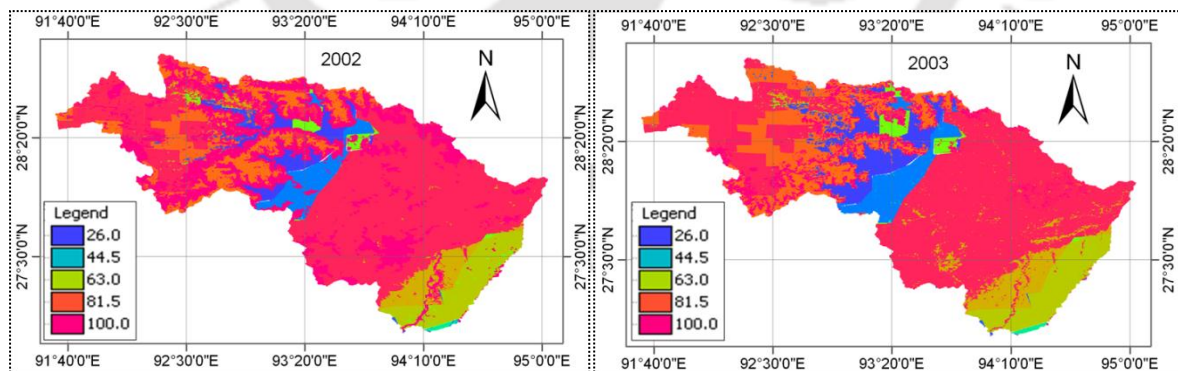
It is seen from the plots that no significant change in runoff will occur during 2020-39. However, for other three time periods, the runoff shows decreasing trends. Decreasing trend of future runoff is also observed for the entire period from 2020-99. It is due to the fact that the rainfall during these time periods also showed decreasing trend as discussed in chapter 6 (Fig. 6.8). Thus, it implies that less the rainfall, less will be the runoff and vice versa.

7.3.3 Runoff analysis by ANN-SCS based hybrid model

Considering three different land use/land cover scenarios, the runoff of the Subansiri River has been determined using an ANN-SCS based hybrid model.

7.3.3.1 Curve numbers for different sub-catchments

The curve number maps were prepared in ILWIS GIS software to determine the CNII values. The maps have been prepared for the Subansiri basin from 2002 to 2012 as shown in Fig.7.15.



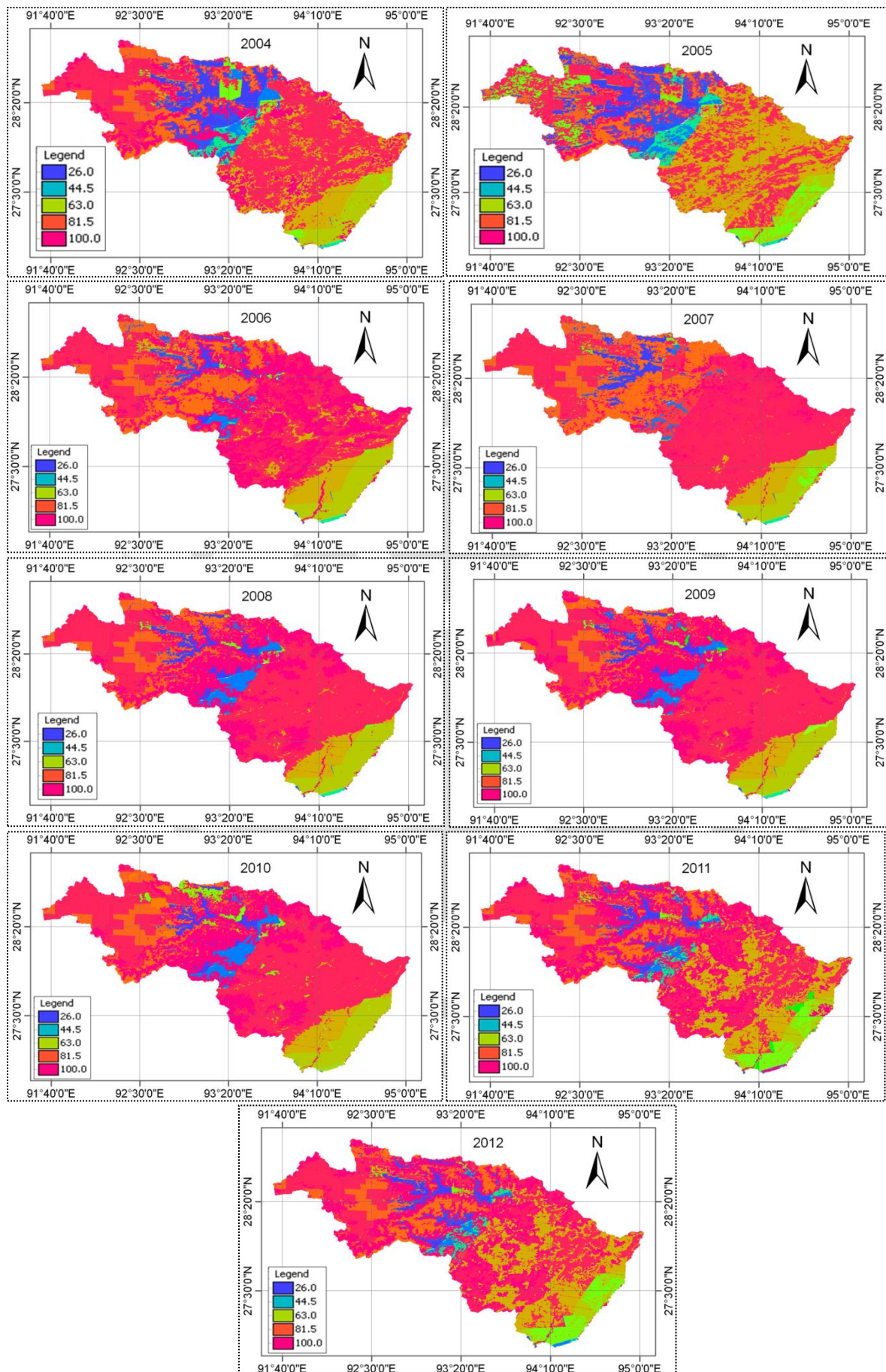
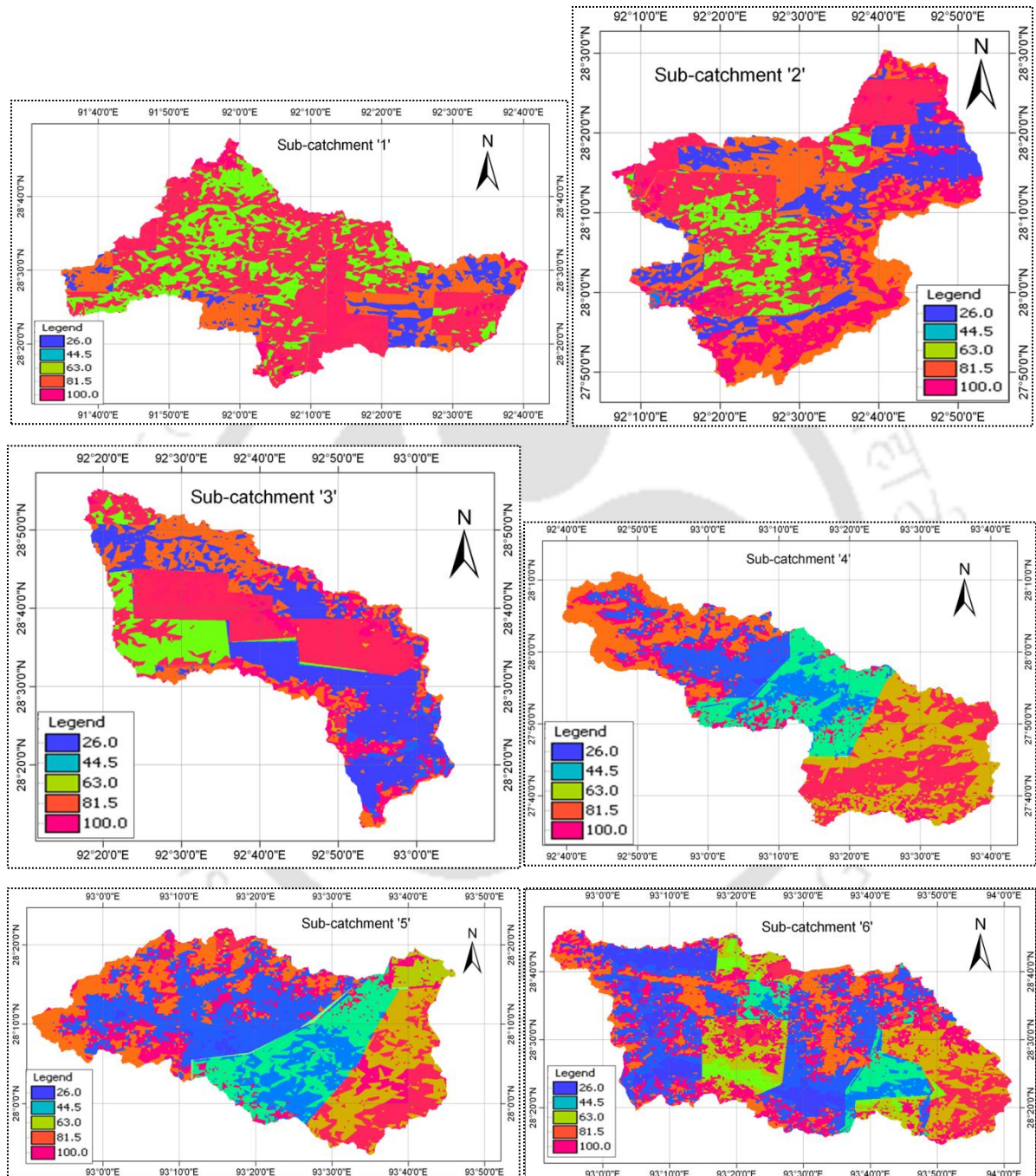


Fig.7.15: Curve number maps of the Subansiri Basin from 2002 to 2012

From these CN maps of the entire Subansiri basin, the CN maps of eleven different sub-catchments have been prepared for each of the year from 2002 to 2012. As an example, Fig.7.16 shows the CN maps prepared for each sub-catchment for the year 2005.



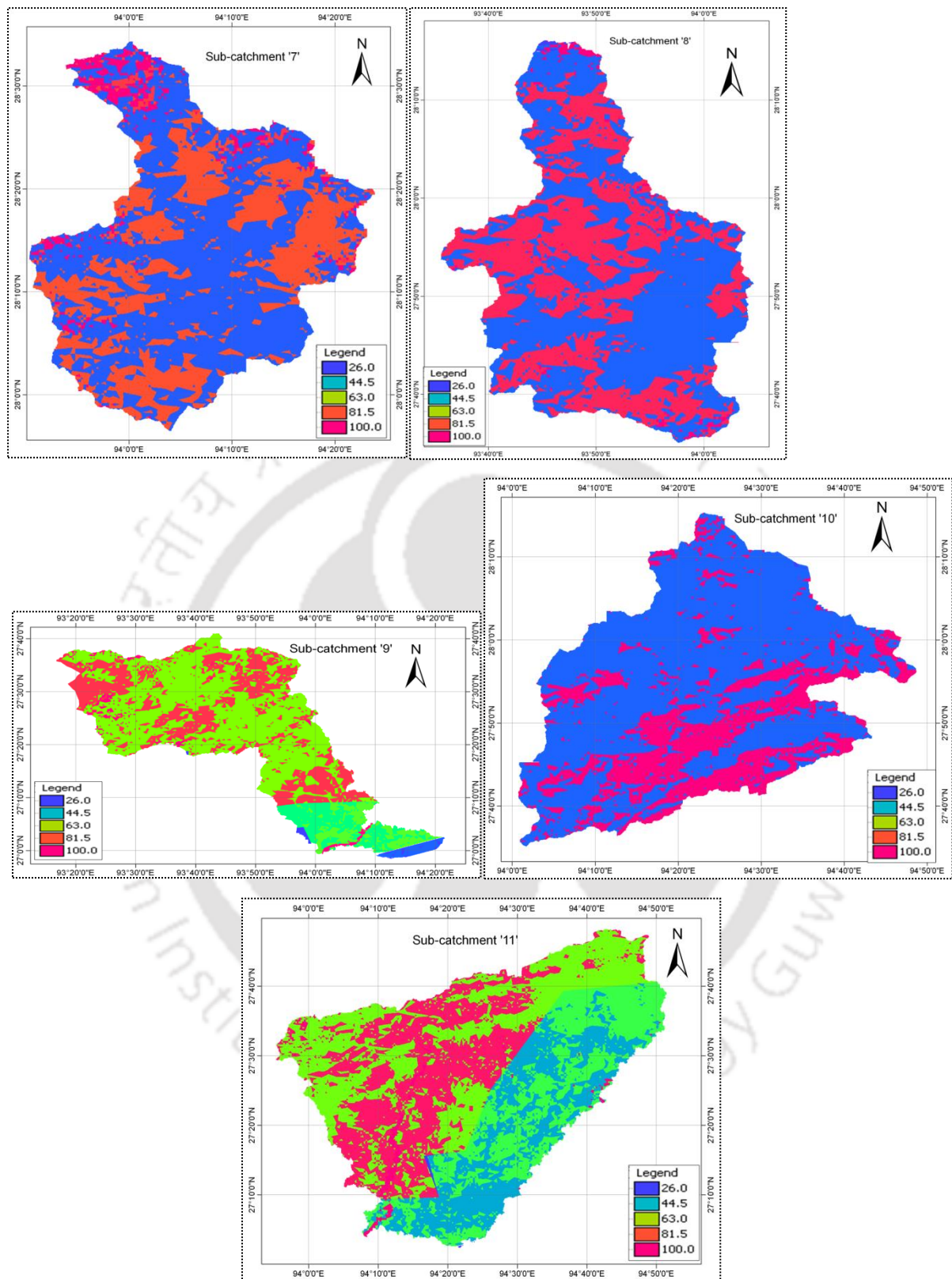


Fig.7.16: Curve number maps of eleven sub-catchments of the Subansiri Basin for the year 2005

It is seen from the maps that CN values vary between 26 and 100 for the Subansiri basin. The average CN value obtained from the histogram of each sub-catchment has been considered as CN II.

The CN values for the scenarios were calculated and the values are shown in Table 7.7 (a,b,c) and Table 7.7 respectively. In the tables, SC stands for sub-catchment and SS stands for sub-scenario.

Table 7.7(a): CNI values for each sub-catchment for the Scenario 1

CNI	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8	SC9	SC10	SC11
1990-2002	51.3	50.1	48.9	43.9	46.0	46.8	65.8	75.1	40.6	65.4	40.6
2003	51.7	48.9	50.8	46.0	48.9	48.9	63.4	67.5	45.6	63.7	44.6
2004	53.0	51.4	48.9	45.0	48.4	47.9	65.2	76.9	45.2	61.9	40.6
2005	54.1	53.8	51.9	45.1	49.8	46.6	65.8	75.1	43.6	66.7	43.6
2006	54.8	51.7	51.5	43.3	46.6	48.9	68.0	72.2	40.6	65.4	40.6
2007	54.2	51.9	52.5	46.6	48.4	45.0	65.2	73.9	46.4	66.4	40.1
2008	58.2	53.8	48.9	45.0	46.0	46.8	65.7	72.9	45.9	67.5	46.8
2009	58.9	52.8	48.9	49.4	48.9	47.7	68.0	75.1	47.7	65.4	44.6
2010	54.8	54.3	53.0	45.1	49.8	48.9	71.2	72.2	45.9	63.7	46.8
2011	63.3	55.5	51.6	47.9	48.9	50.1	72.4	72.2	46.4	64.2	46.4
2012-2020	61.8	58.0	52.3	49.4	53.6	53.6	74.3	73.9	49.4	65.4	48.1

The CN I values for the different sub-catchments lie between 40.1 and 75.1. The minimum has been obtained for sub-catchment 11 in 2007 and the maximum has been obtained in 2009 for the sub-catchment 8.

Table 7.7(b): CNII values for each sub-catchment for the Scenario 1

CNII	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8	SC9	SC10	SC11
1990-2002	71.5	70.5	69.5	65.1	67.0	67.7	82.1	87.8	61.9	81.8	61.9
2003	71.8	69.5	71.1	67.0	69.5	69.5	80.5	83.2	66.6	80.7	65.7
2004	72.9	71.6	69.5	66.1	69.1	68.7	81.7	88.8	66.3	79.5	61.9
2005	73.7	73.5	72.0	66.2	70.3	67.5	82.1	87.8	64.8	82.7	64.8
2006	74.3	71.8	71.7	64.5	67.5	69.5	83.5	86.1	61.9	81.8	61.9
2007	73.8	72.0	72.5	67.5	69.1	66.1	81.7	87.1	67.3	82.5	61.5
2008	76.8	73.5	69.5	66.1	67.0	67.7	82.0	86.5	66.9	83.2	67.7
2009	77.4	72.7	69.5	69.9	69.5	68.5	83.5	87.8	68.5	81.8	65.7
2010	74.3	73.9	72.9	66.2	70.3	69.5	85.5	86.1	66.9	80.7	67.7
2011	80.4	74.8	71.7	68.7	69.5	70.5	86.2	86.1	67.3	81.0	67.3
2012-2020	79.4	76.7	72.3	69.9	73.3	73.3	87.3	87.1	69.9	81.8	68.8

The CN II values for different sub-catchments vary between 61.9 and 88.8.

Table7.7(c): CNIII values for each sub-catchment for the Scenario1

CNIII	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8	SC9	SC10	SC11
1990-2002	85.2	84.6	83.9	81.1	82.4	82.8	91.3	94.8	78.8	91.2	78.8
2003	85.4	83.9	84.9	82.4	83.9	83.9	90.4	91.9	82.1	90.6	81.5
2004	86.1	85.3	83.9	81.7	83.7	83.5	91.1	94.8	81.9	89.9	78.8
2005	86.6	86.4	85.5	81.8	84.5	82.7	91.3	94.3	80.8	91.6	80.8
2006	86.9	85.4	85.4	80.6	82.7	83.9	92.1	93.4	78.8	91.2	78.9
2007	86.6	85.5	85.8	82.7	83.7	81.7	91.1	93.9	82.6	91.6	78.6
2008	88.4	86.4	83.9	81.7	82.4	82.8	91.3	93.6	82.3	91.2	82.8
2009	88.7	85.9	83.9	84.2	83.9	83.3	92.1	94.3	83.3	90.6	81.8
2010	86.9	86.7	86.1	81.8	84.5	83.9	93.1	93.4	82.3	90.5	82.8
2011	90.4	87.2	85.4	83.5	83.9	84.6	93.5	93.4	82.6	90.7	82.5
2012	89.8	88.3	85.7	84.2	86.3	86.3	94.0	93.9	84.2	91.2	83.5

The CNIII values of the sub-catchments lie between 78.8 and 94.8.

Table7.8: CN values for each sub-catchment for each of the sub-scenarios under the Scenario2

	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8	SC9	SC10	SC11
CNI											
SS1(2020-39)	57.1	56.9	50.1	42.8	51.4	50.1	75.8	75.1	47.5	60.9	44.7
SS2(2040-59)	51.7	52.8	49.4	47.9	51.2	49.4	74.6	74.6	48.3	57.1	44.9
SS3(2060-79)	62.1	60.4	55.1	57.8	58.2	55.1	74.6	74.6	54.6	57.6	51.3
SS4(2080-99)	58.4	57.7	52.3	55.2	55.2	52.3	73.1	73.1	51.3	57.6	51.3
CNII											
SS1(2020-39)	76	75.9	70.5	64.1	71.6	70.5	88.2	87.8	68.3	78.8	65.8
SS2(2040-59)	71.8	72.8	69.8	68.7	71.4	69.8	87.5	87.5	69	76	66
SS3(2060-79)	79.6	78.4	74.5	76.6	76.8	74.5	87.5	87.5	74.1	76.4	71.5
SS4(2080-99)	77	76.5	72.3	74.6	74.6	72.3	86.6	86.6	71.5	76.4	71.5
CNIII											
SS1(2020-39)	87.9	87.9	84.6	80.4	85.3	84.6	94.5	94.3	83.2	89.5	81.6
SS2(2040-59)	85.4	85.9	84.2	83.5	85.2	84.2	94.2	94.2	83.6	87.9	81.7
SS3(2060-79)	89.9	89.3	87.0	88.2	88.2	87.0	94.1	94.1	86.8	88.1	85.2
SS4(2080-99)	88.5	88.2	85.7	87.1	87.1	85.7	93.6	93.6	85.2	88.1	85.2

The CNI values lie between 42.8 and 75.8, the CNII values lie between 65.8 and 88.2 and the CNIII values lie between 80.4 and 94.5.

7.3.3.2 Performance of ANN-SCS based hybrid model and future runoff prediction

The simulated rainfalls have been used to calculate runoff of Subansiri catchment. The runoff at each sub-catchment was determined by the SCS curve number method up to the year 2099 by taking different CN values obtained for the different scenarios created. The runoff at the final outlet has been calculated using ANN time series analysis. The R value graphs for training, testing and validation are shown in Fig.7.17.

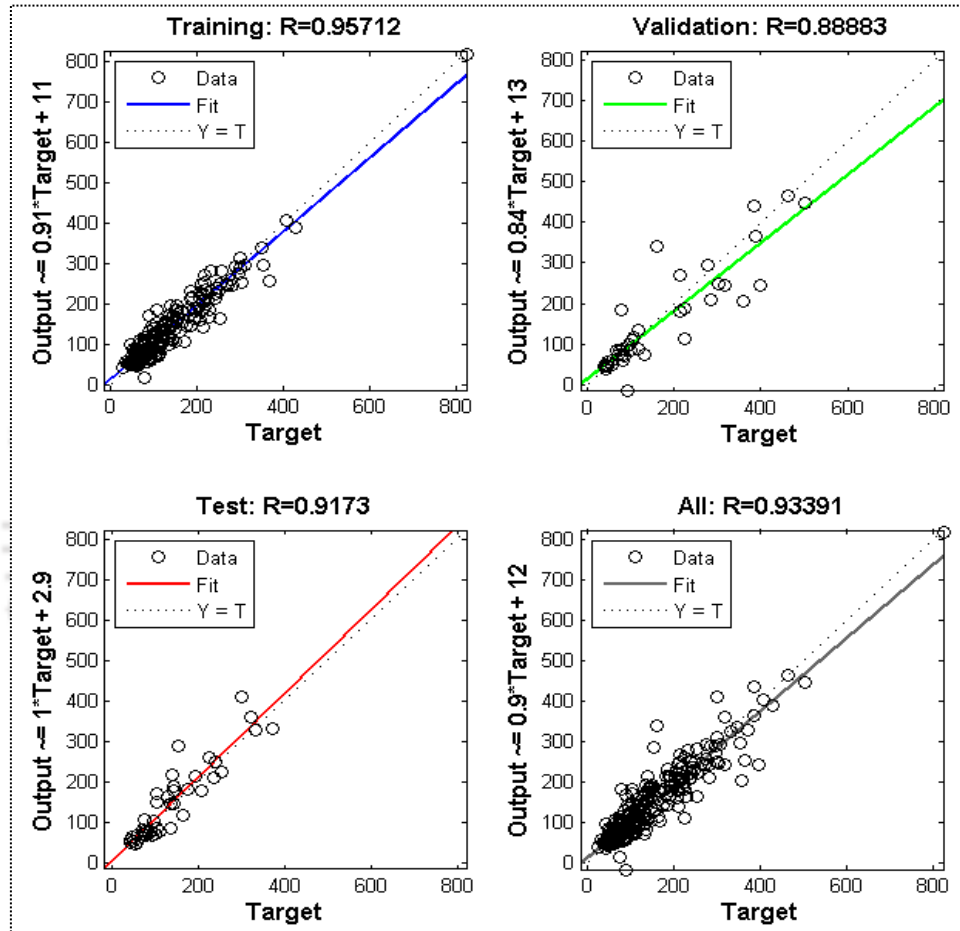


Fig.7.17: Regression plot for ANN-SCS based hybrid model

The coefficient of correlation (R) values obtained for training, validation and testing are 0.95, 0.89 and 0.92 respectively with an overall R value of 0.93. This indicates that the model is efficient enough to be used for simulation of runoff of Subansiri.

Considering 1990 to 2014 runoff as the base, the future monthly runoff has been predicted for all the scenarios for four different time periods viz. 2020-2039, 2040-2059, 2060-2079 and 2080-2099.

Results of the Scenario 1

The results of the Scenario 1 show that for the month of January, compared to 1990-2014, the runoff increases for the period 2020-2039 and then decreases gradually for the rest of the time periods. The same result has been observed for the month of February as well. For the months of March, April and May, runoff increases gradually from 2020-2039 to 2080-2099. For the month of July, runoff first decreases from 2020-2039 to 2060-2079 but increases for the period 2080-2099. November and December show similar changes in runoff. For these two months, runoff first slightly decreases for 2020-2039 compared to the base period 1990-2014. But, from the period 2040-2059 up to 2080-2099, the runoff increases gradually. For the month of September, runoff first increases for 2020-2039 and 2040-2059 and then started decreasing for the rest of the time periods i.e. for 2060-2079 and 2080-2099. The runoff decreases gradually for the month of October. For the month of August, compared to the base period, runoff first increases for the period 2020-2039 and then it suddenly got decreased for the next period i.e. 2040-2059 and then showed an increasing trend for the next two time periods i.e. 2060-2079 and 2080-2099. Fig.7.18 shows the graphical representation of the result of the first scenario. The maximum and minimum runoffs contributed to the annual total runoffs have been analyzed as follows:

For the period 2020-39 and 2040-59, the maximum and minimum runoffs are observed for the months June and February respectively. The runoffs in August and February are observed to be the maximum and minimum respectively for the period 2060-79. For 2080-99, July and October correspond to the maximum and minimum runoffs.

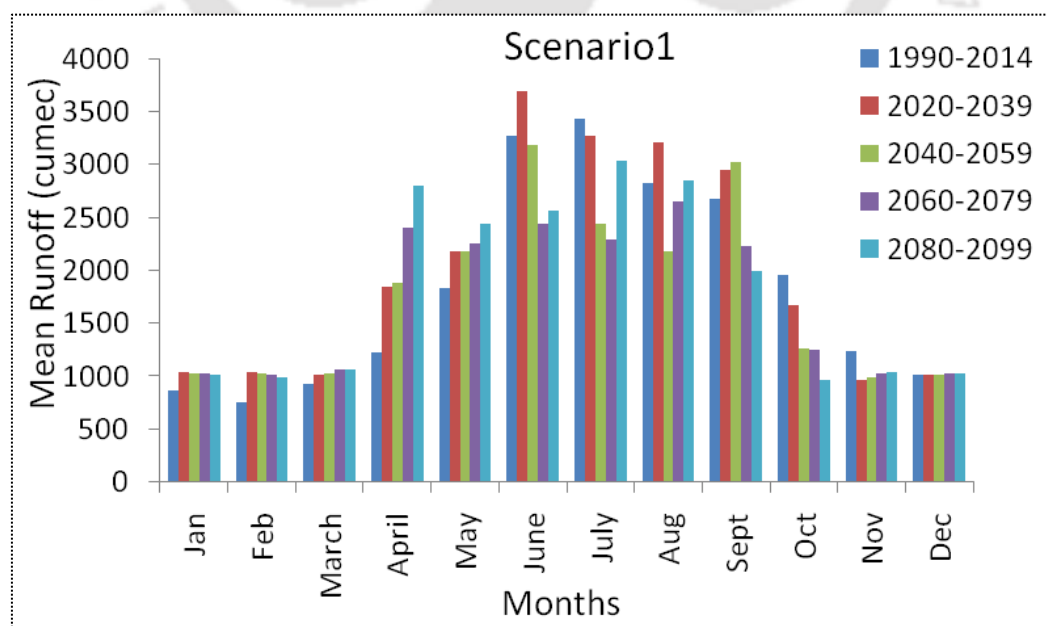


Fig.7.18: Future runoff obtained from Scenario1

The linear trends of future runoff generated under the Scenario 1 have been analyzed for the different time periods and are given in Fig. 7.19.

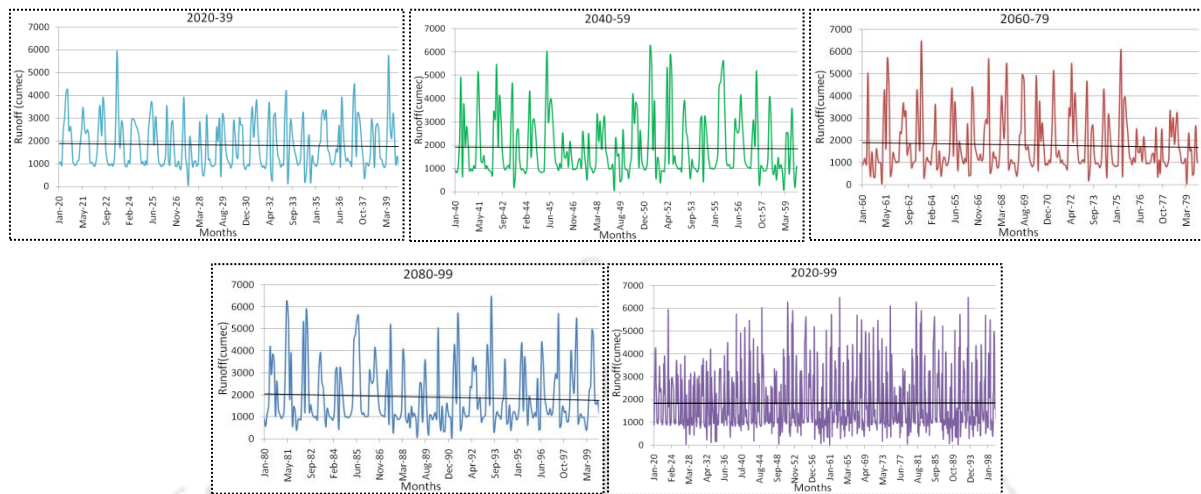


Fig. 7.19: Future trends of runoff of the Subansiri River generated under scenario 1 for different time steps

It is observed that, under this scenario, for all the time steps, the runoff shows decreasing trend. While analyzing the trend from 2020-2099, no significant change is observed during the entire period. This is due to the fact that, for this scenario, the land use/land cover conditions were considered as constant from 2020 to 2099.

Results of the Scenario 2

Under the Scenario 2, four different sub-scenarios were created for four different time periods viz., 2020-39, 2040-59, 2060-79 and 2080-99. The results show that except for the month of April and August, for all other months, the runoff first decreases in the period 2020-39 compared to the base period *i.e.* 1990-2014. The month wise runoff trends for each period are explained below:

For the months of January and February, runoff first decreases during 2040-59 compared to 2020-39 and then increases again for the next two periods *i.e.* 2060-79 and 2080-99. Runoff shows an increasing trend from 2020-39 to 2080-99 for March, April, May, June, July, August and November. For September and October, runoff first increases compared to 2020-39 and then again start decreasing for 2060-79 and 2080-99. For December, the runoff decreases for the period 2040-59 compared to 2020-39 and then again gradually increases for the rest of the periods (Fig. 7.20).

For the sub-scenario1 (2020-39), the maximum and minimum runoffs are observed in the months of June and March, while for the sub-scenario2 (2040-59), July and March

experience the maximum and minimum runoffs respectively. The maximum and minimum runoffs are observed in the months of July and November for the sub-scenario3 (2060-79) and for sub-scenario4 (2080-99), the maximum and minimum runoffs are observed in the months August and November respectively.

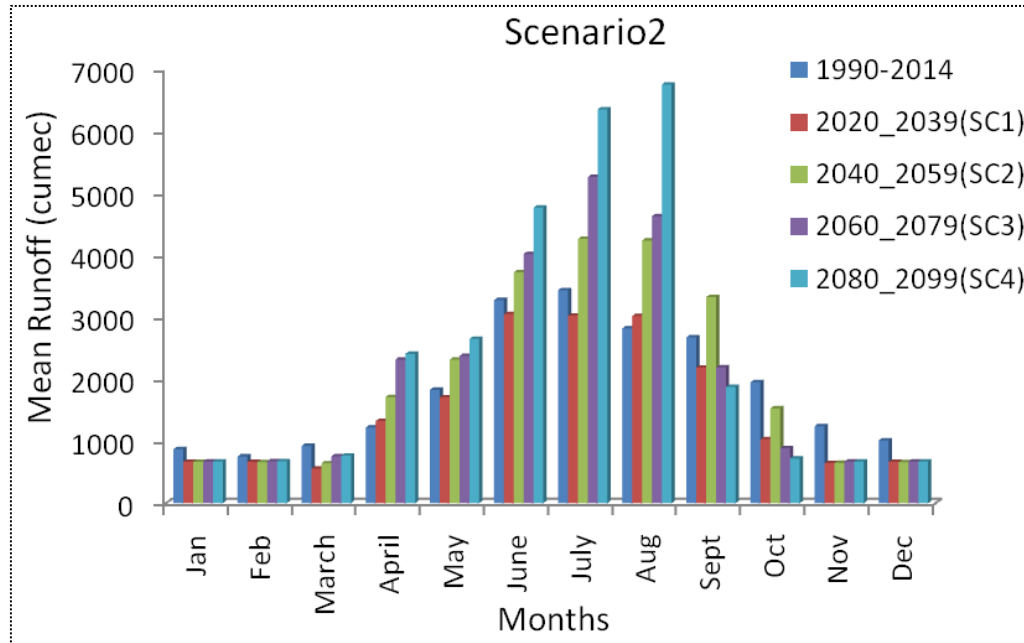


Fig.7.20: Future runoff obtained from Scenario2

The future runoff trends have been analyzed for different time steps and are shown in Fig. 7.21.

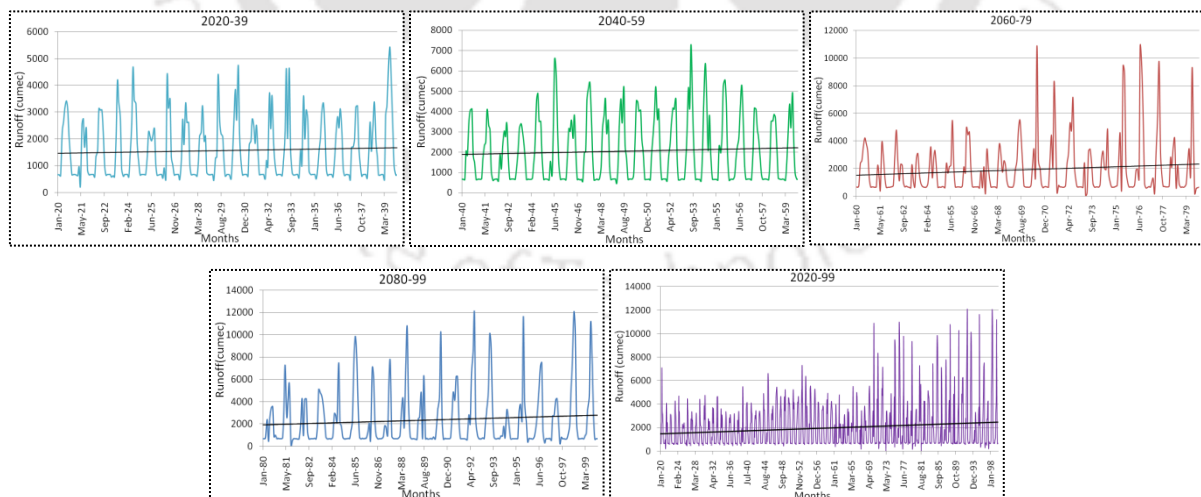


Fig. 7.21: Future trends of runoff of the Subansiri River generated under scenario 2 for different time steps

For all the time steps, including the entire period from 2020-99, the runoff show increasing trends. This is attributed to the fact that under this scenario, various land use/land cover changes have been considered. The decrease in vegetation and snow cover area has major contributions towards the increase in runoff of the Subansiri River in future.

Results of the Scenario 3

Under this scenario the four sub-scenarios created under the Scenario2 have been applied separately for the period 2020 to 2099 and runoff was calculated for the four different time periods, 2020-39, 2040-59, 2060-79 and then 2080-99.

The result of the first sub-scenario shows that from 2020-2039 to 2080-2099, the runoff shows an increasing trend for the month of January, February, March, June, July, August and September. For the month of April, runoff suddenly decreases for the period 2060-79 compared to the previous periods and then again increases for 2080-99. Runoff in the period 2040-59 decreases compared to 2020-39 for the month of May and then again increases for the rest of the periods. October, November and December shows similar trends where, runoff increases from 2020-39 to 2060-79 but decreases again for 2080-99.

For other three sub-scenarios too, the runoff trend was similar to the trend showed in the 1st sub-scenario but with different runoff values. Results are shown in graphical form in Fig.7.22.

For the 1st sub-scenario, the maximum runoffs are observed in May, June, June and July for 2020-39, 2040-59, 2060-79 and 2080-99 respectively while the minimum are observed in December, January, April and February respectively.

The maximum runoffs as predicted for the for 2nd sub-scenario are in May, June, July and July and minimum are in November, December, February and January respectively for the time steps 2020-39, 2040-59, 2060-79 and 2080-99.

For the 3rd sub-scenario, the month May experiences the maximum runoff for the period 2020-39 while for the time periods 2040-59 and 2060-79, the maximum runoff is observed at the month of June. For 2080-99, the maximum runoff is observed in July. January, February, January and December show minimum runoffs for the four time steps respectively.

Similar to the 3rd sub-scenario, for the 4th sub-scenario also the maximum runoffs are observed in the months May and June for the four time periods, while the minimum is observed in January for all the time steps.

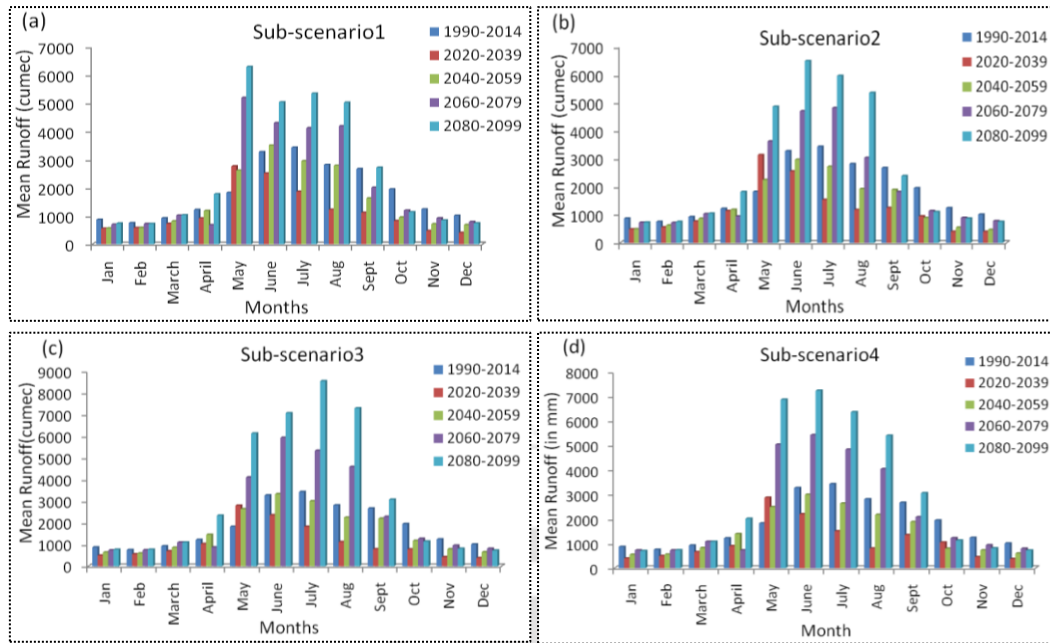


Fig.7.22: Future runoff obtained four different sub-scenarios under the Scenario3

The future runoff trends that would occur under these four sub-scenarios have been analyzed for the different time steps including the entire period from 2020-99 are shown in Fig. 7.23, 7.24, 7.25, 7.26 and 7.27.

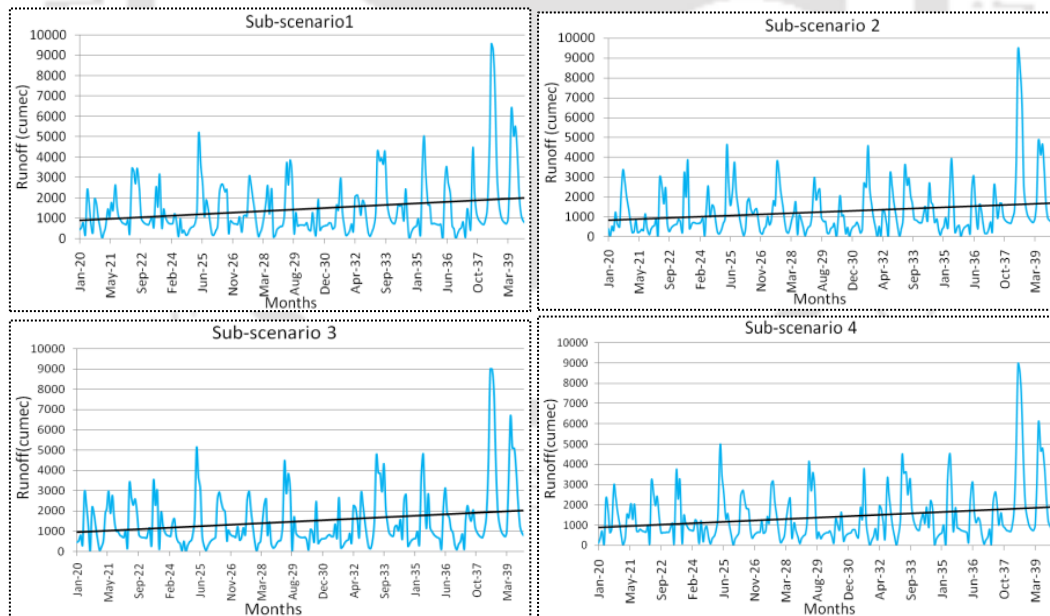


Fig.7.23: Future runoff trend analysis of the Subansiri River for the period 2020-39 under four different sub-scenarios

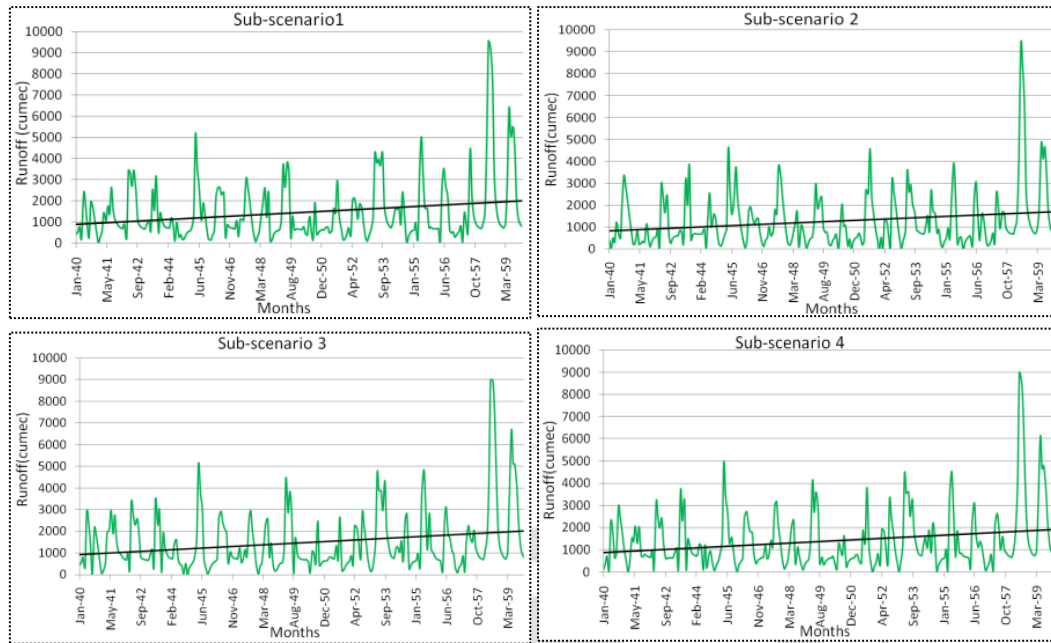


Fig.7.24: Future runoff trend analysis of the Subansiri River for the period 2040-59 under four different sub-scenarios

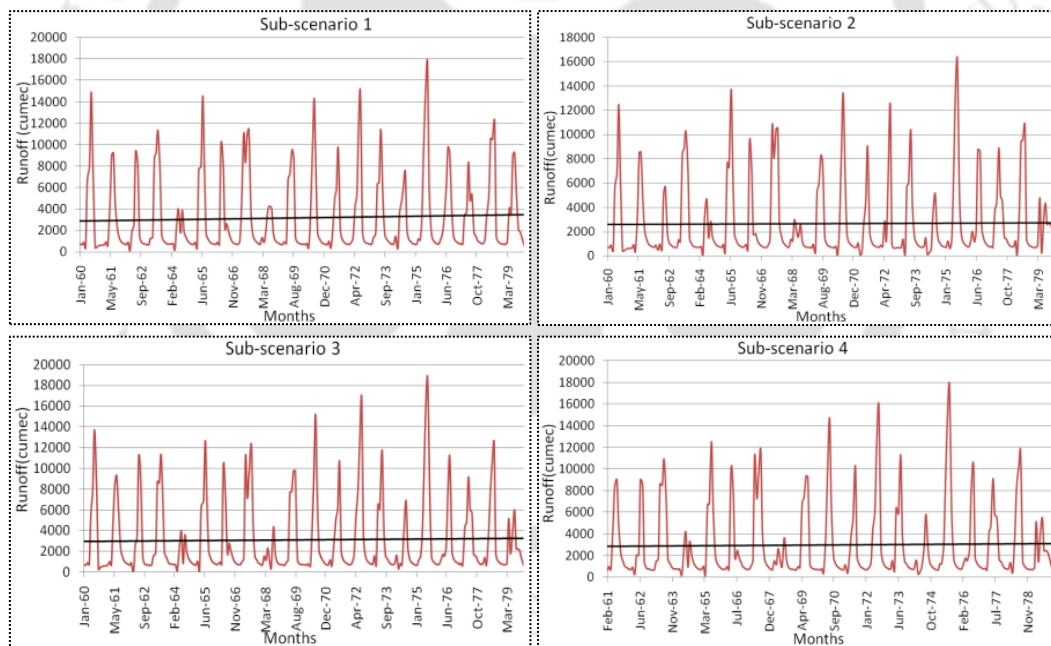


Fig.7.25: Future runoff trend analysis of the Subansiri River for the period 2060-79 under four different sub-scenarios

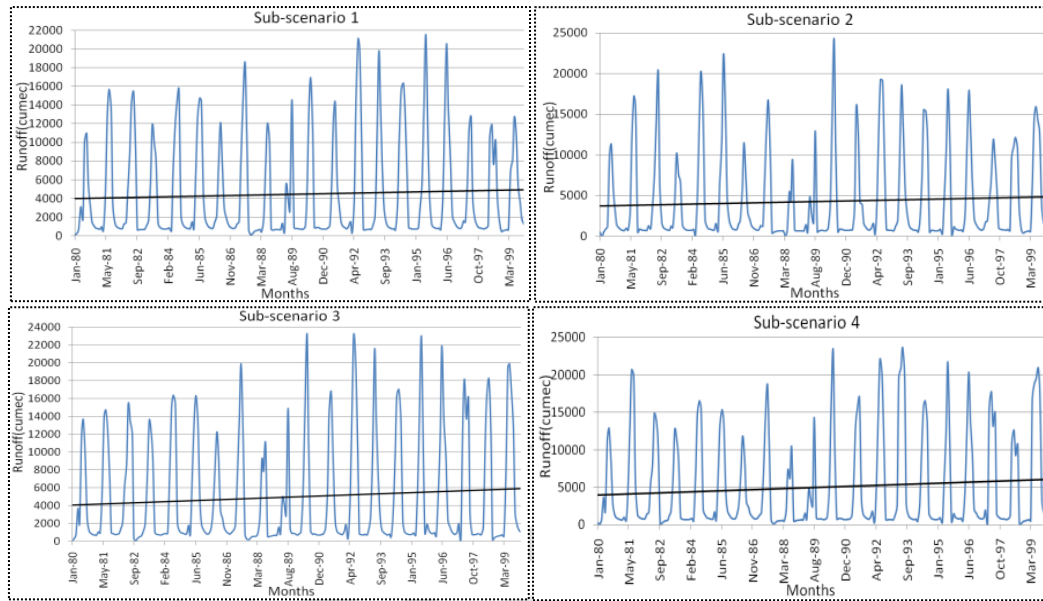


Fig.7.26: Future runoff trend analysis of the Subansiri River for the period 2080-99 under four different sub-scenarios

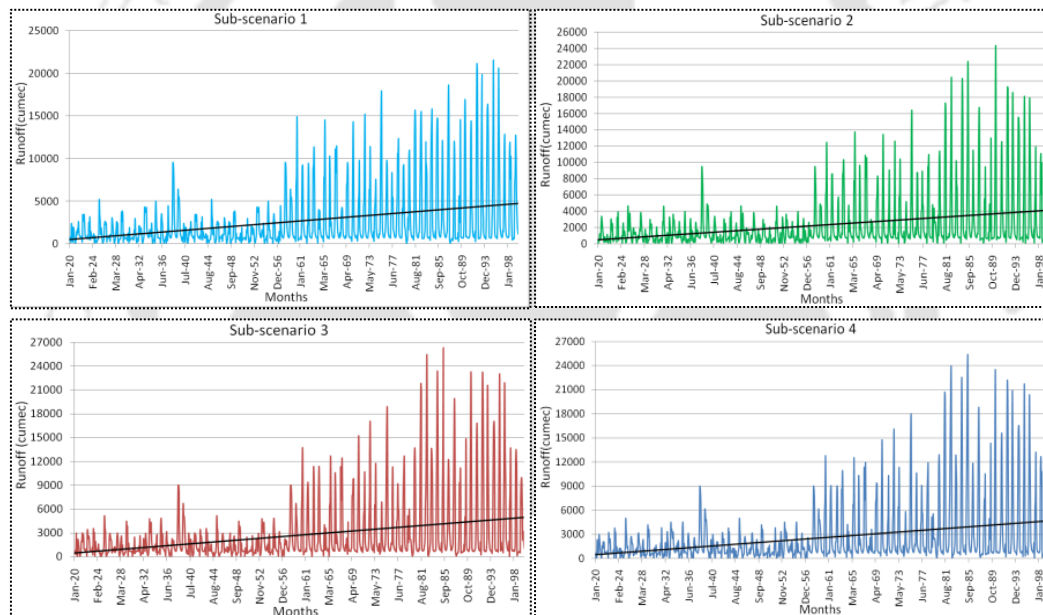


Fig.7.27: Future runoff trend analysis of the Subansiri River for the period 2020-99 under four different sub-scenarios

It is seen that for all the time periods, under the four sub-scenarios, the future runoff show increasing trends. Exception is the period 2060-79, where for all the sub-scenarios, the future runoff trends does not show any significant change. However, for sub-scenario 1, the runoff shows a slightly increasing trend during this time period.

The increase and decrease of runoffs at various time periods for all the scenarios is primarily because of the change in the LULC pattern. For example, evapotranspiration and interception decrease after trees and vegetations are removed in the process of urbanization. Also, an increase in impervious area due to the construction of houses, streets and culverts reduces

infiltration and shorten the time of concentration. Generally, land development & urbanization cause increase in peak discharge and runoff volume.

Snowmelt water also contributes to the runoff of the river. However, the contribution of snowmelt to runoff varies with interaction between climatic factors and environmental factors (Li and Simonovic, 2002). Temperature is identified as critical factor that affects watershed hydrological process because of its contribution to snowmelt, evaporation, surface soil frost and thaw (Anderson, 1973; Tanasienko and Chumbaev, 2008). The runoff-temperature relationship exhibits a global positive correlation (Labat et al., 2004). Moreover, when the area of dense vegetation decreases and is covered by light vegetation and surface water bodies, it results in a higher value of curve number which will lead to the increase in runoff. The reverse case in few particular months may be attributed to other climatic parameters apart from the land use/land cover changes, as climatic parameters have been believed to be the main factors to influence runoff generation.

7.3.4 Comparison of ANN based rainfall-runoff model and ANN-SCS based Hybrid model

In the present study, the runoff of Subansiri has been simulated by two different methods viz., an ANN based rainfall-runoff model where only rainfall has been considered as the input to the model and an ANN-SCS based hybrid model where the input considered are the runoff of eleven different sub-catchments of the Subansiri River basin. In the second method, runoff for each sub-catchment has been determined by the SCS-CN method where rainfall, land use/land cover scenario and hydrologic soil group are the main inputs.

The training, validation and testing of both the ANN models have been performed by the time series analysis in MATLAB software and the regression plots of ANN based rainfall runoff model and ANN-SCS based hybrid model are shown in Fig.7.12 and 7.17 respectively. It is observed from the figures that, the R values for training, validation and testing are less in the simple ANN based rainfall-runoff model compared to the ANN-SCS based hybrid model. The R values are given in Table 7.9.

Table 7.9: R values for the two different runoff simulation models

Model	R values			
	Training	Validation	Testing	All R
ANN based rainfall-runoff model	0.94	0.81	0.73	0.89
ANN-SCS based hybrid model	0.97	0.89	0.92	0.93

It is clear from table 7.9 that the R values obtained during training, validation and testing for the ANN-SCS base hybrid model are 0.97, 0.89 and 0.92 which are better compared to the R values obtained for simple ANN based rainfall runoff model (0.94, 0.81 and 0.73 for training, validation and testing respectively). The overall R value for the hybrid model is 0.93 which is better than the all R value of 0.89 obtained for the simple ANN model. This implies that the ANN-SCS based hybrid model is a better performing model and could efficiently be used to simulate river runoff.

7.4 Conclusions

In this study, the runoff of the Subansiri River at Khabulighat outlet has been simulated using two different models, a simple ANN based rainfall-runoff model and an ANN-SCS based hybrid model. To perform the analysis the entire Subansiri basin has been divided into eleven different sub-catchments and the average rainfall at each sub-catchment has been determined. The rainfall at each sub-catchment has been analyzed for future four time steps, 2020-39, 2040-59, 2060-79 and 2080-99. The rainfall analysis for the entire period from 2020-99 showed that the different sub-catchments of the Subansiri basin will experience less rainfall in the future.

The average rainfall for each sub-catchment has been put as the input to the ANN based rainfall-runoff model. Decreasing trend of runoff of Subansiri has been observed for the four different time steps, which is because rainfall also showed decreasing trends in future and it has direct impact on runoff. The runoff of the river has also been simulated using ANN-SCS based hybrid model. The runoffs at eleven different sub-catchments have been determined using SCS curve number method. Different land use/land cover scenarios have been created to study their effect on runoff of the river. While analyzing, the output from all the scenarios, it has been observed that the mean runoff increases for most of the months from 2020 to 2099 except for a few particular months. This may be attributed to various other climatic factors apart from the scenarios created in this study on the basis of land use/land cover changes. Moreover, except for the scenario 1, the runoffs show increasing trends for different future time under the conditions considered for the scenarios 2 and 3.

The performance of both the models has been assessed on the basis of R values. The ANN-SCS based hybrid model gave better R values compared to the simple ANN based rainfall-runoff model. This depicts better simulation efficiency of the ANN-SCS based hybrid model.



CHAPTE 8

DETERMINATION OF FUTURE POWER POTENTIAL OF THE SUBANSIRI LOWER HYDRO ELECTRIC PROJECT

8.1 Introduction

8.1.1 Hydroelectric Power Plant

Rivers have been altered for human development for many years and it is now almost impossible to find a river that has not been modified for one purpose or another (Sheail, 1988). Dams are one of the major ways where river systems have been directly altered (McCartney, 2009). In a hydroelectric power plant, a dam is constructed across a river to raise water to a desired level and to regulate the flow as per rules, to create a reservoir. It also consists of a station where the process of generation of electric power takes place. Hydropower is called renewable source of energy as it uses and not consumes the water for generation of electricity, and the hydropower leaves this vital resource available for other uses.

The advantages of hydropower as identified by experts the world over include the following:

- i. It saves scarce fossil fuels
- ii. It is relatively non-polluting and hence is environment-friendly
- iii. It has higher efficiency (about 90%) as compared to thermal (around 35%) and gas (around 50%)
- iv. By storing water it increases water availability to flora and fauna around it
- v. The emission of greenhouse gases from hydropower projects is comparatively less than fossil fuel power plants of equal capacity and hence it helps in reducing global warming
- vi. Unlike the thermal plant where the plant life is limited, the hydropower plant has long operating life
- vii. As the hydropower plants are located in remote regions, it leads to the development of backward areas.
- viii. It provides additional benefits in terms of irrigation, flood control, drinking water supply, recreation, navigation, pisciculture, tourism etc.

8.1.2 Downstream Impact of reservoir operation

Construction of dams modifies the downstream flow regime by altering the discharge of a river. However, the change in discharge is highly dependent on the size and purpose of the dam, but all are expected to have some impact on the hydrology of river downstream (Williams and Wolman, 1984). Not only discharge, but the sediment regime of a river also gets altered due to construction of dams. Dams control and alter the natural flow regimes of rivers and in the process can have distinct effect on sediment supply (Baxter, 1977; Newson, 1997). Reservoirs trap the coarse bedload and a significant proportion of the fine material and hence the sediment supply downstream of a dam can be significantly reduced (Brandt, 2000; Brierley and Fryiers, 2005). Due to change in flow and sediment regimes, degradation and aggradation processes take place at downstream. As the sediments are trapped behind the dam, the released water is relatively free of sediment because of which the flow has excess energy. To satisfy the required sediment load, the river first degrades the channel bed followed by eroding the channel banks (Petts, 1984; Gordon and Meentemeyer, 2006). Degradation in regulated rivers relatively takes place at much higher rate than the non-regulated rivers due to less sediment load (Knighton, 1998). Although degradation occurs initially below the dams, aggradation may occur further downstream of the river (Petts, 1984). Even though a large amount of sediment is trapped behind a dam, source of sediment downstream can still exist which include materials from bed degradation and channel bank erosion immediately below the dam and from unregulated tributaries injecting sediment into the mainstream (Petts, 1984; Petts and Gurnell, 2005).

Apart from the impact on the sediment load transported, the operation of reservoir has various other downstream impacts. These impacts are briefly described here.

Impact on water quantity

Flood moderation reservoirs store the flood water in the reservoir during peak floods, and then slowly release the water. Such reservoirs reduce the flood peak which in turn reduces the frequency, extent and duration of floodplain inundation. Reduction of channel-forming discharge and truncated sediment transport alters the channel and floodplain morphology (Acreman et al., 2000). Due to the change in water quantity, the shape of the river will be fixed or the river channels will be separated from the floodplain (FISRWG, 1998).

Impact on water quality

Storage of water in reservoirs alters the water quality. Anaerobic processes take place inside the reservoirs where the velocities are very low and water column depth is extremely large compared to normal flow depth. This process is even more intensive if the water and sediment contain excess amount of nutrients (organic matter, nitrogen and phosphorous). Due to excess algal growth and anaerobic processes eutrophication and deoxygenation take place in the reservoirs. In warmer climates, reservoirs with increased eutrophication can suffer from toxic algal blooms, the excessive growth of aquatic plants and the production of methane (WMO, 2006(a)). Again, the biological activities of the river at downstream is further affected when agricultural pesticides, toxic industrial pollution, heavy metals from upstream mining operations etc. get accumulated in the reservoir (Dyson et al., 2008). The change in temperature in different layers of large reservoirs also affects the downstream water. Large storage reservoirs normally tend to stratify. In such case, the water in the upper layers acquires the same air temperature that prevails outside the reservoir, while the bottom layers remain cooler. When the water from such reservoirs is released through the outlets provided near the bottom, the released water is much cooler than the normal stream flow. This may be harmful to the fish and other aquatic lives and also to the aquatic invertebrates. Constant release of such water will affect the species that are dependent on temperature variations for reproduction and maturation. When streams are excessively dewatered, because of no downstream releases, the unnaturally low flows with smaller depth of flow can warm more easily holding less dissolved oxygen. Many aquatic species can tolerate a limited range of temperature. Any change in the range of temperatures can have profound effects on their composition. In winter, on the other hand, such streams can become very cold and sometimes freeze (FISRWG, 1998).

Impacts on social and economic activities and environmental conditions

Fisheries: A dam constructed in the upper reaches of a river has substantial impact on the availability of fish downstream (Dyson et al., 2008). The variety of aquatic environments that exists in alluvial reaches is used by the fishes for spawning. When a river reach is subjected to constant flows, it may not be able to provide a variety of aquatic environments appropriate for the survival of certain species. Many habitats are lost in the lateral channels and in the floodplain, resulting in a sharp decrease in local and regional biodiversity (WMO, 2006(a)). Postel and Richter (2003) stated that inadequate low flows may result in overcrowding of fish

in poor-quality water with no option to move to other feeding areas and depletion of population of species sensitive to higher water temperatures and lower oxygen conditions. Moreover, due to absence of high flows, fish may not be able to access the floodplains for spawning and feeding.

Groundwater recharge: Construction of dams reduces the floodplain inundation which in turn reduces infiltration and consequent groundwater recharge. This will affect the groundwater resources and associated ecological and economic benefits. This also has adverse impact on the base flow and groundwater interactions and degrades riverine habitats (WMO, 2006(a)). The species that are dependent on shallow groundwater will be affected much because of the lowering of the groundwater table.

Preserving ecosystems: Dams and reservoirs have the potential to alter the flow regimes and separate river channels from the floodplains. They tend to impede the natural ecological and morphological processes and oversimplify the river corridor, resulting in a spatially homogeneous ecosystem, which is not able to provide varied habitat features for a diverse range of species (WMO, 2015). It is therefore, important to maintain the structure and function of fluvial ecosystems because most of the ecosystem services provided by river corridors depend on these and they are lost when rivers are simplified (WMO, 2006(a)).

River management facilities: Because of the low sediment load at the immediate downstream of a dam, degradation of riverbed and erosion of river banks take place. This will expose the foundation of existing infrastructure such as bridges. This condition has also the possibility that it rots the foundation of embankment and pile work etc.

Recreational activities: Rivers, coastal and banks of other water bodies are used for recreational purposes. The reduction in river discharge has negative effect on the recreation value. For example, on the rivers where sightseeing boats are operated, the reduction in river discharge may result in non-feasibility of their operation. Moreover, in alluvial floodplains, the reduction in such discharge may shift the main channels of the river from the city banks, thereby resulting in lost opportunities (WMO, 2015).

Flushing of pollutants and sediments: In some cities, the urban waste water is not treated before it is released to the river. In such condition, floods can have a flushing effect to remove the pollutants. Construction of dams reduces the river discharge. This will block the dilution of the polluted reaches leading to a polluted environment.

Navigation: In reservoirs, where the main purposes are irrigation and public water supply, sufficient water is withdrawn from the river channel. In such cases, the downstream release may not be sufficient for navigation purposes.

Salt intrusion: In estuarine reaches, during high tide, the salt-rich sea water moves up to the river and then again pushed back by the river during high flows. This creates a stable equilibrium condition of fresh and saltwater in the estuarine areas thereby creating a habitat rich in biodiversity. Due to low flow from the river which is result of construction of dam, this equilibrium gets disturbed. When saltwater enters the river, salt concentration in irrigation water and ground water rises, resulting in severe adverse effects on the sources of public water supply and irrigation. Increase in salt concentration also affects the various aquatic lives that are otherwise comfortable under the equilibrium condition.

8.1.3 Subansiri Lower Hydroelectric Project (SLHEP)

Subansiri Lower Hydro Electric Project is one of the biggest hydroelectric projects under construction in India. It is an interstate project involving Assam and Arunachal Pradesh. The project is located about 470 km away from Guwahati, 55 km from North Lakhimpur town and 16 km from Gogamukh, a small town in Assam on NH-52. The dam site is 2.3 km upstream of Gerukamukh village on Assam/Arunachal Pradesh border across the river Subansiri. The left abutment of the dam is in Assam and right abutment is in Arunachal Pradesh. The location of dam site on the river Subansiri is 27°33'15'' N latitude and 94°15'30'' E longitude. The most significant aspect of this project is that all the components of the project are confined within 1.5 km radius. The project has a 116m high concrete gravity dam with a surface powerhouse of 2000MW capacity. The river length is approximately 126 km from the dam site to the confluence with Brahmaputra near Jamuguri (Bakalial et al., 2014). The reservoir storage capacity is 1365 Mm³. The dam heads up the river discharge, which further leads to Power House through 8 nos. of Head Race Tunnels of 9.5m diameter (Horse shoe shaped) each. Water after flowing through the turbines shall be discharged back to river through Tail Race Channel. Thus diverted discharge in the river comes back to the original river course within a stretch of 0.5 km unlike other Hydro Projects where the diverted water joins the river course after 20-30 km depending on the site conditions. Indeed, there is no consumptive use of water on hydropower development. All the water gets released back into the river course downstream. In this way, no part of the river is going to be dried up due to dam operation. However, it is expected that there will be a diurnal

variation of the river flow which may have some negative impacts at the downstream. There are number of perennial tributaries joining Subansiri river downstream of dam namely Geruka (2.5 km), Dulang (4.89 km), Dirpai (5.35 km), Chauldha (5.55 km), Gaghar (26.4 km), Bogi Nadi and Dirgha Nala (30 km), Kokoi Nala (35.5 km) etc. which will also contribute to the discharge and river bed material in the river Subansiri.

The initiation of the project has caused great fear among the downstream dwellers, which had the fate of experiencing downstream flood hazard caused by breaching of a huge barrier resulting from landslips caused by the great 1950 Assam earthquake. It is an apprehension amongst the people that epicenter of 1950 earthquake of 8.6 in the Richtar scale was very near to the Subansiri Lower Project dam site. In fact the epicenter of the said earthquake was 240 km away from the Subansiri project in Mishmi hills. This earthquake had actually occurred in a particular tectonic setup which does not exist at Subansiri Lower Project site. The tectonic setup of the area plays an important role for seismogenic source during the event.

Lower Subansiri basin covers the northern part of Assam mostly inhabited by agrarian people. The river is migratory in nature. The river is migrating towards the west against the natural slope of the basin. This is due to presence of many geotectonic activities within the basin. The downstream catchment of Subansiri river continues as linear depression though the river carries and deposits huge sediment flux into the basin. In the upper catchment of Subansiri, occurrence of devastating flood associated with intense rainfall is very common. Due to the Subansiri project there would be abrupt diurnal fluctuation of flow discharge from 6 cumec to 2560 cumec.

8.1.3.1 Principal features of Subansiri Lower Hydroelectric Project

The full reservoir level (FRL) of the project is EL 205.0m corresponding to a storage capacity of 1365.0 Mm³ and maximum water level (MWL) is 208.25 m with storage volume of 1470.0 Mm³. The flood cushion of about 441.6 Mm³ is provided for the period of high inflow like June, July and August months, which is the volume between EL 205.0 m and EL 190.0 m. The maximum draw down level (MDDL) is 181.0 m with storage volume of 720 Mm³. Height of dam above river bed level is 116.0 m and from the deepest foundation level is 133.0 m.

Water from the dam will be diverted to the surge tank through side tunnel from where it will be delivered through eight penstocks having 9.5 m diameter and with varying lengths of

106.70 m, 106.88 m, 106.64 m, 106.34 m, 105.82 m, 105.86 m and 106.004 m for the target power generation of 2000MW (8 x 250). Maximum tailrace water level is 112.0 m and normal tailrace water level is 108.96 m whereas minimum tailrace water level is 105.0 m. The probable maximum tailrace water level is 122.5 m.

In the present study, the future power potential of the Subansiri Lower Hydroelectric Project has been analyzed by using simulation model for the three different land use/land cover scenarios as described in Chapter 7. The results were analyzed for four different future time steps viz., 2020-39, 2040-59, 2060-79 and 2080-99.

8.2 Materials and Methods

8.2.1 Reservoir simulation model

Reservoir simulation method is the most widely used method because of its mathematical simplicity and flexibility. It provides a rapid means for evaluating the anticipated performance of water resources systems. Simulation model can be physical or symbolic, hand operated or computerized. The main components that constitute a simulation model are the inputs; physical relationships and constraints; operating rules; and the outputs. The advantages of simulation technique include, (i) Simulation model is easier to adopt than developing a mathematical model in case where complex relationships of a predictable and random nature exists; (ii) In problems where it is difficult to predict or identify bottlenecks, simulation is used to foresee these unknown difficulties; (iii) Data for further analysis can be generated by a simulation model; (iv) The simulation model of a system once constructed, may be employed as often as desired to analyze different situations and (v) For problems where all values of the variables are not known, or partly known, simulation models are useful for solving such problems. However, the main disadvantages of simulation technique are, (i) Simulation does not produce optimal results; (ii) Each simulation run is like a single experiment conducted under a given set of conditions. It is also a time consuming procedure; and (iii) In very large and complex problems, the large number of variables and the interrelationships between them make the problem very hard to program. In reservoir operation, simulation can be used to determine hydropower generation, flood peak attenuation, irrigation allocation etc.

In the case of reservoir operation for hydropower generation it consists of a power plant that has a storage reservoir, the head, flow and storage are all interdependent variables (Vedula and Majumdar, 2005). The data required for simulation are, the inflow series at a reservoir; the storage-area-elevation relationship for the reservoir; and, the power plant efficiency.

8.2.2 Data used

The data used for the simulation of the reservoir are listed below:

- a) Monthly runoff of Subansiri River as simulated by the ANN-SCS based hybrid model up to the year 2099 for three different land use/land cover scenarios have been used as the inflow to the reservoir.
- b) Maximum water level (MWL): 208.25m
- c) Full reservoir level (FRL): 205m
- d) Maximum draw down level (MDDL): 181m
- e) Tailrace water level: 108.96m
- f) Dead storage: 720 Mm³
- g) Storage capacity of the reservoir at FRL: 1365 Mm³
- h) Plant capacity: 2000 MW
- i) Efficiency: 90%
- j) Minimum downstream release: 6 m³/s

8.2.3 Methodology

8.2.3.1 Capacity-Area-Elevation relationship for the reservoir

Fig. 8.1 shows the relationship between reservoir capacity vs. elevation, area vs. elevation, and, reservoir capacity vs. area determined by the method of curve fitting. The polynomial equations developed for the relationships are,

Reservoir capacity and reservoir elevation relationship

$$\text{Elevation (m)} = -5 \times 10^{-5} S_t^2 + 0.130 \times S_t + 112.3 \quad (8.1)$$

Where, S_t is the reservoir capacity in Mm³.

Reservoir area and reservoir elevation relationship

$$\text{Elevation (m)} = -0.086 \times A_t^2 + 5.949 \times A_t + 97.06 \quad (8.2)$$

Where, A_t is the reservoir area in Mm².

Reservoir capacity and reservoir area relationship

$$\text{Area (Mm}^2\text{)} = -8 \times 10^{-6} S_t^2 + 0.031 \times S_t + 2.113 \quad (8.3)$$

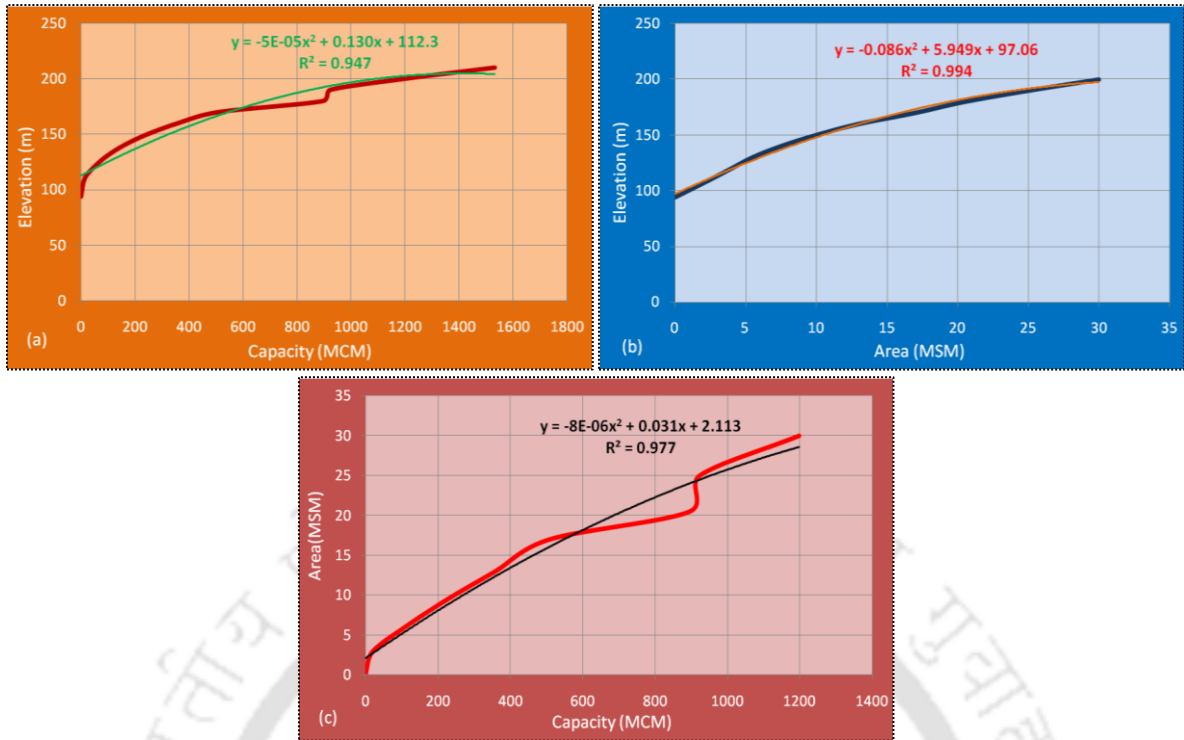


Fig. 8.1: Capacity-Area-Elevation curves: (a) elevation vs. capacity, (b) elevation vs. area and (c) area vs. capacity

8.2.3.2 Problem formulation

8.2.3.2.1 Hydropower Generation

The expression for hydropower generation is given by the formula,

$$kWH_t = 2725 R_t H_t \eta \quad (8.4)$$

For a period of one month, the expression becomes,

$$P = \frac{(2725 \times R_t \times H_t \times \eta)}{(1000 \times 30 \times 24)} \text{ MW} \quad (8.5)$$

$$= 0.003785 R_t H_t \eta \text{ MW} \quad (8.6)$$

Thus,

$$R_t = \frac{P}{0.003785 H_t \eta} \quad (8.7)$$

Where,

P= power in MW

R_t = release to penstock in MCM in period t

H_t = net head in m in period t

η = plant efficiency

8.2.3.2.2 Constraints

The following constraints have been considered during the simulation process:

a) Continuity constraint

$$S_{t+1} = S_t + Q_t - R_t - R_m \quad (8.8)$$

where,

S_{t+1} = storage in Mm^3 at the end of the time period t or beginning of time period $t+1$;

S_t = storage in Mm^3 at the beginning of the period t ;

Q_t = reservoir inflow in Mm^3 during the period t ;

R_t = release required in the period t to generate the specified power corresponding to the net head;

R_m = minimum downstream release = $6 \text{ m}^3/\text{s} = 15.55 \text{ Mm}^3$.

b) Reservoir storage constraint

Reservoir storage cannot be lowered below the dead storage volume of 720 Mm^3 . The maximum storage of the reservoir should not be greater than full reservoir level (FRL) volume of 1365 Mm^3 .

$$S_d < S_{t+1} < S_{max} \quad (8.9)$$

where,

S_d = storage capacity of the reservoir at MDDL = dead storage volume = 720 Mm^3 ;

S_{max} = storage capacity of the reservoir at FRL = 1365 Mm^3 .

c) Release constraint (Rai, M.R., 2010)

Release from the reservoir should be such that at the end of time t the reservoir storage level does not go above FRL.

$$R_{t \max} = S_{t-1} + Q_t - S_d - R_m \quad (8.10)$$

where,

$R_{t \max}$ = maximum release in time t .

8.3 Results and Discussions

The future power potential of the Subansiri Lower Hydroelectric Project has been determined by simulating the reservoir for hydropower generation. The power potential has been determined for the three different land use/land cover scenarios as described in Chapter 7. Table 8.1 gives the power in MW for each of the scenario.

Table 8.1: Power in MW obtained for different scenarios

Time periods	Scenario1 (Power in MW)	Scenario2 (Power in MW)	Scenario3 (Power in MW)			
			Sub-scenario1	Sub-scenario2	Sub-scenario3	Sub-scenario4
1990-2014	312183	312183	312183	312183	312183	312183
2020-2039	282787	236789	184575	186920	192215	186876
2040-2059	270376	278735	213385	190384	214823	218173
2060-2079	256202	258877	268605	259389	274923	269291
2080-2099	264851	261958	279869	275326	288020	282178

Results of the Scenario 1

Fig. 8.1 shows the power in MW determined for the different time periods under the Scenario 1. For this scenario, compared to the historical period 1990-2014, where power obtained during this period was 312183 MW, the future power obtained for SLHEP gradually decreases from 2020-39 to 2060-99 with values 282787MW for 2020-39, 270376MW for 2040-59, 256202MW for 2060-79 respectively. During 2080-99 the power again increases to 264851MW.

From this analysis it can be said that, as compared to 1990-2014, the power potential during 2020-39, 2040-59, 2060-79 and 2080-99 will decrease by 9.42%, 13.39%, 17.93% and 15.16% respectively under the Scenario 1. Thus, there is a possibility that the power potential of the SLHEP will be decreased the most during 2060-79.

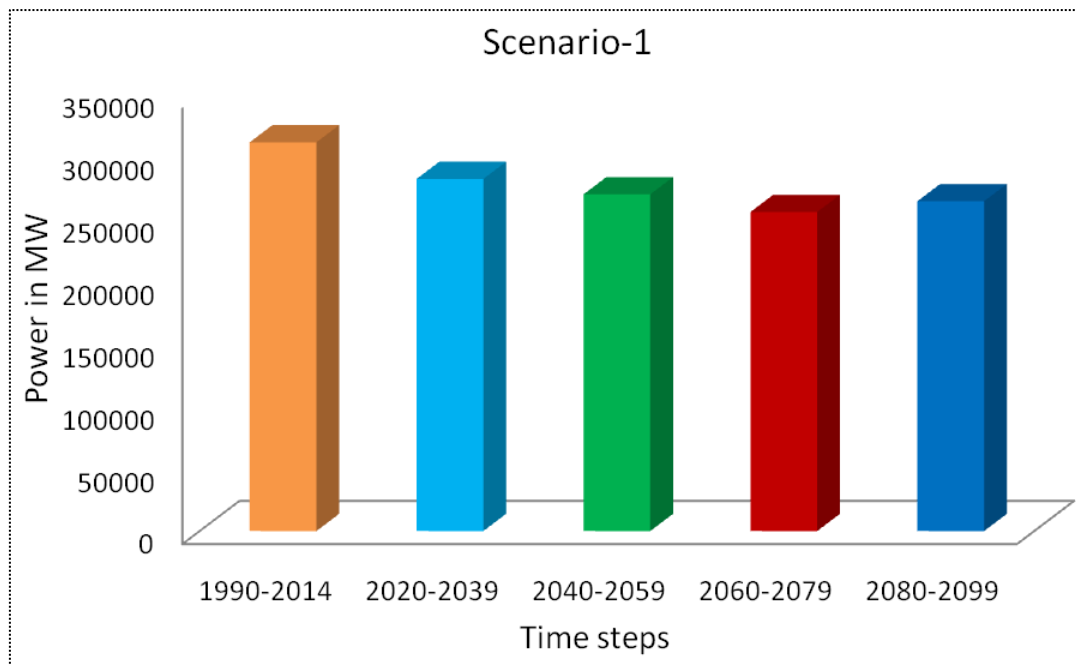


Fig. 8.2: Future power obtained at different time steps from the SLHEP under the Scenario 1

Trend analyses have been performed for these future time steps as shown in Fig 8.3. It can be observed that for each of the time period, the power potentials show decreasing trends. As discussed in the previous chapter, the runoff for these periods also showed decreasing trends. These runoffs have been used as the inflow to the reservoir. Hence, because of the decrease in inflow, the power generation also decreases. The overall future trend analysis for the entire period from 2020-99 also shows decreasing trend in power potential.

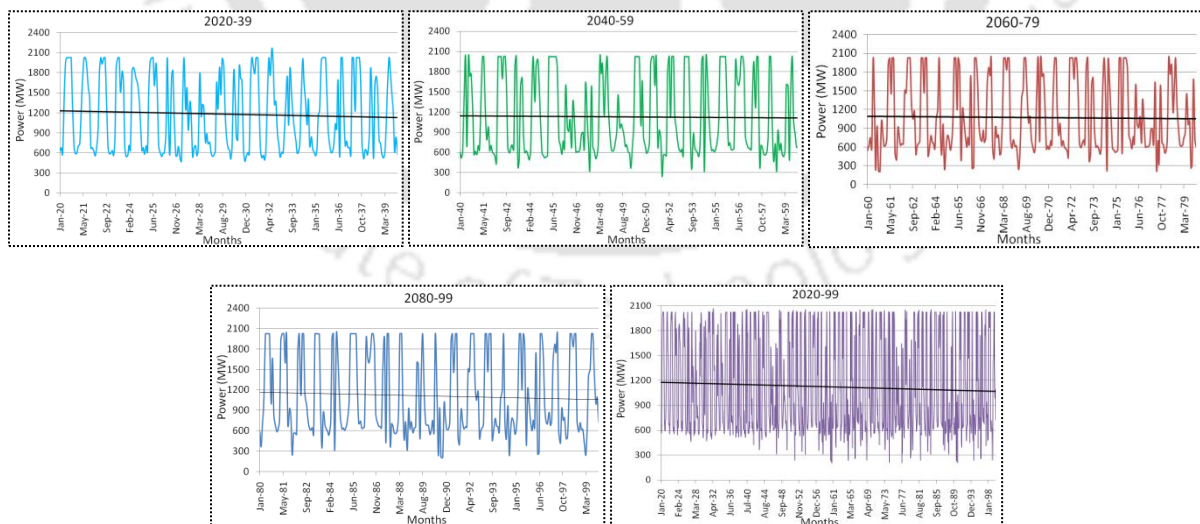


Fig. 8.3: Trend analysis of future power potential of SLHEP under the Scenario 1

Results of the Scenario 2

Under this scenario there are four sub-scenarios for the four different time steps. Fig. 8.4 shows the power generated for each of the time steps. It is observed from the figure that the different time periods show alternate increase and decrease in the generated power. The power for 2020-39, 2040-59, 2060-79 and 2080-99 have been obtained as, 236789MW, 278735MW, 258877MW and 261958MW respectively.

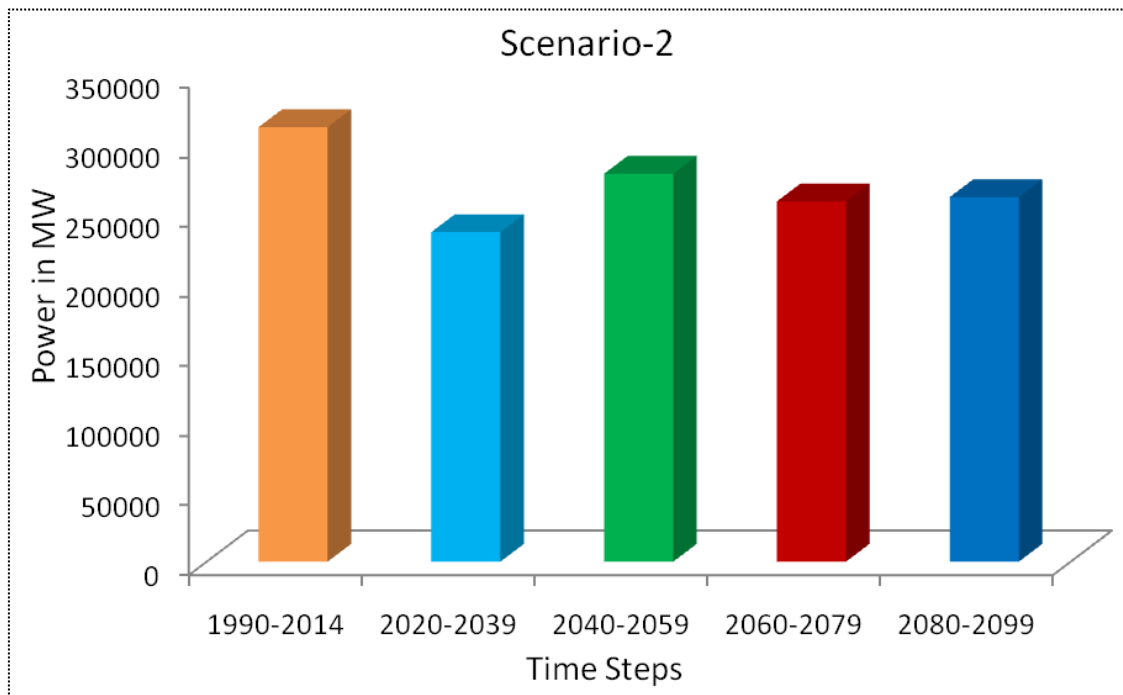


Fig. 8.4: Future power obtained at different time steps from the SLHEP under the Scenario 2

The percent decrease in power potential during these four time steps as compared to that in 1990-2014 are, 24.15%, 10.71%, 17.07% and 16.08% respectively. Thus, there is a possibility that under the land use land cover conditions assumed for the Scenario 2, the power generation will be the minimum during 2020-39. However, for the next time period, 2040-59, the power potential will not vary much compared to the historical period.

The future trends of power potential for different time steps have also been analyzed for the Scenario 2 are shown in Fig. 8.5.

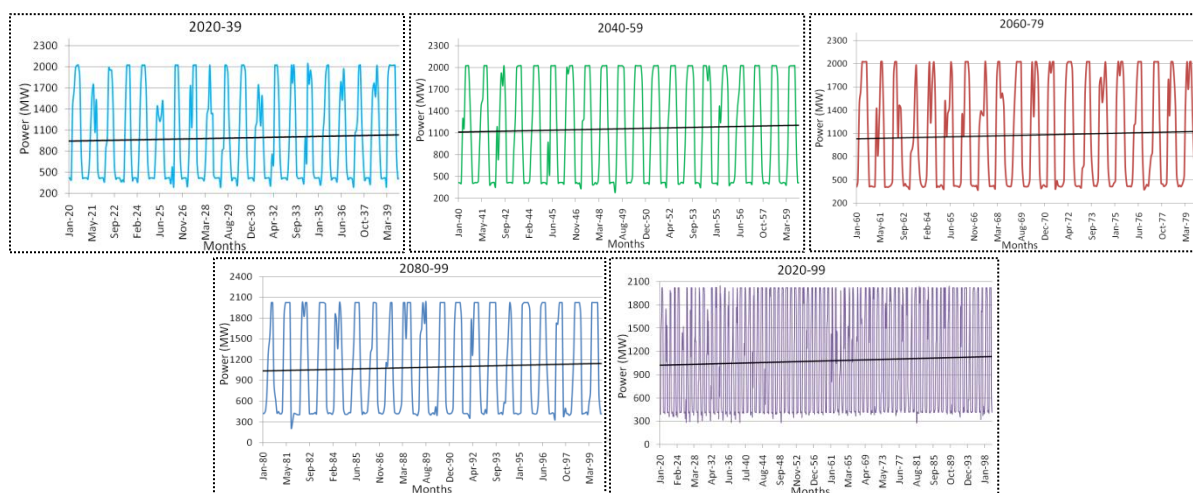


Fig. 8.5: Trend analysis of future power potential of SLHEP under the Scenario 2

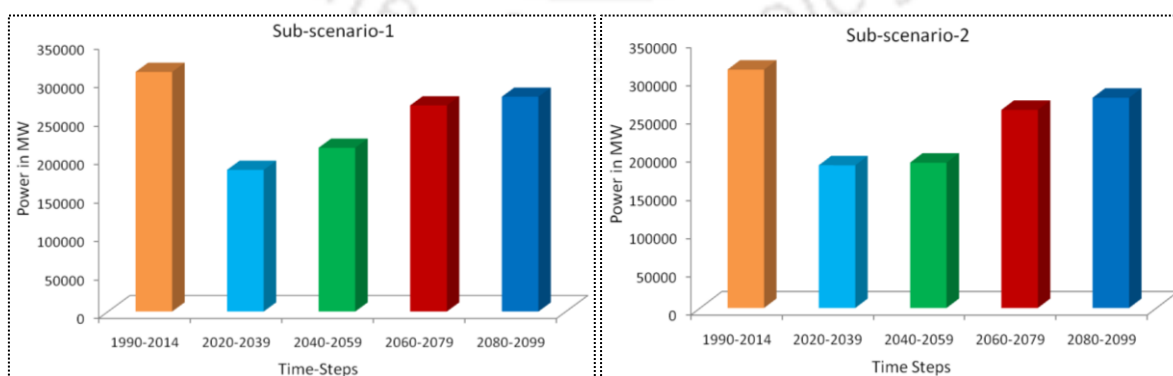
It is observed from Fig. 8.5 that future power potential of the SLHEP will have increasing trend for different time periods including the entire period from 2020-99 under the Scenario 2. The increasing trends in runoff during these periods for the Scenario 2 have led to the increasing trends in the power potential.

Results of the Scenario 3

The power obtained for different sub-scenarios under the Scenarion3 are shown in Fig. 8.6.

For all the four sub-scenarios it is observed that the power first decreases for the period 2020-39 compared to the historical period and then starts increasing again up to the year 2099.

For the sub-scenario 1, the power obtained for 2020-39, 2040-59, 2060-79 and 2080-99 are 184575MW, 213385MW, 268605MW and 279869MW respectively. As compared to 1990-2014, the power potential will be decreased by 40.88% during 2020-39. For the other time periods i.e. 2040-59, 2060-79 and 2080-99, the power potential will be decreased by 31.64%, 13.96% and 10.35% respectively compared to that in 1990-2014.



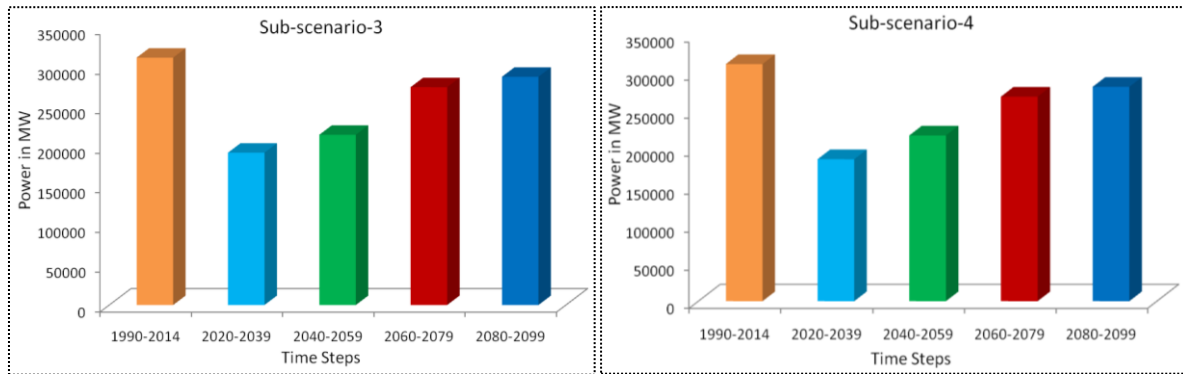


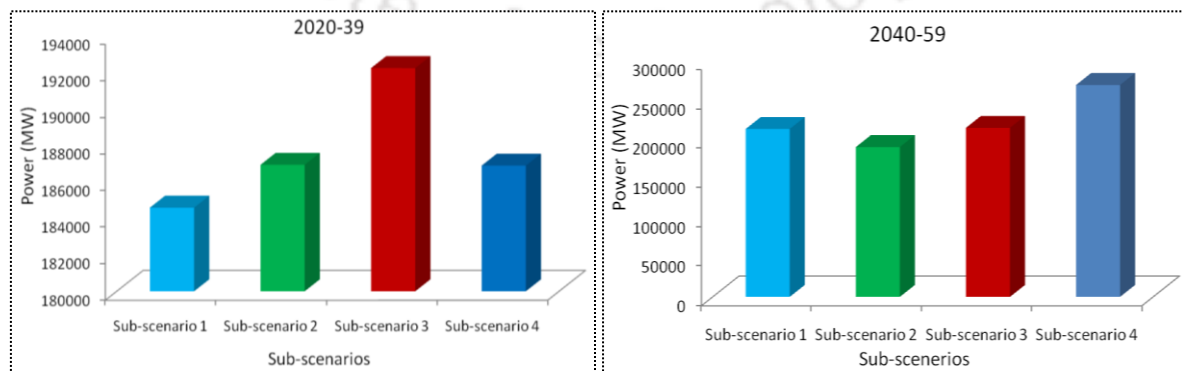
Fig. 8.6: Future power obtained at different time steps for the SLHEP under the Scenario 3

For the sub-scenario 2, 186920MW, 190384MW, 259389MW and 275326MW of power have been obtained for 2020-39, 2040-59, 2060-79 and 2080-99 respectively. The percent decrease in power potential as compared to that in the historical period for these four time periods are, 40.12%, 39.01%, 16.91% and 11.81% respectively.

The power obtained for these time periods under sub-scenario3 are 192215MW, 214823MW, 274923MW and 288020MW respectively. The power potential will be decreased by 38.43%, 31.18%, 11.94% and 7.74% respectively for 2020-39, 2040-59, 2060-79 and 2080-99 as compared to the historical period.

Again, 186876MW of power during 2020-39, 218173MW for 2040-59, 269291MW for 2060-79 and 282178MW for 2080-99 have been obtained under the sub-scenario 4 with percent decrease of 40.14%, 30.11%, 13.74% and 9.61% respectively as compared to the historical period 1990-2014.

Another analysis has been performed under the Scenario 3 to see the variation of future power potential of the project for each of the time periods under the four different sub-scenarios (Fig. 8.7).



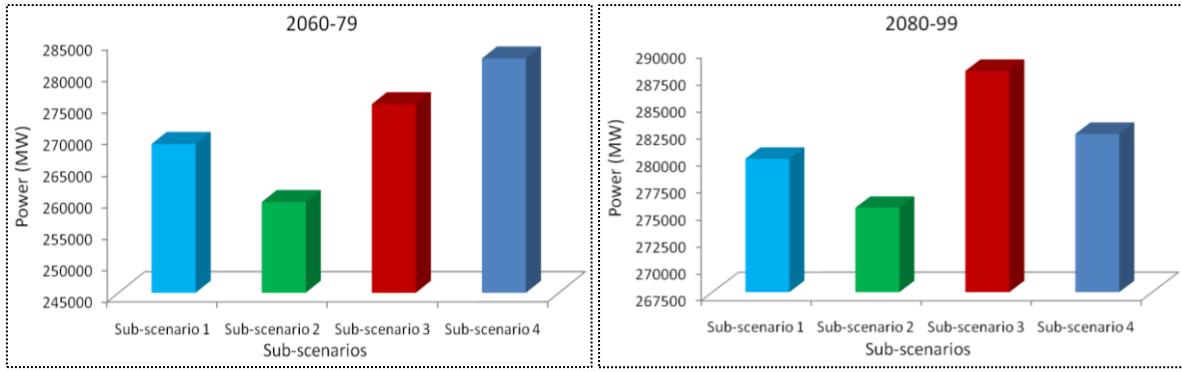


Fig. 8.7: Future power obtained for SLHEP for each time period under the four sub-scenarios

It is seen that during the period 2020-39, the minimum and the maximum powers were obtained under the sub-scenario 1 and 3 with 184575MW and 192215MW respectively.

During 2040-59, the minimum power was obtained for the sub-scenario 2 (190384MW) and the maximum was obtained for the sub-scenario 4 (218173MW).

The minimum powers during the periods 2060-79 and 2080-99 have been obtained for sub-scenario 2 with 259389MW and 275326MW of powers respectively. However the maximum power during 2060-79 has been obtained for sub-scenario 4(269292MW) and during 2080-99, the maximum power has been obtained for sub-scenario 3(288020MW).

Thus from this analysis, it can be said that, there is a possibility of occurrence of maximum hydropower generation during 2080-99, under the conditions considered for the sub-scenario 3. On the other hand, the power generation will be the minimum during 2020-39 for sub-scenario 1.

The linear trends of power potential of the SLHEP have been analyzed for each time period including the entire period from 2020-99 for the four different sub-scenarios of the Scenario 3. The results are plotted in Fig. 8.8, 8.9, 8.10, 8.11 and 8.12 respectively.

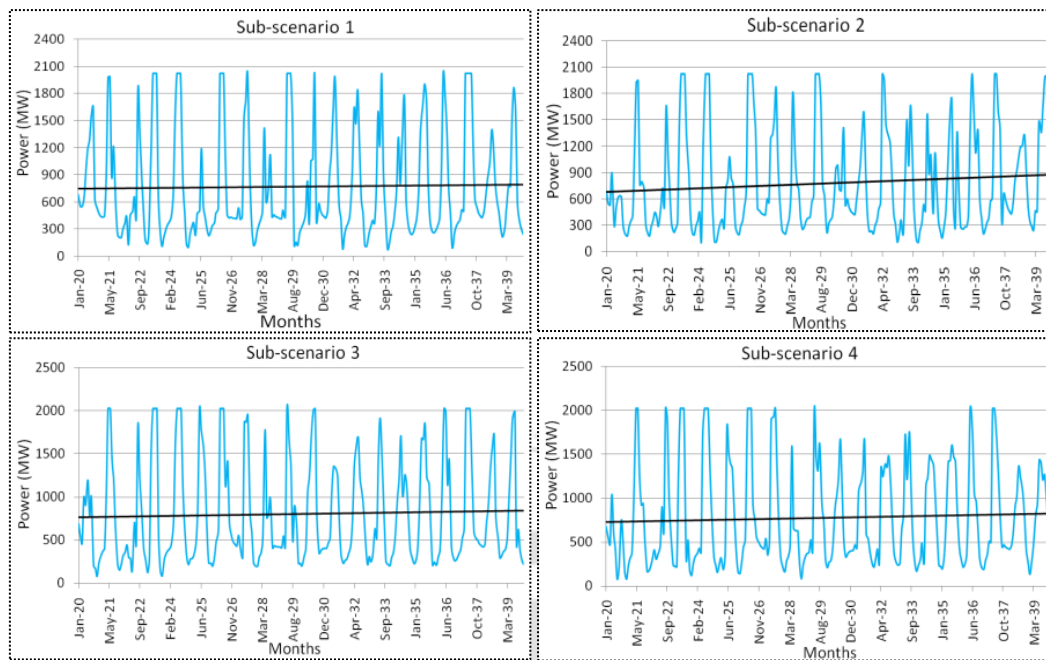


Fig. 8.8: Trends showing power potential of SLHEP for the four different sub-scenarios under scenario 3 for 2020-39.

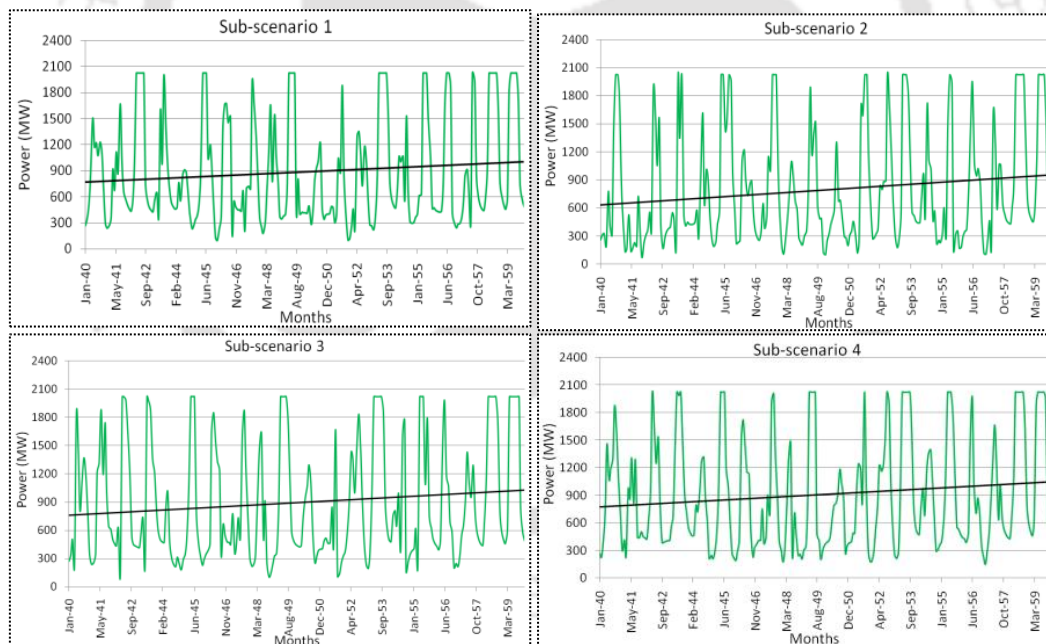


Fig. 8.9: Trends showing power potential of SLHEP for the four different sub-scenarios under scenario 3 for 2040-59.

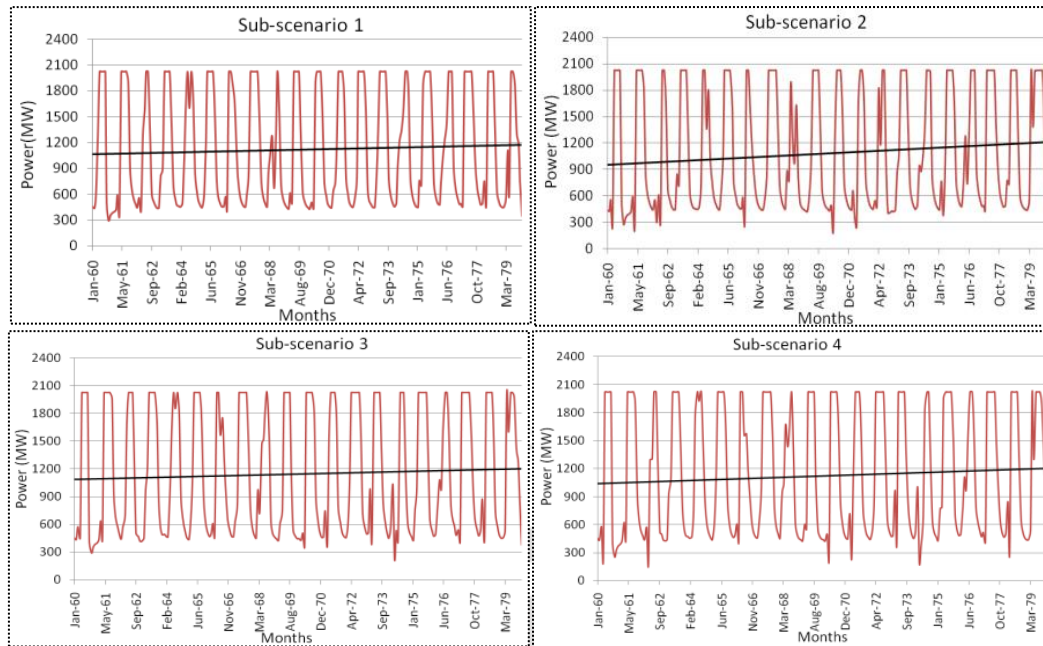


Fig. 8.10: Trends showing power potential of SLHEP for the four different sub-scenarios under scenario 3 for 2060-79.

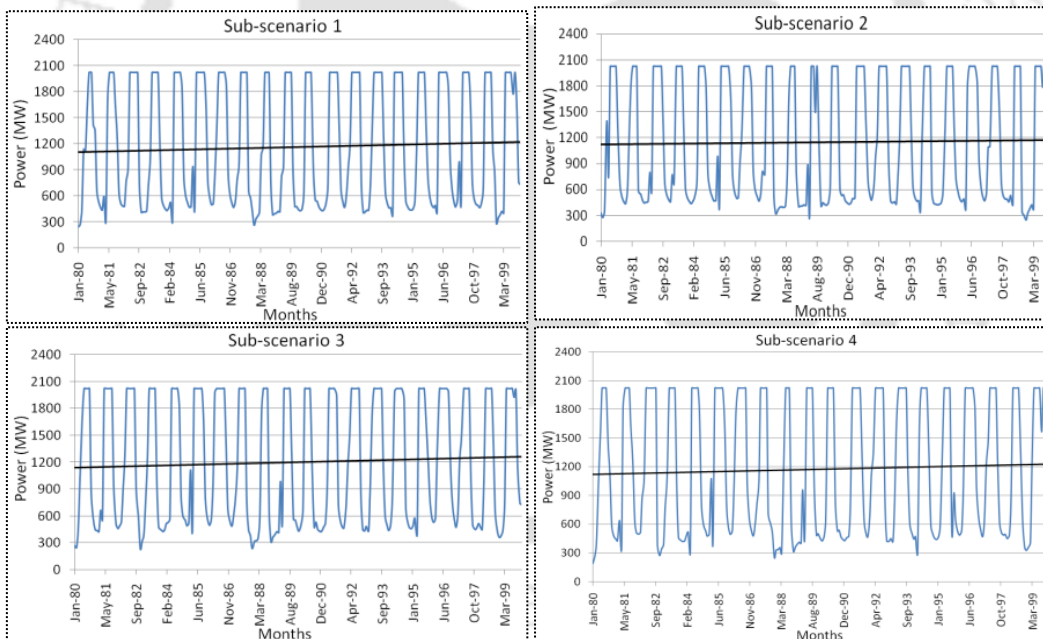


Fig. 8.11: Trends showing power potential of SLHEP for the four different sub-scenarios under scenario 3 for 2080-99.

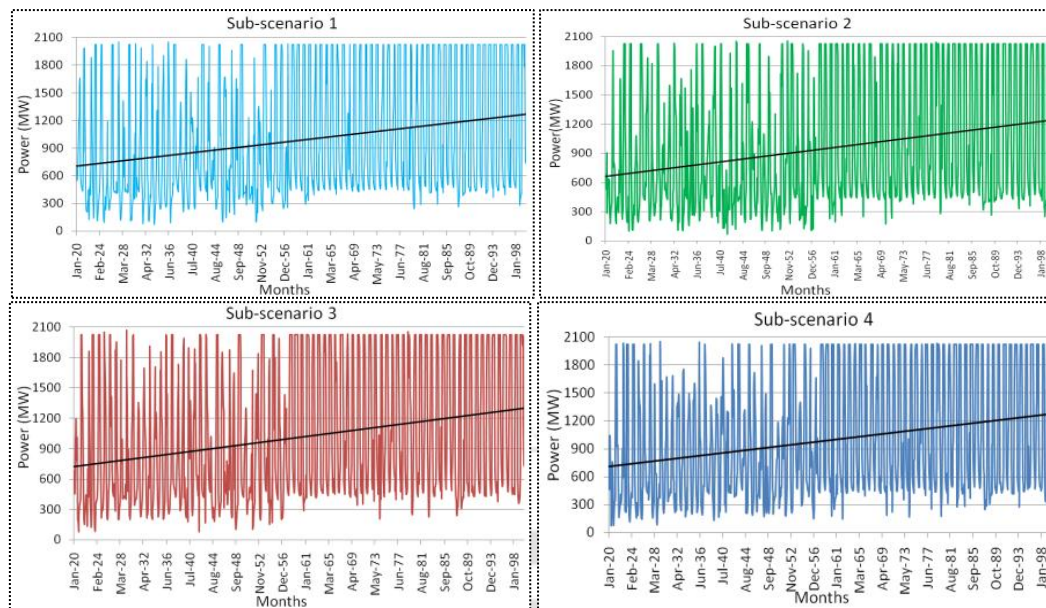


Fig. 8.12: Trends showing power potential of SLHEP for the four different sub-scenarios under the Scenario 3 for 2020-99

It is observed from the figures that the future power potential of SLHEP shows increasing trends for each of the time step under the different sub-scenarios of the Scenario 3. The increasing trends of runoff of the river Subansiri for each time step under this scenario as shown in Fig. 7. 21-25 in chapter 7, have a significant impact on increase in power potential of the hydropower project.

8.4 Conclusions

In this study, the future power potential of Subansiri Lower Hydroelectric Project has been analyzed using simulation model. Continuity constraint, storage constraint and reservoir release constraint are the three different constraints considered in the model. The runoffs of the river Subansiri as simulated by ANN-SCS based hybrid model under different land use/land cover scenarios have been used as the inflows to the reservoir. It has been observed from the study that for the Scenario 1, where constant LULC conditions have been assumed from 2012 to 2099 the future power potential shows decreasing trends for all the four different time periods. For the other scenarios, where various changes in each LULC category were considered, the future power potential show increasing trends for different time periods from 2020-99. Although the power potentials for the different time periods showed increasing trends from 2020-99 under Scenario 2 and 3, in no case, increase in power potential has been observed compared to the power potential of the historical period from 1990 to 2014.



CHAPTER 9

SUMMARY AND CONCLUSIONS

9.1 General

In the present study, the snow cover areas of the Brahmaputra and the Subansiri River Basins have been determined for a period of 13 years from 2002 to 2015 for the months of January, April, July and October. Trend analyses have been performed to see the change in the snow cover areas of the said basins for these months with respect to the change in temperature over the basins. Part of the discharge of the Brahmaputra and the Subansiri Rivers is influenced by the melting of snow at the upper part of the catchments which falls in the Himalayan range. As mentioned in various literatures, the snow and glaciers in the Himalayan regions are gradually retreating due to the increase in temperature. This snowmelt water have profound impact on the discharge of these rivers and a trend analysis has been performed in this study to see the effect of decrease in snow cover area on the discharges of the river Brahmaputra and the Subansiri. Land use/land cover assessment is one of the most important parameters to meaningfully plan for land resource management. Remote Sensing and Geographical Information System (GIS) provide an excellent means of spatial data analysis and interpretation. Here, in this study, the land use/land cover change detections have also been analyzed for the Brahmaputra and the Subansiri River Basins for one complete decade from 2002 to 2012 for the months of January, April and October using remote sensing and GIS technique. The Subansiri catchment experiences heavy rainfall and thus it has major impact on the runoff of this river. Hence, it is of utmost importance to study the change in future pattern of rainfall. The rainfall over the basin has been downscaled and predicted up to the year 2099 to analyze the possible future change in rainfall pattern. Due to change in rainfall, the flow scenario of the river will also be changed. To study the impact of rainfall on runoff of a river, various hydrological models are available. Empirical models establish the relationship between rainfall and runoff and contain no physical transformation function to relate input to output. Rainfall alone cannot explain the runoff variance efficiently which can be attributed to antecedent moisture content, rainfall intensity, and physical characteristics of the catchment such as soil, slope and land use/land cover conditions. Thus, the main constraint of the empirical models is that these numerical models are incapable of modelling

the influence of change in vegetation and other land use land cover types on various hydrological components. Hence, in this study, the accuracy of two models, one, an ANN based rainfall-runoff model and another, an ANN-SCS based hybrid model have been compared and the future flow scenario of the river Subansiri has been analyzed accordingly up to the year 2099. The impact of change in this future flow scenario of the river Subansiri on the power potential of the Subansiri Lower Hydroelectric Project have also been studied for different future time periods.

9.2 Conclusions

The following conclusions can be drawn from the present study.

- Study on change in snow cover area of the Brahmaputra and the Subansiri River basins and its impact on the discharge of the rivers

The snow cover areas of both the Brahmaputra and the Subansiri basins have been determined by the Normalized Difference Snow Index (NDSI) method starting from 2002 to 2015 for the months of January, April, July and October using MODIS satellite data of 500m resolution. The temperature data of HadCM3 GCM has been used to study the impact of change in temperature on the change in snow cover areas of the basins. It has been observed that for both the basins, for the month of January, the snow cover area showed an increasing trend with respect to the decreasing trend of temperature. However, for other three months, from 2002 to 2015, decreasing trends of snow cover areas have been observed with respect to the increasing trends of temperature. The percent changes in snow cover area from 2003 to 2015 with respect to the snow cover area of 2002 have also been analyzed. It has been found that for the Brahmaputra basin, except for the years 2003 and 2012, the other remaining years showed negative percent change. This is because the average snow cover areas of these years were less compared to that of 2002. For the Subansiri River Basin, except for the year 2003 where a positive change has been seen, for other remaining years from 2004 to 2015, the average snow cover area showed less values compared to the snow cover area of 2002 and because of this negative percent change in average snow cover area have been observed for these years.

The linear trend analysis between change in snow cover area and change in discharge of the rivers Brahmaputra and Subansiri showed that when the snow cover area decreases the discharge of the rivers increases and vice versa leading to the conclusion that snowmelt water influences the discharge of the rivers at downstream.

- Land use/land cover change detection study of the Brahmaputra and the Subansiri River Basins.

The land use/land cover change detections have been studied for both the basins from 2002 to 2012 for three different months viz., January, April and October using supervised classification method and maximum likelihood classifier algorithm. MODIS data of 500m resolution has been used to classify the basins into five different classes, bare soil, surface water bodies, dense vegetation, light vegetation and snow cover area. Apart from the changes that have taken place in the basins for the entire period from 2002 to 2012, year wise changes have also been carried out for the different months. The major output of this study is that, dense vegetation and snow cover area have decreased notably during this period. On the other hand, significant increases in light vegetation and bare soil have been observed during 2002-12. This may be attributed to the fact that increase in population has played an active role towards diminishing dense vegetation cover and increase in light vegetation and bare soil. Again, due to increase in temperature which is a consequence of climate change melting of snow occurred in the basins leading to decrease in the snow cover area.

- Future rainfall pattern analysis over the Subansiri River Basin using Statistical Downscaling Techniques.

The rainfall over the Subansiri basin has been downscaled at 24 different locations by both multiple linear and non-linear regression based statistical downscaling techniques and by Artificial Neural Network model. The APHRODITE's gridded rainfall data and HadCM3 GCM climatic parameters of A2 scenario have been used as the predictand and the predictors respectively. The regression analyses have been performed for two conditions, one, by taking the climatic parameters of one HadCM3 point that falls within the basin and one, by taking the weighted average values of the climatic parameters of the four HadCM3 points that fall in and around the Subansiri basin. On the basis of MAE, MSE, RMSE and R^2 values it has been found that multiple non-linear regression based statistical downscaling technique with weighted average values outperformed the other downscaling methods. Hence, by using this multiple non-linear regression based statistical downscaling technique, the future rainfall at the 24 locations have been predicted up to the year 2099 for four different time steps viz., 2020-39, 2040-59, 2060-79 and 2080-99. No significant change has been observed for the period 2020-39, while for the other three time steps, the rainfall showed decreasing trends. The analysis on spatial variation of rainfall over the basin showed that the basin will receive

less rainfall during 2080-99 compared to the other time periods. The spatial change in rainfall pattern for wet, dry and months with moderate rainfall showed potential decrease of rainfall in the wet months and months with moderate rainfall and increase of rainfall in the dry months in future.

➤ Analysis of future flow scenario of the Subansiri River

Using the rainfall as predicted by the non-linear regression based statistical downscaling technique, the future runoff of the Subansiri River has been predicted using an ANN based rainfall-runoff model and an ANN-SCS based hybrid model. The accuracy of the models were compared on the basis of coefficient of correlation (R) values and found that the hybrid model where effect of land use/land cover had also been incorporated performed better. Future three different land use/land cover scenarios have been created and the flow scenario of the river has been analyzed for the times periods, 2020-39, 2040-59, 2060-79 and 2080-99 for all the scenarios. It has been observed that for the Scenario 1, where it was assumed that LULC condition will not change from 2012 and will remain constant up to 2099, the runoff showed decreasing trends for the different time periods. However, for the other two scenarios, where different changes in the LULC classes have been incorporated including decrease in dense vegetation, bare soil and snow cover area as well as increase in the light vegetation, the runoff showed increasing trend for the future four different time steps. The infiltration rate decreases because of deforestation and urbanization which lead to increase in surface runoff. Again, the melting of snow also contributes to the runoff of the river.

➤ Future power potential of Subansiri Lower Hydroelectric Project

By considering the runoff obtained from the ANN-SCS based hybrid model for different land use/land cover scenarios as the inflow to the reservoir, the future power potential of the Subansiri Lower Hydroelectric Project has been analyzed up to 2099 using reservoir simulation model. It has been observed from the study that except under the Scenario 1 where the future power potential decreases, for other two scenarios, it increases for the different time periods. Thus, it can be said that runoff has a direct impact on the power potential of the hydropower plant. Under Scenario 1, the runoff showed decreasing trends for different time periods. As a result, the power potential under this scenario also showed decreasing trends in future. Again, for other two scenarios, the runoff showed increasing trends and hence, power potential also showed increasing trends. In other words, the change in climate in near future will also affect the power potential of the SLHEP.

9.3 Recommendations for future work

- ✓ In this study, MOD09A1.5 (MODIS/Terra Surface Reflectance 8-Day L3 Global 500m SIN Grid) MODIS data of 500m resolution has been used to determine the snow cover area. However, other available high resolution remote sensing data can be used to determine the snow cover area more accurately.
- ✓ Only the trend analyses have been performed here to study the change in snow cover area with respect to change in temperature. More detailed analysis can be done to study the future possible changes in the snow cover areas of the basins for each degree rise in temperature.
- ✓ The land use/land cover change detection has been done in this study by considering only five classes, bare soil, surface water bodies, dense vegetation, light vegetation and snow cover area. The urbanization has been included in the light vegetation. However, detail analysis can be performed by taking into account settlement as a different class.
- ✓ The land use/land cover change detection in this study has been performed using MODIS 500m resolution data which is very coarse and is useful for mapping large basins. However, using high resolution data, if the analysis can be made on sub-catchment basis, the results will be more realistic.
- ✓ The climatic parameters of only one GCM *i.e.* the HadCM3 GCM have been used in the present study. However, data from more GCMs can be used and compared and if the best one is used for the analysis, it will give better results.
- ✓ Probabilistic analysis can be made for the future flow scenario of the river using different GCMs.
- ✓ Only simulation model has been used to study the future power potential of the Subansiri Lower Hydroelectric Project under different land use/land cover scenarios. However, different optimization models like linear programming, dynamic programming, ANN, Genetic Algorithm etc. can be used to analyze the future probable power potential of the project in more detail.



REFERENCES

- Abulohom, M.S., Shah, S.M.S. and Ghumman, A.R.(2001), 'Development of a rainfall–runoff model, its calibration and validation.' *Journal of Water Resources Management*, 15:149-163.
- Acreman, M.C., Farquharson, F.A.K., McCartney, M.P., Sullivan, C., Campbell, K., Hodgson, N., Morton, J., Smith, D., Birley, M., Knott, D., Lazenby, J., Wingfield, R. and Barbier, E.B. (2000), 'Managed Flood Releases from Reservoirs: Issues and Guidance. Report to UK Department for International Development and the World Commission on Dams.' *Centre for Ecology and Hydrology*, Wallingford, United Kingdom.
- Adeniyi P.O and Omojola A. (1999), 'Land use/land cover change evaluation in Sokoto-Rima Basin of North Western Nigeria based on Archival of the Environment (AARSE) on Geoinformation Technology Applications for Resource and Environmental Management in Africa.' Pp 143-172.
- Adepoju, M.O., Millington, A.C. and Tansey, K.T. (2006), 'Land Use/ Land Cover Change Detection in Metropolitan Lagos (Nigeria): 1984–2002.' *American Society for Photogrammetry and Remote Sensing*, Annual Conference, Reno, Nevada, May 1–5.
- Afzal, M.T., Arslan, M., Zafar, S. and Waqar M.M. (2014), 'Satellite covered snow cover status and trends in the Indus valley.' *Journal of space technology*, 4(1): 26-31.
- Agarwal, A. and Singh, R.D. (2004), 'Runoff modeling through back propagation artificial neural network with variable rainfall–runoff data.' *Water Resources Management*, 18: 285–300.
- Ageta, Y., Iwata, S., Yabuki, H., Naito, N., Sakai, A. and Narama, C. (2000), 'Expansion of glacier lakes in recent decades in the Bhutan Himalayas.' In M. Nakawo, C.F. Raymond, and A. Fountain (Eds.), *Debris-Covered Glaciers*, 264, IAHS Publications.
- Ahlamann, H.W. (1948), 'Glaciological Research on the north Atlantic coasts.' Research Series No. 1. London: *Geographical Society*, 83 pp.
- Ahlmann, H.W. (1935), 'Scientific results of the Norwegian-Swedish Spitzbergen expedition 1934, Part 5: The Fourteenth of July Glacier.' *Geografiska Annaler*, 17: 167–218.
- Ahmed J.A. and Sarma, A.K. (2005), 'Genetic algorithm for optimal operation policy of a multipurpose reservoir.' *Water resources management*, 19: 145-161.
- Ahmed, I., Verma, V. and Verma, M.K. (2015), 'Application of curve number method for estimation of runoff potential in GIS environment.' *2nd International Conference*

- on Geological and Civil Engineering IPCBEE, Singapore. DOI: 10.7763/IPCBEE. 2015. V80. 4.
- Akbari, S. and Singh, R. (2012), 'Hydrological modelling of catchments using MIKE SHE.' *IEEE-International Conference on Advances in Engineering, Science and Management*, 335–340.
- Altansukh, O. (2012), 'Tuul River and its Catchment Area Delineation from Satellite Image.' *Computational Water, Energy and Environmental Engineering*, 1:0-23.
- Amin, A., Amin, A. and Singh, S.K. (2012), 'Study of urban land use dynamics in Srinagar city using geospatial approach.' *Bull. Envi. Sci. Res.*, 1 (2): 18–24.
- Amirhossien, F., Alireza, F., Kazem, J. and Mohammadbagher, S. (2015), 'A Comparison of ANN and HSPF Models for Runoff Simulation in Balkhichai River Watershed, Iran.' *American Journal of Climate Change*, 4: 203-216.
- Anderson, A. (2008), 'Using MODIS cloud products to study glaciations level.' *GEST Graduate Student Summer Program*, Michigan Technological University.
- Anderson, E.A. (1973), 'National weather service river forecast system- snow accumulation and ablation model.' NOAA Tech. Memo. NWS HYDRO-17, US Dept. Commer., Washington, DC, USA.
- Angstrom, A. (1933), 'On the dependence of ablation on air temperature, radiation and wind.' *Geografiska Annaler*, 15: 264–71.
- Arctic Climate Impact Assessment,(2005), 'Arctic Climate Impact Assessment.' *Cambridge University Press*. 1042pp.
- Armstrong R.L. (2010), 'The Glaciers of the Hindu Kush-Himalayan Region. A summary of the science regarding glacier melt/retreat in the Himalayan, Hindu Kush, Karakoram, Pamir, and Tien Shan mountain ranges.' *Technical Paper. Kathmandu. ICIMOD and USAID*. ISBN 978 92 9115 173 8.
- Arnell, N.W. (1999), 'Climate Change and Global Water Resources.' *Glob. Env. Change*, 9: 31–49.
- Arnell, N.W., Hudson, D.A. and Jones, R.G. (2003), 'Climate change scenarios from a regional climate model: Estimating change in runoff in southern Africa.' *Journal of Geophysical Research - Atmospheres*, 108 (D16): AR 4519.
- Arnold, J.G., Allen, P.M. and Bernhardt, G. (1993), 'A comprehensive surface–groundwater flow model.' *Journal of Hydrology*, 142: 47–69.
- Arunkumar, R. and Jothiprakash, V. (2012), 'Optimal reservoir operation for hydropower generation using non-linear programming model.' *J. Inst. Eng. India Ser. A*, 93(2):111–120.

- Bakalial, B., Biswas, S.P., Borah S. and Baruah, D. (2014), 'Checklist of fishes of Lower Subansiri river drainage, Northeast India.' *Annals of Biological Research*, 5(2):55-67.
- Banasik, K. (2010), 'Empirical determination of runoff curve number for a small agricultural watershed in Poland.' *2nd Joint Federal Interagency Conference, Las Vegas, NV*, June 27 - July 1, 2010.
- Bansode, A. and Patil, K.A. (2014), 'Estimation of runoff using SCS curve number method and ArcGIS.' *International Journal of Scientific & Engineering Research*, 5(7):1283.
- Bardossy, A., Van Mierlo, J.M.C.(2000), 'Regional precipitation and temperature scenarios for climate change.' *Hydrological Sciences Journal*, 45: 559-575.
- Barnett, T. P., Adam, J. C. and Lettenmaier, D. P. (2005), 'Potential impacts of a warming climate on water availability in snow-dominated regions.' *Nature*, 438(7066): 303–309. doi:10.1038/nature04141.
- Barnett, T. P., Adam, J.C. and Lettenmaier, D.P. (2005), 'Potential impacts of a warming climate on water availability in snow-dominated regions.' *Nature*, 438: 303–309, doi:10.1038/nature04141.
- Basist, A., D. Garrett, R. Ferraro, N. G. and Mitchell, K. (1996), 'A comparison between snow cover products derived from visible and microwave satellite observations.' *J. Appl. Met.*, 35: 163-177.
- Bastawesy, M.A.E., Ali, R.R. and Nasr, A.H. (2008), 'The use of Remote Sensing and GIS for Catchment Delineation in Northwestern Coast of Egypt: An Assessment of Water Resource and Soil Potential.' *The Egyptian Journal of Remote Sensing and Space Sciences*, 11:3-16.
- Baxter, R.M. (1977), 'Environmental effects of dams and impoundments.' *Annual review of ecology, evolution and systematics*, 8:255-83.
- Becker, L., Yeh, W.W.G., Fults, D. and Sparks, D. (1976), 'Operation models for the central valley project.' *J. Water Resour. Plann. Manage.*, 102: 101-115.
- Bellman, R. (1957), 'Dynamic Programming.' *Princeton Univ. Press*, Princeton, New Jersey.
- Bellman, R. and Dreyfus, S.E. (1962), 'Applied Dynamic Programming.' *Princeton Univ. Press*, Princeton, New Jersey.
- Benestad, R.E. (2009), 'Downscaling precipitation extremes.' *Theoretical and Applied Climatology*, 100(1-2): 1-21.
- Bengtsson, L. (1980), 'Evaporation from snow cover.' *Nordic Hydrol.*, 11, 221–234.

- Beniston, M. (2003), 'Climatic change in mountain regions: A review of possible impacts.' *Climate Change*, 59: 5–31.
- Beniston, M., Diaz, H.F. and Bradley, R.S. (1997), 'Climatic change at high elevation sites; a review.' *Climatic Change*, 36: 233–251.
- Berberoglu, S., Evrendilek, F., Ozkan, C. and Donmez, C. (2007), 'Modeling forest productivity using Envisat MERIS data.' *Sensors*, 7: 2115-2127.
- Bergstrom, S., Carlsson, B., Gardelin, M., Lindstrom, G., Pettersson, A. and Rummukeinen, M. (2001), 'Climate change impacts on runoff in Sweden- assessments by global climate models, dynamical downscaling and hydrological modeling.' *Climate Research*, 16: 101-112.
- Berthier, E., Arnaud, Y., Kumar, R., Ahmad, S., Wagnon, P. and Chevallier, P. (2007), 'Remote sensing estimates of glacier mass balances in the Himachal Pradesh (western Himalaya, India).' *Remote Sensing of Environment*, 108: 327-338.
- Beven, K. (1983), 'Surface water hydrology-runoff generation and basin structure.' *Rev. Geophys.*, 21(3): 721-730.
- Beven, K., Warren, R., and Zaoui, J. (1980), 'SHE: Towards a methodology for physically-based distributed forecasting in hydrology.' *Hydrological Forecasting*, The Oxford Symposium, IAHS-AISH, 133–137.
- Bhagawat, R. (2011), 'Application of remote sensing and GIS, land use/land cover change in Kathmandu metropolitan city. Nepal.' *J. Theor. Appl. Inform. Technol.*, 23 (2): 80–86.
- Bishop, M.P., Kargel, J.S., Kieffer, H.H., MacKinnon, D.J., Raup, B.H. and Shroder, J.F. (2000), 'Remote sensing science and technology for studying glacier processes in High Asia.' *A. Glaciol.*, 31: 164-170.
- Bishop, M.P., Shroder, J.F. and Ward, J.L. (1995), 'SPOT multispectral analysis for producing supraglacial debris-load estimates for the Batura Glacier, Pakistan.' *Geocarto International*, 10: 81–90.
- Bocchiola, D., Diolaiuti, G., Soncini, A., Mihalcea, C., D'Agata², C., Mayer³, C., Lambrecht, A., Rosso, R. and Smiraglia, C. (2011), 'Prediction of future hydrological regimes in poorly gauged high altitude basins: the case study of the upper Indus, Pakistan.' *Hydrology and Earth System Sciences*, 15(7): 2059-2075,
- Bolch, T., Menounos, B. and Wheate, R. (2010), 'Landsat-based inventory of glaciers in western Canada, 1985–2005.' *Remote Sensing of Environment*, 114: 127–137.
- Bolch, T., Yao, T., Kang, S., Buchroithner, M. F., Scherer, D., Maussion, F., Huintjes, E. and Schneider, C. (2010), 'A glacier inventory for the western Nyainqentanglha Range

- and the Nam Co Basin, Tibet, and glacier changes 1976–2009.’ *The Cryosphere*, 4: 419–433.
- Bora, M. and Goswami, D.C. (2016), ‘Spatio-temporal landuse/landcover (LULC) change analysis of Kolong River basin, Assam, India using Geospatial technologies.’ *International Journal of Geomatics and Geosciences*, 6(3):1676-1684.
- Bouraoui, F., Vachaud, G., Li, L.Z.X., Le Treut, H., Chen, T., 1999. Evaluation of the impact of climate changes on water storage and groundwater recharge at the watershed scale. *Climate Dynamics* 15, 153–161.
- Box, G.E. and Jenkins, G.M. (1976), ‘Time Series Analysis: Forecasting and Control.’ *Prentice Hall*, San Francisco, California, 1976.
- Bradley, R.S., Keimig, F.T. and Diaz, H.F. (2004), ‘Projected temperature changes along the American cordillera and the planned GCOS network.’ *Geophysical Research Letters*, 31, L16210. doi:10.1029/2004GL020229.
- Braithwaite, R. J. and Olese, O.B. (1989), ‘Calculations of glacier ablation from air temperature, West Greenland.’ In: *Glacier Fluctuations and Climate Change* (ed. by J. Oerlemans), 219–233. Kluwer, Dordrecht, The Netherlands.
- Brandt, S. (2000), ‘Classification of geomorphological effects downstream of dams.’ *Catena*, 40(4): 375-401.
- Brath, A., Montanari, A., Moretti, G. (2006), ‘Assessing the effect on flood frequency of land use change via hydrological simulation (with uncertainty).’ *Journal of Hydrology* 324(1-4), 141-153.
- Braun, L.N., Brun, E., Durand, Y., Martin, E. and Tourasse, P. (1994), ‘Simulation of discharge using different methods of meteorological data distribution, basin discretization and snow modelling.’ *Nordic Hydrol.*, 25, 129–144.
- Brierley, G.J. and Fryiers, K.A. (2005), ‘Geomorphology and river management: applications of the river styles framework. *Blackwee*, Oxford.
- Brodzik, M. and R. Armstrong. (2013), ‘ Northern Hemisphere EASE-Grid 2.0 Weekly Snow Cover and Sea Ice Extent, Version 4.’
- Brondizio, E.S., Moran, E.F. and Wu, Y. (1994), ‘Land use change in the Amazon estuary: patterns of Caboclo settlement and landscape management.’ *Hum. Ecol.*, 22 (3): 249–278.
- Brown, A. J., Hannaford, J. F. and Hall, R. L. (1979), ‘Application of snow covered area to runoff forecasting in selected basins of the Sierra, Nevada, California.’ *Proc. Final Workshop on Operational Applications of Satellite Snow Cover Observations*, NASA CP-2116: 185-200.

- Brown, J., Herper, J. and Humphrey, N. (2010), 'Cirque glacier sensitivity to 21st century warming: Sperry Glaciers, Rocky Mountain, USA.' *Global and Planetary Change*, 74: 91-98.
- Buma, J. and Dehn, M. (2000), 'Impact of climate change on a landslide in South East France, simulated using different GCM scenarios and downscaling methods for local precipitation.' *Climate Research*, 15 (1): 69–81.
- Bunting, J.T. and d'Entremont, R.P. (1982), 'Improved cloud detection utilizing defense meteorological satellite program near infrared measurements.' Air Force Geophysics Laboratory, Hanscom AFB, MA, AFGL-TR-82-0027, *Environmental Research Papers*, 765: 91.
- Burred, S.G., Hayden, H.H., Burrard, S. and Heron, A.M. (1934), 'The glaciers and rivers of the Himalayas and Tibet. In A Sketch of the Geography and Geology of the Himalaya Mountains and Tibet, Part III.' *Survey of India and Geological Survey of India Publication*, 141–276.
- Burrough, P.A. (1986), 'Principles of geographical Information Systems for Land Resources Assessment.' *Oxford Univ. Press*, New York, 193p.
- Cai, X., Wang, D., Zhu, T. and Ringler, C. (2009), 'Assessing the regional variability of GCM simulations.' *Geophysical Research Letters*, 36, L02706.
- Cancelliere, A., Giuliano, G., Ancarani, A. and Rossi, G. (2002), 'A neural network approach for deriving irrigation reservoir operating rules.' *J. water Resour. Mgmt.*, 16: 71-88.
- Cannon, A.J., Whitfield, P.H., 2002. Downscaling recent streamflow conditions in British Columbia, Canada using ensemble neural network models. *Journal of Hydrology* 259 (1), 136–151.
- Cantelaube, P. and Terres, J.-M. (2005), 'Seasonal weather forecasts for crop yield modelling in Europe.' *Tellus A.*, 57: 476–487. doi:10.1111/j.1600-0870.2005.00125.
- Carmen Sanchez de Cos, C., Sanchez-Laulhe, J.M., Jimenez-Alonso, C., Sancho-Avila, J.M. and Rodriguez-Camino, E. (2013), 'Physically based evaluation of climate models over the Iberian Peninsula.' *ClimDyn*, 40:1969–1984.
- Chadwick, R., Coppola, E. and Giorgi, F. (2011), 'An artificial neural network technique for downscaling GCM outputs to RCM spatial scale.' *Nonlin. Processes Geophys.*, 18,:1013–1028.
- Chander, G., Markham, B.L. and Helder, D.L. (2009), 'Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors.' *Rem. Sen. Envi.*, 113 (5): 893–903.

- Chang, A. T. C., Foster J. L., and Rango, A. (1991), 'Utilization of surface cover composition to improve the microwave determination of snow water equivalent in a mountainous basin.' *Intl. J. Remote Sensing*, 12: 2311-2319.
- Chang, A., Foster, J. and Hall, D. K. (1987), 'NIMBUS-7 derived global snow cover parameters.' *Ann. Glaciol.* 9: 39-44.
- Changchun, X., Yaning, C. and Weihong, L. (2008), 'Potential impact of climate change on snow cover area in the Tarim River basin.' *Environ. Geol.*, 53: 1465-1474.
- Changnon, S.A. and Demissie, M. (1996), 'Detection of changes in streamflow and floods resulting from climate fluctuations and land use-drainage changes.' *Climatic Change*, 32(4): 411-421.
- Chaturvedi, M.C. and Srivastava, D.K. (1981), 'Study of a complex water resources system with screening and simulation models.' *Water Resour. Res.*, 17(4): 783-794.
- Chavda D. B, Makwana J. J, Parmar H. V, Kunapara A. N. and Prajapati G. V.(2016), 'Estimation of Runoff for Ozat Catchment using RS and GIS Based SCS-CN Method.' *Curr World Environ*, 11(1).
- Chen J., Brissette, P., and Leconte, R. (2012), 'Coupling statistical and dynamical methods for spatial downscaling of precipitation.' *Climatic Change*, 114 (3-4): 509-526.
- Chen, J., Brissette, F.P. and Leconte, R. (2011), 'Uncertainty of downscaling method in quantifying the impact of climate change on hydrology.' *Journal of Hydrology*, 401: 190-202.
- Chen, S. M., Wang, Y. M. and Tsou, I. (2013), 'Using artificial neural network approach for modelling rainfall-runoff due to typhoon.' *Journal of Earth System Science*, 122: 399-405.
- Chen, X., Yan, J.F., Chen, Z., Luo, G.P. and Xu, W.K. (2008), 'A geospatial analysis approach for assessing the impact of land use on ground water resources in the SanGong Oasis region.' *Jour. Agri. Food Env. Sc.*, 2(1): 1-10.
- Cheng, C.S., Guilong, L., Qian, L. and Heather, A. (2011b), 'A Synoptic Weather-Typing Approach to Project Future Daily Rainfall and Extremes at Local Scale in Ontario, Canada.' *J. Climate*, 24: 3667-3685.
- Chiew, F.H.S., Kirono, D.G.C., Kent, D.M., Frost, A.J., Charles, S.P., Timbal, B., Nguyen, K.C. and Fu, G. (2010), 'Comparison of runoff model using rainfall from different downscaling methods for historical and future climates.' *Journal of Hydrology*, 387(1-2): 10-23.
- Chiew, F.H.S., Whetton, P.H., McMahon, T.A., Pittock, A.B.(1995), 'Simulation of the impacts of climate change on runoff and soil moisture in Australian catchments.' *Journal of Hydrology*, 167: 121-147.

- Chilar, J. (2000), 'Land cover mapping of large areas from satellites: status and research priorities.' *Inter. J. Rem. Sen.*, 21: 1093–1114.
- Chitra, N.R. and Thampi, S.G. (2013), 'Bias correction of ANN based statistically downscaled precipitation data for the Chaliyar river basin.' *International Journal of Innovative Research in Science, Engineering and Technology*, 2(1): 6-11.
- Chow, T. V., Maidment, R. D. and Mays, W. L. (1988), '*Applied hydrology*(2010 ed.).' New York, NY: Tata McGraw-Hill.
- Chu, V.W., Smith, L.C., Rennermalm, A.K., Forster, R.R., Box, J.E. and Reeth, N. (2009), 'Sediment plume response to surface melting and supraglacial lake drainages on the Greenland ice sheet.' *Journal of Glaciology*, 55(194):1072-1082.
- Collins, M., Tett, S.F.B. and Cooper, C. (2001), 'The internal climate variability of HadCM3, a version of the Hadley Centre coupled model without flux adjustments.' *Climate Dynamics*, 17:61-81.
- Costa, M.H., Botta, A. and Cardille, J.A. (2003), 'Effects of large-scale changes in land cover on the discharge of the Tocantins River, Southeastern Amazonia.' *Journal of Hydrology*, 283: 206-217.
- Crane, R.G. and Hewitson, B.C. (1998), 'Doubled CO₂ precipitation changes for the Susquehanna Basin: Down-Scaling from the Genesis General Circulation Model.' *International Journal of Climatology*, 18: 65–76.
- Dahe, P.D. and Srivastava, D.K. (2000), 'Assessment of reliable reservoir yield for irrigation project.' *Proceedings of the National seminar on Irrigation strategies-present and future.* I irrigation management and training institute Thuvakudy, Tiruchirappalli, Tamil Nadu, India, pp.5-15.
- Dahe, P.D. and Srivastava, D.K. (2002), 'Multireservoir multiyield model with allowable deficit in annual yield.' *J. Water Res. Plng. and Mgmt.*, ASCE, 182(6): 406-414.
- Daliakopoulos, I.N. and Tsanis, I.K. (2016), 'Comparison of an artificial neural network and a conceptual rainfall–runoff model in the simulation of ephemeral streamflow.' *Hydrological Sciences Journal- Journal Des Sciences Hydrologiques*, <http://dx.doi.org/10.1080/02626667.2016.1154151>.
- Daniel, L. C., James, D. H., Emily, H. W., Mingjun, S. and Zhenkui, Z. (2002), 'A Comparison of Land use and Land cover Change Detection Methods.' *ASPRS-ACSM Annual Conference and FIG 22nd Congress*, p. 2.
- DeBeer, C.M. and Sharp, M.J. (2009), 'Topographic influences on recent changes of very small glaciers in the Monashee Mountains, British Columbia, Canada.' *Journal of Glaciology*, 55 (192): 691–700.

- Deeprasertkul, P. (2015), 'Linear Programming for optimal reservoir operation of Chao Phraya River Basin.' *International Journal of Innovative Research in Science, Engineering and Technology*, 4(9): 8054-8063.
- DeFries, R.S. and Chan, J. (2000), 'Multiple criteria for evaluating machine learning algorithms for land cover classification from satellite data.' *Remote Sensing of Environment*, 74: 503-515.
- Devamane, M.G., Jothiprakash, V. and Mohan, S. (2006), 'Non-linear programming model for multipurpose multi-reservoir operation. *Hydrol. J.* 29(3-4), 33-46.
- Dhar, O.N. and Nandargi, S. (2000), 'A study of floods in the Brahmaputra Basin in India.' *Int. J. Climatol.*, 20: 771-781.
- Dibike, Y.B. and Coulibaly, P. (2005), 'Hydrologic impact of climate change in the Saguenay watershed: comparison of downscaling methods and hydrologic models.' *Journal of Hydrology*, 307(1-4): 457 145-163.
- Dimiyati, M., Mizuno, K. and Kitamura, T. (1996), 'An analysis of land use/cover change using the combination of MSS Landsat and land use map: a case study in Yogyakarta, Indonesia.' *Inter. J. Rem. Sen.*, 17: 931-944.
- Donia, N. (2009), 'Application of Remotely Sensed Imagery to Watershed Analysis; A Case Study of Lake Karoun Catchment, Egypt.' *Thirteenth International Water Technology Conference, IWTC, Hurgada*, 1035-1049.
- Dorfman, R. (1962), 'Mathematical models. The multistructure approach in design of water resources systems.' *Harvard Univ. Press*, Mass., Cambridge.
- Dozier, J. (1989), 'Spectral signature of alpine snow cover from the Landsat Thematic Mapper.' *Remote Sensing of Environment*, 28: 9-22.
- Driver, N.E. and Tasker, G.D. (1990), 'Techniques for estimation of storm-runoff loads, volumes, and selected constituent concentrations in urban watersheds in the United States.' *U.S. Geological Survey Water- Supply Paper*, 2363: 44 p.
- Dunne, S.S., Lynch, P., McGrath, R., Semmler, T., Wang, S., Hanafin, J., Nolan, P., 2008. The impacts of climate change on hydrology in Ireland. *Journal of Hydrology* 356, 28-45.
- Dwarakish, G.S. and Ganasri, B.P. (2015), 'Impact of land use change on hydrological systems: A review of current modeling approaches.' *Cogent Geoscience*, 1: 1115691.
- Dyson, M.G., Bergkamp and Scanlon, J. (2008), 'Flow- the essentials of environmental flows.' Second edition. *IUCN*, Gland, Switzerland.

- Dyurgerov, M. (2002), 'Glacier mass balance and regime: data of measurements and analysis.' *Occasional Paper No. 55. Institute of Arctic and Alpine research*, University of Colorado, Boulder, CO.
- Dyurgerov, M.D. and Meier, M.F. (2005), 'Glaciers and Changing Earth System: A 2004 Snapshot.' *Institute of Arctic and Alpine Research*, University of Colorado, Boulder, Colorado, pp.117.
- Ehsani, N., Fekete, B.M., Vorosmarty, C.J. and Tessler, Z. D. (2016), 'A neural network based general reservoir operation scheme.' *Stoch Environ Res Risk Assess* 30(4): 1151-1166.
- El Bastawesy, M. (2014), 'Hydrological Scenarios of the Renaissance Dam in Ethiopia and Its Hydro-Environmental Impact on the Nile Downstream.' *J. Hydro. Engin.*, [http://dx.doi.org/10.1061/\(ASCE\)HE.1943-5584.0001112](http://dx.doi.org/10.1061/(ASCE)HE.1943-5584.0001112).
- El-Asmar, H.M., Hereher, M.E. and El Kafrawy, S.B. (2013), 'Surface area change detection of the Burullus Lagoon, North of the Nile delta, Egypt, using water indices: a remote sensing approach.' *Egypt. J. Rem. Sens. Space Sci.*, 16: 119–123.
- Elfert, S. and Bormann, H. (2010), 'Simulated impact of past and possible future land use changes on the hydrological response of the Northern German lowland "Hunte" catchment.' *Journal of Hydrology*, 383: 245–255.
- El-Raey, M., Nasr, S., El-Hattab, M. and Frihy, O. (1995), 'Change detection of Rosetta Promontory over the last forty years.' *Int. J. Remote Sen.*, 16: 825–834.
- Eriksson, M., Xu, J., Shrestha, A.B., Vaidya, R.A., Nepal, S., and Sandstorm, K. (2009), 'The Changing Himalayas: Impact of climate change on water resources and livelihoods in the greater Himalayas. Perspectives on water and climate change adaptation.' *ICIMOD Kathmandu*.
- Fan, F., Deng, Y., Hu, X. and Weng, Q. (2013), 'Estimating composite curve number using an improved scs-cn method with remotely sensed variables in Guangzhou, China.' *Remote Sens.*, 5: 1425-1438.
- Faucher, M., Burrows, W.R. and Pandolfo, L. (1999), 'Empirical-statistical reconstruction of surface marine winds along the western coast of Canada.' *Climate Research*, 11(3): 173–190.
- Feyen, L., Vazquez, R., Christiaens, K., Sels, O., and Feyen, J. (2000), 'Application of a distributed physically-based hydrological model to a medium size catchment.' *Hydrology and Earth System Sciences*, 4: 47–63.
- Finger, D., Heinrich, G., Gobiet, A., and Bauder, A. (2012), 'Projections of future water resources and their uncertainty in a glacierized catchment in the Swiss Alps and the subsequent effects on hydropower production during the 21st century.' *Water Resour. Res.*, 48, W02521, doi:10.1029/2011wr010733, 2012.

- FISRWG (Federal Interagency Stream Restoration Working Group). (1998), 'Stream Corridor Restoration: Principles, Processes, and Practices'. 15 Federal agencies of the US government). GPO ItemNo. 0120-A; SuDocs No. A 57.6/2:EN 3/PT.653.
- Fistikoglu, O. and Okkan, U. (2011), 'Statistical Downscaling of Monthly Precipitation Using NCEP/NCAR Reanalysis Data for Tahtali River Basin in Turkey.' *Journal of hydrologic engineering*, 2: 157-164.
- Fohrer, N., Haverkamp, S., Eckhardt, K. and Frede, H. (2001), 'Hydrologic response to land use changes on the catchment scale.' *Physics and Chemistry of the Earth*, Part B 26(7-8): 577-582.
- Foster, J. L., Hall, D. K. and Chang, A. T. C. (1987), 'Remote sensing of snow.' *Eos* 68(32): 681-4.
- Foster, J. L., Hall, D. K., Chang, A. T. C. and Rango, A. (1984), 'An overview of passive microwave snow research and results.' *Rev. Geophys. Space Phys.*, 22:195-208.
- Foster, J. L., Owe, M. and Rango, A. (1982), 'Snow cover and temperature relationship in North America and Eurasia.' *J. Clim. Appl. Met.*, 22:460-469.
- Fountain, A.G., Hoffman, M.J., Granshaw, F. and Riedel, J. (2009), 'The 'benchmark glacier' concept does it work? Lessons from the North Cascade Range, USA.' *Annals of Glaciology*, 50: 163-168.
- Fowler, H.J., Blenkinsop, S. and Tebaldi, C. (2007), 'Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modeling.' *International Journal of Climatology*, 27(12): 1547-1578.
- Frauenfelder, R. and Kaab A. (2009), 'Glacier mapping from multi-temporal optical remote sensing data within the Brahmaputra river basin.' *Proceedings, 33rd International Symposium on Remote Sensing of Environment*, 4-8th May, Stresa, Italy. Tucson, Arizona: International Center of Remote Sensing of Environment. Paper 299, 4 pages.
- Frei, A. and Robinson, D.A. (1999), 'Northern hemisphere snow extent: regional variability 1972-1994.' *Int J Climatol*, 19(14):1535-1560.
- Fung, T and Zhang, Q. (1989), 'Land use change detection and identification with Landsat digital data in the Kitchener-Waterloo area.' *Indian Remote Sensing and Methodologies of Land use Change Analysis*, eds C.R. Bryant, E.F. LeDrew, C.
- Gafurov, A. and Bardossy, A. (2009), 'Cloud removal methodology from MODIS snow cover product.' *Hydrology and Earth System Sciences*, 13:1361-1373.
- Gao, Y., Xie, H., Yao, T. and Xue, C. (2010), 'Integrated assessment on multi-temporal and multi-sensor combinations for reducing cloud obscuration of MODIS snow cover

- products of the Pacific Northwest USA.’ *Remote Sensing of Environment*, 114: 1662-1675.
- Gaume, E. and Gosset, R. (2003), ‘Over-parameterization, a major obstacle to the use of artificial neural networks in hydrology.’ *Hydrology and Earth System Sciences*, 7 (5): 693–706.
- Georgakakos, K.P. and Smith, D.E. (2001), ‘Soil moisture tendencies into the next century for the conterminous United States.’ *Journal of Geophysical Research-Atmospheres*, 106 (D21): 27367–27382.
- Ghumman, A.R., Ghazaw, Y.M., Sohail, A.R. and Watanabe, K. (2011), ‘Runoff forecasting by Artificial Neural Network and Conventional model.’ *Alexandria Engineering Journal*, 50: 345–350.
- Giri, C. and Jenkins, C. (2005), ‘Land cover mapping of Greater Mesoamerica using MODIS data.’ *Can. J. Remote Sensing*, 31(4): 274-282.
- Gleick, P.H. (1987), ‘Regional hydrologic consequences of increases in atmosphere CO₂ and other trace gases.’ *Clim Change*, 10:137–161.
- Goddard Institute for Space Studies. (2013), ‘NASA Finds 2012 Sustained Long-Term Climate Warming Trend. Accessed January 16, 2014.’
- Gogoi, C., Goswami, D.C. and Phukan, S. (2013), ‘Flood risk zone mapping of the Subansiri sub-basin in Assam, India.’ *International Journal of Geomatics and Geosciences*, 4(1):75-88.
- Goldberg, D. E. (1989), ‘Genetic Algorithms in Search, Optimization and Machine Learning, Reading, MA: Addison-Wesley.’
- Gomez-Landesa E. (1997), ‘Evaluacion de Recursos de Agua en Forma de Nieve mediante Teledeteccion usando satelites de la sine NOAA (Evaluation of water resources in the form of snow by remote sensing using NOAA satellites).’ *PhD thesis, Universidad Politenica de Madrid, Madrid, Spain.*
- Goodison, B. E., (1989), ‘Determination of areal snow water equivalent on the Canadian prairies using microwave radiometry.’ *Proc. IGARSS’89*, Vancouver, July 1989, 3: 1243-1246.
- Gordon, C., Cooper, C., Senior, C.A., Banks, H., Gregory, J.M., Johns, T.C., Mitchel, J.F.B. and Wood, R.A. (2000), ‘The simulation of SST, sea ice extents and ocean heat transports in a version of the Hadley Centre coupled model without flux adjustments.’ *Climate Dynamics*, 16(2-3): 147-168.
- Gordon, E. and Mentemeyer, R.K. (2006), ‘Effects of dam operation and land use on stream channel morphology and riparian vegetation.’ *Geomorphology*, 82:412-429.

- Goswami, D.C. (1998), 'Fluvial Regime and Flood Hydrology of the Brahmaputra River, Assam.' Flood Studies in India, Kale V.S. (ed), Memoir 41, *Geological Society of India*, pp 53-75.
- Granshaw, F.D. and Fountain, A.G. (2006), 'Glacier change (1958–1998) in the North Cascades National Park Complex, Washington, USA.' *Journal of Glaciology*, 52 (177): 251-256.
- Grayson, R. B., Moore, I. D. and McMahon, T. A. (1992), 'Physically based hydrologic modeling: Is the concept realistic?' *Water Resources Research*, 26: 2659–2666.
- Griggs, M. (1968), 'Emissivities of natural surfaces in the 8- to 14-micron spectral region.' *J. Geophys. Res.*73: 7545-51.
- Groisman, P., Karl, T.R. and Knight, R.W. (1994), 'Observed impact of snow cover on the heat balance and the rise of continental spring temperatures.' *Science*, 263: 198-200.
- GSI, (1977), 'Contributions to geomorphology and geohydrology of the Brahmaputra Valley.' *Geological Survey of India, Miscellaneous publication*, 32, p 291
- Guldal, V. and Tongal, H.(2010), 'Comparison of recurrent neural network,adaptive neuro-fuzzy inference system and stochastic models inEgirdir Lake level forecasting.' *Journal of Water Resource Management*, 24: 105–128.
- Guo, J., Chen, H., Xu, C.Y., Guo, S. and Guo, J. (2011), 'Prediction of variability of precipitation in the Yangtze River Basin under the climate change conditions based on automated statistical downscaling.' *Stoch Environ Res Risk Assess.* doi:10.1007/s00477-011-0464.
- Haeberli, W. and Beniston, M. (1998), 'Climate change and its impact on glaciers and permafrost in the Alps.' *AMBIO*, 27: 258-265.
- Haeberli, W., Hoelzle, M., Paul, F. and Zemp, M. (2007), 'Integrated monitoring of mountain glaciers as key indicators of global climate change: The European Alps.' *Annals of Glaciology*, 46: 150-160.
- Haigen, Z., Shengtian, Y., Zhiwei, W., Xu, Z., Ya, L. and Linna, W. (2015), 'Evaluating the suitability of TRMM satellite rainfall data for hydrological simulation using a distributed hydrological model in the Weihe River catchment in China.' *Journal of Geographical Sciences*, 25: 177–195.
- Hakeem, S.A., Bilal, M., Pervez, A. and Tahir, A.A. (2014), 'Remote Sensing Data Application to Monitor Snow Cover Variation and Hydrological Regime in a Poorly Gauged River Catchment- Northern Pakistan.' *International journal of Geosciences*, 5: 27-37.

- Halff, A. M., Halff, H. M. and Azmoodeh, M. (1993), 'Predicting runoff from rainfall using neural network.' In *Engineering hydrology*, (pp.760-765). New York, NY: American Society of Civil Engineers.
- Hall W.A., Butcher, W.S. and Esogbue, A. (1968), 'Optimization of the operation of a multipurpose reservoir by dynamic programming.' *Water Resour. Res.*, 4(3): 471-477.
- Hall W.A., Tauxe, G.W. and Yeh, W.W-G. (1969), 'An alternative procedure for the optimization of operation for planning with multiple river, multiple purpose systems.' *Water Resour. Res.*, 5(6): 1367-1372.
- Hall, D.K. and Martinec, J. (1985), 'Remote Sensing of Ice and Snow.' *Chapman and Hall Ltd.*: New York; 189.
- Hall, D.K. and Riggs, G.A.(2007), 'Accuracy assessment of the MODIS snow products.' *Hydrological Processes*, 21(2):1534-1547.
- Hall, D.K., Andrew, B.T., James, L.F., Alfred, T.C.C. and Milan, A. (2000a), 'Inter-comparison of satellite derived snow-cover maps.' *Ann Glaciol*, 31:369–376.
- Hall, D.K., Foster, J.L., Verbyla, D.L., Klein, A.G. and Benson, C.S.(1998), 'Assessment of snow-cover mapping accuracy in a variety of vegetation-cover densities in central Alaska.' *Remote Sensing of environment*, 66(2): 129-137.
- Hall, D.K., Kelly, R.E.J., Riggs, G.A., Chang, A.T.C. and Foster, J.L. (2002), 'Assessment of the relative accuracy of hemispheric-scale snow-cover maps.' *Ann. Glaciolog*, 34: 24-30.
- Hall, D.K., Riggs, G.A. and Salomonson, V.V. (1995), 'Development of methods for mapping global snow cover using moderate resolution imaging spectroradiometer data.' *Remote Sens. Environ.*, 54: 127-140.
- Hall, D.K., Riggs, G.A., Salomonson, V.V., DiGirolamo, N. and Bayr, K.J. (2002), 'MODIS snow cover products.' *Remote Sens. Environ.*, 83(1-2):181–194.
- Hansen, M., DeFries, R. S., Townshend, J. R. G., and Sohlberg, R., (2000), 'Global land cover classification at 1 km spatial resolution using a classification tree approach.' *International Journal of Remote Sensing*, 21: 1331–1364.
- Harpham, C., and Wilby, R. L.(2005), 'Multi-site downscaling of heavy daily precipitation occurrence and amounts.' *J. Hydrol.*, 312: 235–255, 2005.
- Hasebe, M. and Kumekawa, T. (1994), 'The effect of wind speed on the snowmelt runoff process: laboratory experiment.' *Snow and Ice Covers, Interactions with the Atmosphere and Ecosystems (Proceedings of Yokohama Symposia J2 and J5, July 1993)*. IAHS Publ. no. 423, 1994.

- Hashmi, M.Z., Shamseldin, A.Y. and Melville, B.W. (2011), 'Comparison of SDSM and LARS-WG for simulation and downscaling of extreme precipitation events in a watershed.' *Stoch Environ Res Risk Assess*, 25:475–484.
- Hassan, H., Hanaki, K. and Matsuo, T. (1998), 'A modeling approach to simulate impact of climate change in lake water quality: Phytoplankton growth rate assessment.' *Water Science and Technology*, 37 (2): 177–185.
- Hawkins, R. H.(1993), 'Asymptotic determination of runoff curve numbers from data.' *J. Irrig. Drain. Eng. ASCE*, 119: 334–345.
- He, M. and Hogue, T. S. (2012), 'Integrating hydrologic modeling and land use projections for evaluation of hydrologic response and regional water supply impacts in semiarid environments.' *Environmental Earth Science*, 65: 1671–1685.
- Hejduk, L., Hejduk, A. and Banasik, K. (2015), 'Determination of Curve Number for snowmelt-runoff floods in a small catchment.' Published by *Copernicus Publications* on behalf of the International Association of Hydrological Sciences. Proc. IAHS, 370, 167–170.
- Hessel, R., Messing, I., Liding, C., Ritsema, C. and Stolte, J. (2003), 'Soil erosion simulations of land use scenarios for a small Loess Plateau catchment.' *CATENA*, 54(1-2): 289-302.
- Hewitson, B. and Crane, R. (1996), 'Climate downscaling: techniques and application.' *Climate Research*, 07 (2): 85–95.
- Heydari, M., Othman, F. and Waderi, K. (2015), 'Developing optimal reservoir operation for multiple and multipurpose reservoirs using mathematical programming.' *Mathematical Problems in Engineering*, article ID 435752, 11 pages.
- Hjelmfelt, A.T., Kramer, L.A. and Burwell, R.E. (1982), 'Curve numbers as random variables.' *Proc. Int. Symposium on Rainfall-Runoff Modeling*, Water Resources Publishers, Littleton, Colo., 365–373.
- Hoai, N.D., Udo, K. and Mano, A. (2011). 'Downscaling Global Weather Forecast Outputs Using ANN for Flood Prediction.' *Journal of Applied Mathematics*. Article ID 246286, 14 pages, 2011. doi:10.1155/2011/246286.
- Hock, R. (2005), 'Glacier melt: A review of processes and their modeling.' *Progress in Physical Geography*, 29(3): 362-391.
- Holland, J.H. (1992), 'Adaptation in neural and artificial systems.' *Mass Inst. of Technol.* MIT Press, Cambridge, Mass.
- Hong, Y. and Adler, R.F. (2008), 'Estimation of global SCS curve numbers using satellite remote sensing and geospatial data.' *International Journal of Remote Sensing*, 29:2471-477.

- Houghton, J.T., Ding, Y. and Griggs, D.J. (2001), 'Climate change 2001- The Scientific Basis Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change (IPCC).' *Cambridge University Press*, London, p 944.
- Hsu, K.L., Gupta, H.V. and Sorooshian, S. (1995), 'Artificial neural network modeling of the rainfall-runoff process.' *Water Resour. Res.*, 31: 2517–2530.
- Hu, J. and Zhang, Y. (2013), 'Seasonal change of land use/land cover (LULC) detection using MODIS data in rapid urbanization regions: A case study of the Pearl River Delta Region (China).' *IEEE Journal of selected topics in applied earth observations and remote sensing*, 6(4): 1913-1920.
- Hu, Y., Maskey, S. and Uhlenbrook, S. (2013), 'Downscaling daily precipitation over the Yellow River source region in China: a comparison of three statistical downscaling methods.' *TheorApplClimatol*, 112(3–4):447–460.
- Huang, M.B. and Zhang, L. (2004), 'Hydrological responses to conservation practices in a catchment of the Loess Plateau, China.' *Hydrological Processes*, 18(10): 1885-1898.
- Huang, M.B., Gallichand, J., Dong, C.Y., Wang, Z.L. and Shao, M.A. (2007), 'Use of Moisture Data and Curve Number Method for Estimating Runoff in the Loess Plateau of China.' *Hydrological Processes*, 21: 1471-1481.
- Huang, S., Zang, W., Xu, M., Li, X., Xie, X., Li, Z. and Zhu, J. (2015), 'Study on runoff simulation of the upstream of Minjiang River under future climate change scenarios.' *Natural Hazards*, 75: 139–154.
- Huss, M.(2011), 'Present and future contribution of glacier storage change to runoff from macroscale drainage basins in Europe.' *Water Resour. Res.*, 47, W07511, doi:10.1029/2010WR010299, 2011.
- Huss, M., Farinotti, D., Bauder, A., and Funk, M. (2008), 'Modelling runoff from highly glacierized alpine drainage basins in a changing climate.' *Hydrol. Process.*, 22: 3888–3902, doi:10.1002/hyp.7055, 2008.
- Huss, M., Juvet, G., Farinotti, D., and Bauder, A.(2010), 'Future high mountain hydrology: a new parameterization of glacier retreat.' *Hydrol. Earth Syst. Sci.*, 14: 815–829.
- Huth, R. (2004), 'Sensitivity of local daily temperature change estimates to the selection of downscaling models and predictors.' *J Clim*, 17(3):640–652.
- Immerzeel, W. (2007), 'Historical trends and future predictions of climate variability in the Brahmaputra basin.' *International Journal of Climatology*, 28(2): 243-254.
- Immerzeel, W., Van Beek, L. P. and Bierkens, M. F. P. (2010), 'Climate Change Will Affect the Asian Water Towers.' *Science*, 328: 1382–1385.

- Immerzeel, W.W., Droogers, P., Jong, S.M. and Bierkens, M.F.P. (2008), 'Large-scale monitoring of snow cover and runoff simulation in Himalayan river basins using remote Sensing.' *Remote Sensing of Environment*, 113: 40-49.
- Intergovernmental Panel on Climate Change (IPCC). (2007), 'IPCC *Fourth Assessment Report* - Climate Change 2007: The Physical Science Basis.'
- Intergovernmental Panel on Climate Change (IPCC). (2007a), 'The Physical Science Basis. Contribution of Working Group I to the *Fourth Assessment Report of the IPCC*, Geneva.'
- Intergovernmental Panel on Climate Change (IPCC). (2007b), 'Climate Change 2007: Mitigation of Climate Change.' Contribution of working Group III to the *Fourth Assessment Report of the IPCC*. IPCC, Geneva.
- Intergovernmental Panel on Climate Change (IPCC). (2013), 'IPCC *Fifth Assessment Report* - Climate Change 2013: The Physical Science Basis.'
- IPCC (1995) IPCC second report of assessment of climate change. *Cambridge University Press*, London, p 16.
- IPCC, 2001a, In: Houghton, J.T., Ding, Y., Griggs, D.J., Noguer, M., van der Linden, P.J., Dai, X., Maskell, K., Johnson, C.A. (Eds.), Report Climate Change- The Scientific Basis.
- Isik, S., Kalin, L., Schoonover, J. E., Srivastava, P. and Lockaby, G. B. (2013), 'Modeling effects of changing land use/cover on daily streamflow: An artificial neural network and curve number based hybrid approach.' *Journal of Hydrology*, 485: 103–112.
- IUCN, International Union for Conservation of Nature (2014), 'Physical assessment of the Brahmaputra River.' Ecosystems for life- A Bangladesh-India initiative.
- Jabari, S., Sharkh, M.A. and Mimi, Z. (2009), 'Estimation of runoff for agricultural watershed using SCS curve number and GIS.' *Thirteenth International Water Technology Conference*, IWTC 13, 2009, Hurgahba, Egypt.
- Jacoby, H.D. and Loucks, D.P. (1972), 'Combined use of optimization and simulation models in river basin planning.' *Water Resour. Res.*, 8(6): 1401-1414.
- Jain, M.K., Mishra, S.K., Babu, P.S., Venugopal, K. and Singh, V.P. (2006), 'Enhanced Runoff Curve Number Model Incorporating Storm Duration and a Nonlinear I a –S Relation.' *Journal of Hydrologic Engineering*, 11(6): 631-635.
- Jain, S.K. (2001), 'Modelling of Streamflow and Sediment Studies in the Satluj Basin using Remote Sensing and GIS.' *Indian Institute of Technology*, Roorkee, India.

- Jaisawal, R.K., Saxena, R. and Mukherjee, S. (1999), 'Application of Remote Sensing technology for Landuse/landcover change analysis.' *J.Indian Soc. Remote Sens.*, 27(2):123-128.
- Jaisawal, R.K., Saxena, R. and Mukherjee, S. (2001), 'Land use/ Land cover mapping using IRS 1C LISS III false colour composite (a case study of a part of Shahdol district, Madhya Pradesh.' *Journ. Tropical Forestry*, 17(1): 33–40.
- Jasper, K., Calanca, P., Gyalistras, D. and Fuhrer, J. (2004), 'Differential impacts of climate change on the hydrology of two alpine river basins.' *Climate Research*, 26 (2): 113–129.
- Jayakumar, S. and Arockiasamy, D.I. (2003), 'Land use/Land cover mapping and change detection in part of Eastern ghats of Tamilnadu using remote sensing and GIS.' *J. Indian Society of Remote Sensing*, 31(4): 251-260.
- Jensen, J.R. (1996), 'Digital Image Processing: a Remote Sensing Perspective.' *Englewood Cliffs*, New Jersey: Prentice Hall.
- Jeong D. I., St-Hilaire, A., Ouarda, T. B. M. J. and Gachon, P. (2012), 'Comparison of transfer functions in statistical downscaling models for daily temperature and precipitation over Canada.' *Stochastic Environmental Research and Risk Assessment*, 26(5): 633- 653.
- Jones, P. D., Harpham, C., Kilsby, C., Glenis, V. and Burton, A. (2009), 'Projections of future daily climate for the UK from the Weather Generator.' *Tech. Rep. 1*, UK Met Office.
- Jost, G., Mor, R.D., Menounos, B. and Wheate, R. (2012), 'Quantifying the contribution of glacier runoff to streamflow in the upper Columbia River Basin, Canada.' *Hydrol. Earth Syst. Sci*, 16: 849–860.
- Jotiprakash, V and Shanthi, G. (2006), 'Single reservoir operating policies using genetic algorithm.' *J. of Water Resources Management*, 20: 917–929.
- Kaab, A. (2005), 'Combination of SRTM3 and repeat ASTER data for deriving alpine glacier flow velocities in the Bhutan Himalaya.' *Remote Sensing of Environment*, 94(4): 463-474.
- Kachhwala, T.S. (1985) 'Temporal monitoring of forest land for change detection and forest cover mapping through satellite remote sensing.' In: *Proceedings of the 6th Asian Conference on Remote Sensing*. National Remote Sensing Agency, Hyderabad, 77–83.
- Kaishan, S., Zongmin, W., Qingfeng, L., Dianwei, L., Ermoshin, V.V., Ganzei, S.S., Zhang, B., Chunying, R., Lihong, Z. and Du, J. (2011), 'Land use/land cover (LULC) classification with MODIS time series data and validation in the Amur river basin.' *Geography and Natural Resources*, 32(1): 9-15.

- Kamga, F.M. (2001), 'Impact of greenhouses gas induced climate change on the runoff of the upper Benue River (Cameroon).' *J. Hydrol.*, 252:145–156.
- Kamiguchi, K., Arakawa, O., Kitoh, A., Yatagai, A., Hamada, A. and Yasutomi, N. (2010), 'Development of APHRO JP, the first Japanese highresolution daily precipitation product for more than 100 years.' *Hydrol. Res. Lett.*, 4: 60–64.
- Kamodkar, R.U. and Regulwar, D.G. (2013), 'Multipurpose Reservoir Operating Policies: A Fully Fuzzy Linear Programming Approach.' *J. Agr. Sci. Tech.*, 15: 1261-1274.
- Kannan, N., Santhi, C., Williams, J.R. and Arnold, J.G.(2007), 'Development of a continuous soil moisture accounting procedure for curve number methodology and its behavior with different evapotranspiration methods.' *Hydrological Processes*. Published online in Wiley Inter Science. doi: 10.1002/hyp.6811.
- Karamouz, M. and Houck, M.H. (1982), 'Annual and monthly reservoir operating rules generated by deterministic optimization.' *Water Resour. Res.*, 18(5): 1337-1344.
- Karamouz, M., Fallahi, M., Nazif, S. and Farahani, M.R. (2012), 'Long Lead Runoff Simulation Using Data Driven Models.' *International Journal of Civil Engineering*, 10(4): 328-336.
- Karamouz, M., Fillahi, M., Nazif, S. and Farahani, M.R. (2009), 'Long Lead Rainfall Prediction Using Statistical Downscaling and Artificial Neural Network Modeling.' *Transaction A: Civil Engineering*, 16(2): 165-172.
- Kargel, J., Abrams, M., Bishop, M., Bush, A., Hamilton, G. and Jiskoot, H. (2005), 'Multispectral imaging contributions to global land ice measurements from space.' *Remote Sensing of Environment*, 99(1-2): 187-219.
- Karl, T. R., Wang, W. C., Schlesinger, M. E., Knight, R. W. and Portman, D. (1990), 'A method of relating general circulation model simulated climate to the observed climate, Part I: Seasonal statistics.' *Journal of Climate*, 3: 1053–1079.
- Kaser, G., Cogley, J. G., Dyurgerov, M. B., Meier, M. F. and Ohmura, A. (2006), 'Mass balance of glaciers and ice caps: Consensus estimates for 1961–2004.' *Geophysical Research Letters*, 33, L19501. doi:10.1029/ 2006GL027511.
- Kaser, G., GroBhauser, M. and Marzeion, B. (2010), 'Contribution potential of glaciers to water availability in different climate regimes.' *PANS*, 107(47): 20223-20227.
- Kaul, M.K. (1999), 'Inventory of the Himalayan Glaciers: A contribution to the International Hydrological Programme.' In M.K. Kaul (Ed.). 165 pp.
- Ke, C.Q. and Li, P.J. (1998), 'Spatial and temporal characteristic of snow cover over the Qinghai-Xizang Plateau.' *Acta Geogr Sin*, 53(3):209–215.

- Kettle, H. and Thompson, R. (2004), 'Statistical downscaling in European mountains: verification of reconstructed air temperature.' *Climate Research*, 26: 97-112.
- Khoram, S. and John, A.B. (1991), 'A regional assessment of land use/land cover types in Sicily with Landsat TM data.' *Internat. Jour. Remote Sensing*, 12(1): 69-78.
- Khosbayan, B., Tsolmona, R. and Uranchimegb, Y. (2008), 'Estimation of glaciers and snow coverage in western part of Mongolia using MODIS snow products.' *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXVII, part B7.
- Kim, M., Kim, S., Kim, J., Heo, J., Park, J.S., Kwon, W.T. and Suh, M.S. (2004), Statistical downscaling for daily precipitation in Korea using combined PRISM, RCM, and quantile mapping: Part 1, methodology and evaluation in historical simulation.' *Asia-Pacific J Atmos Sci.*, 52: 79, doi:10.1007/s13143-016-0010-3.
- Kirkby, M.J. and Chorley, R.J. (1967), 'Through flow, overland flow and erosion.' *Internat. Assoc. Sci. HydroI. Bull.*, 12(3): 5-21.
- Klein, A.G., Hall, D.K. and Riggs, G.A. (1998), 'Global snow cover monitoring using MODIS.' In *Proceedings of 27th International Symposium on Remote Sensing of Environment*, Tromso, Norway, June, 1998; pp. 363-366.
- Knighton, D. (1998), 'Fluvial forms and processes: a new perspective.' *Arnold*, London.
- Kruse, R. and Gebhardt, J. (1993), 'Fuzzy Probability Theory and Fuzzy Statistics.' *Advances in Statistical Software*, 93: 605-610.
- Kueh, S.M. and Kuok, K.K. (2016), 'Precipitation downscaling using the artificial neural network BatNN and development of future rainfall intensity-duration-frequency curves.' *Climate Research*, 68 (1):73-89.
- Kuldeep, T. and Kamlesh, K. (2011) 'Land Use / Land cover change detection in Doon valley (Dehradun Tehsil), Uttarakhand: using GIS& Remote Sensing Technique.' *International Journal of Geomatics and Geosciences*, 2(1): 34-41.
- Kulkarni, A.V., Singh, S.K., Mathur, P. and Mishra, V.D. (2006), 'Algorithm to monitor snow cover using AWiFS data of RESOURCESAT-1 for the Himalayan region.' *Int. J. Remote Sens.* 27: 2449-2457.
- Kulkarni, A. V. (1992), 'Mass balance of Himalayan glaciers using AAR and ELA methods.' *Journal of Glaciology*, 38(128): 101-104.
- Kulkarni, A.V., Bahuguna, I.M., Rathore, B.P., Singh, S.K., Randhawa, S.S., Sood, R.K. and Dhar, S. (2007), 'Glacial retreat in Himalaya using Indian remote sensing satellite data.' *Curr. Sci.*, 92:69-74.

- Kulkarni, A.V., Mathur, P., Singh, S. K., Rathore, B.P. and Thakur, N.K. (2004), 'Remote sensing based techniques for snow cover monitoring for the Himalayan region.' *International symposium on snow monitoring and avalanches (ISSMA-04)*, Manali, India, pp. 399–405.
- Kulkarni, A.V., Srinivasulu, J., Manjul, S.S. and Mathur, P. (2002b), 'Field based spectral reflectance to develop NDSI method for the snow cover.' *J. Indian Soc. Remote Sens.*, 30:73–80.
- Kumar, A.R.S., Sudheer, K.P., Jain, S.K. and Agarwal, P.K. (2005), 'Rainfall-Runoff Modeling Using Artificial Neural Networks: Comparison of Network Types.' *Hydrological Processes*, 19: 1277-1291.
- Kumar, M. and Singh, R.K. (2013), 'Digital Image Processing of Remotely Sensed Satellite Images for Information Extraction.' *Conference on Advances in Communication and Control Systems 2013 (CAC2S 2013)*: 406-410.
- Kyle, H.L., Curran, R.J., Barnes, W.L. and Escoe, D. (1978), 'A cloud physics radiometer.' *Third Conference on Atmospheric Radiation*, Davis, CA, pp. 107-109.
- Labat, D., Ronchail, J. and Calde, J. (2004), 'Wavelet analysis of Amazon hydrological regime variability.' *Geophysical Research Letters*, 31: L02501.
- Lafdani, E.K., Nia, A.M., Pahlavanravi, A., Ahmadi, A. and Jajarmizadeh, M. (2013), 'Daily rainfall-runoff prediction and simulation using ANN, ANFIS and conceptual hydrological MIKE 11/NAM models.' *International Journal of Engineering & Technology Sciences (IJETS)*, 1 (1): 32-50.
- Lal, M. (2001), 'Climatic change- implications for India's water resources.' *Journal of Indian Water Resources Society*, 21:101–119.
- Lal, M. and Singh, S.K. (2001), 'Global warming and monsoon climate.' *Mausam*, 52:245–262.
- Law, A.M. and Kelton, W.D. (1991), 'Simulation Modeling and Analysis.' Second Edition, *McGraw-Hill*, New York; 299.
- Leaf, C.F. (1969), 'Aerial photographs for operational streamflow forecasting in the Colorado Rockies.' *Proc. 37th Western Snow Conf*, Salt Lake City, UT.
- Lebedeva, L. and Semenova, O. (2011), 'Evaluation of climate change impact on soil and snow processes in small watersheds of European part of Russia using various scenarios of climate.' *Die Bodenkultur*, 77–82, 62 (1–4).
- Legesse, D., Vallet-Coulomb, C. and Gasse, F. (2003), 'Hydrological response of a catchment to climate and land use changes in Tropical Africa: Case study South Central Ethiopia.' *Journal of Hydrology*, 275: 67–85.

- Leica Geosystems. (2002a), 'IMAGINE Field Guide.' Atlanta, Georgia.
- Letreguilly, A., Reynaud, L. (1990), 'Space and time distribution of glacier mass balance in the northern hemisphere.' *Arctic and Alpine Research*, 22:43-50.
- Leys, V. (2009), 'Sea Level rise and Storm Events.' In: CBCL Ltd, Our Coast: Live Work. Play. Protect. *The 2009 Nova scotia State of the Coast Technical Report*, 160- 174.
- Li, L.H. and Simonovic, S.P. (2002), 'System dynamics model for predicting floods from snowmelt in North American Prairie Watersheds.' *Hydrological Processes*, 16: 2645–2666.
- Li, Z., Liu, W.Z., Zhang, X.C. and Zheng, F.L. (2009), 'Impacts of land use change and climate variability on hydrology in an agricultural catchment on the Loess Plateau of China.' *Journal of Hydrology*, 377: 35-42.
- Liang, T.G., Huang, X.D., Wu, C.X., Liu, X.Y., Li, W.L. and Guo, Z.G. (2008), 'An application of MODIS data to snow cover monitoring in a pastoral area: A case study in Northern Xinjiang, China.' *Remote Sensing of Environment*, 112(4):1514-1526.
- Lillesand, T.M., Kiefer, R.W. and Chipman, J.W. (2004), 'Remote Sensing and Image Interpretation.' Ed. 5. *John Wiley & Sons Ltd*.
- Lin, Y. P., Verburg, H. P., Chang, C. R., Chen, H. Y. and Chen, M. H. (2009), 'Developing and comparing optimal and empirical land-use models for the development of an urbanized watershed forest in Taiwan.' *Landscape and Urban Planning*, 92: 242–254.
- Lin, Y. P., Wu, P. J. and Hong, N. M. (2008), 'The effects of changing the resolution of land-use modeling on simulations of land-use patterns and hydrology for a watershed landuse planning assessment in Wu-Tu, Taiwan.' *Landscape and Urban Planning*, 87: 54–66.
- Lioubimtseva, E., Cole, R., Adams, J.M. and Kapustin, G. (2005), 'Impacts of climate and land-cover changes in arid lands of Central Asia.' *Journal of Arid Environments*, 62(2): 285-308.
- Liu, C.M., Li, D.F., Tian, Y., Hao, F.H. and Yang, G.L. (2003), 'An application study of DEM based distributed hydrological model on macroscale watershed.' *Progress in Geography*, 22(5): 437-445.
- Liu, P., Zhao, J., Li, L. and Shen, Y. (2012), 'Optimal reservoir operation using stochastic dynamic programming.' *Journal of Water Resource and Protection*, 4: 342-345.
- Lo, C.P. and Choi, J. (2004), 'A hybrid approach to urban land use/cover mapping using Landsat 7 enhanced thematic mapper plus (ETM+) images.' *Inter. J. Rem. Sen.*, 25 (14): 2687–2700.

- Loaiciga, H.A., Valdes, J.B., Vogel, R., Garvery, J., Schwarz, H. (1996), 'Global warming and hydrological cycle.' *Journal of Hydrology*, 174: 83-127.
- Lorup, J. K., Refsgaard, J. C. and Mazvimavi, D. (1998), 'Assessing the effect of land use change on catchment runoff by combined use of statistical tests and hydrological modelling: Case studies from Zimbabwe.' *Journal of Hydrology*, 205: 147-163.
- Loucks, D.P. (1968), 'Computer models for reservoir regulation.' *J. Sanitary Engg. Div., ASCE*, 94(SA4): 657-671.
- Loucks, D.P., Stedinger, J.R. and Haith, D.A. (1981), 'Water resources system planning and analysis.' *Prentice Hall*, eaglewood Cliffs, New Jersey.
- Luckman, A., Quincey, D. and Bevan, S. (2007), 'The potential of satellite radar interferometry and feature tracking for monitoring flow rates of Himalayan Glaciers.' *Remote Sensing of Environment*, 111:172-181.
- MacCracken, M. C., Barron, E. J., Easterling, D. R., Felzer, B. S., and Karl, T. R. (2003), 'Climate change scenarios for the U.S. national assessment.' *Bull. Am. Met. Soc.*, 84: 1711-1723.
- Majumdar, P.P. and Ramesh, T.V.S. (1997), 'Real time reservoir operation for irrigation.' *Water Resour. Res.*, 33(5): 1157-1164.
- Maria, C.M., Wenceslao, G.M., Manuel, F.B., Jose, M.P.S. and Roman, L.C. (2004), 'Modelling of the monthly and daily behaviour of the runoff of the Xallas River using Box-Jenkins and neural networks methods.' *Journal of Hydrology*, 296: 38-58.
- Marino, M.A. and Loaiciga, H.A. (1985), 'Dynamic model for multireservoir operation.' *Water Resour. Res.*, 21(5): 619-630.
- Marino, M.A. and Mohammadi, B. (1983), 'Reservoir management: a reliability programming approach.' *Water Resour. Res.*, 21(5): 619-620.
- Martinec, J. (1985), 'Snowmelt runoff models for operational forecasts.' *Nordic Hydrology*, 16: 129-136.
- Martinec, J. (1972), 'Evaluation of air photos for snowmelt-runoff forecasts, Proceedings of the Banff Symposium - The Role of Snow and Ice in Hydrology.' *IAHS - AISH Publication*, 107:915-926.
- Masanganise, J., Chipindu, B., Mhizha, T., Mashonjowa, E. and Basira, K. (2013), 'An evaluation of the performances of Global Climate Models (GCMs) for predicting temperature and rainfall in Zimbabwe.' *International Journal of Scientific and Research Publications*, 3: 1-11.

- Mathur, Y.P. and Nikam, S.J. (2009), 'Optimal Reservoir Operation Policies Using Genetic Algorithm.' *International Journal of Engineering and Technology*, 1(2): 1793-8236.
- Matson, M. (1991), 'NOAA satellite snow cover data.' *Paleogeography and Paleoecology*, 90:213-280.
- Matson, M., Roeplewski, C.F. and Varnadore, M.S. (1986), 'An Atlas of Satellite-Derived Northern Hemisphere Snow Cover Frequency.' *National Weather Service. Washington D.C.*, 75 p.
- Maurer, E. P. and Hidalgo, H. G. (2008), 'Utility of daily vs. monthly large-scale climate data: an inter-comparison of two statistical downscaling methods.' *Hydrol. Earth Syst. Sci.*, 12: 551–563.
- Maurer, E.P., Rhoads, J.D., Dubayah, R.O. and Lattenmaier, D.P. (2003), 'Evaluation of the snow-covered area data product from MODIS.' *Hydrological Processes*, 17(1): 59-71.
- Mavromatis, T. and Jones, P.D. (1999), 'Evaluation of HadCM2 and Direct Use of Daily GCM Data in Impact Assessment Studies.' *Climate Change*, 41: 583-614.
- McCabe, G.J., Clark, M.P. and Serreze, M.C. (2001), 'Trends in Northern Hemisphere Surface Cyclone Frequency and Intensity.' *J. Climate*, 14: 2763-2768.
- McCartney, M. (2009), 'Living with dams: managing the environmental impact.' *Water Policy*, 11(1): 121-139.
- McColl, C. and Aggett, G. (2007), 'Land-use forecasting and hydrologic model integration for improved land-use decision support.' *Journal of Environmental Management*, 84: 494–512.
- McCuen, R.H. (2002), 'Approach to Confidence Interval Estimation for Curve Numbers.' *Journal of Hydrologic Engineering*, 7(1): 43-48.
- McMahon, T.A., Peel, M.C. and Karoly, D.J. (2014) Uncertainty in runoff based on Global Climate Model precipitation and temperature data- Part1: Assessment of Global Climate Models. *Hydrol. Earth Syst. Sci. Discuss*, 11: 4531-4578.
- McMullen C.P. and Jabbour, J. (Eds.). (2009), 'Climate Change Science Compendium.' *UN Environmental Programme*, Geneva. 72pp.
- Mehta, A., Sinha, V.K. and Ayachit, G. (2012), 'Land use/land cover study using remote sensing and GIS in an arid environment.' *Bull. Envi. Sci. Res.*, 1 (3–4): 4–8.
- Meier, W.L. and Beightler, C.S. (1967), 'An optimization method for branching multi-stage water resources systems.' *Water Resour. Res.*, 3(3): 645-652.

- Mendenhall and Beaver (1994), 'Introduction to Probability and Statistics.' *Ninth Edition*, International Thomson Publishing.
- Mendes, D. and Marengo, J.A. (2010), 'Temporal downscaling: a comparison between artificial neural network and autocorrelation techniques over the Amazon Basin in present and future climate change scenarios.' *TheorApplClimatol*, 100:413–421, doi: 10.1007/s00704-009-0193-y.
- Meyer, W.B. (1995), 'Past and Present Land-use and Land-cover in the U.S.A.' *Consequences*,1(1): 25-33.
- Miao, C., Duan, Q., Yang, L. and Borthwick, A.G.L. (2012), 'On the applicability of temperature and precipitation data from CMIP3 for China.' *PLoS ONE*, 7: e44659. doi:10.1371/journal.pone.0044659, pp. 1-10.
- Michel, C., Andreassian, V. and Perrin, C.(2005), 'Soil Conservation Service Curve Number method: How to mend a wrong soil moisture accounting procedure?' *Water Resour. Res.*, 41, W02011.
- Mirza, M. M. Q. (2002), 'Global warming and changes in the probability of occurrence of floods in Bangladesh and implications.' *Glob.Env.Change*, 12: 127–138.
- Mishra, S.K. and Singh, V.P. (1999), 'Another look at SCS-CN method.' *Journal of Hydrologic Engineering*, ASCE 4(3), Paper 5120, 257-264.
- Mishra, S.K. and Singh, V.P. (2003), 'Soil conservation service curve number (SCS-CN) methodology.' *Kluwer Academic, Dordrecht*, The Netherlands, ISBN 1-4020-1132-6.
- Misson, L., Rasse, D.P., Vincke, C., Aubinet, M. and Francois, L. (2002), 'Predicting transpiration from forest stands in Belgium for the 21st century.' *Agricultural and Forest Meteorology*, 111 (4): 265– 282.
- Mitra, A.K., Das Gupta, M., Singh, S.V. and Krishnamurti, T.N. (2003), 'Daily rainfall for the Indian monsoon region from merged satellite and raingauge values: Large scale analysis from real time data.' *J.Hyrdrometeorology*, 4:769-781.
- Moller-Jensen L (1997), 'Classification of urban land cover based on expert systems, object models and texture.' *Computer, Environment and Urban Systems*, 21(3/4): 291-302.
- Moosavian, S.A.A. Ghafari, A., Salimi, A. and Abdi, N.(2008), 'Non-linear multiobjective optimization for control of hydropower plants network. *ASME International Conference on Advanced Intelligent Mechatronics*, 2008, pp. 1278–1283.
- Mousavi, S.J., Ponnambalam, K. and Karray, F. (2005), 'Reservoir operation using a dynamic programming fuzzy rule-based approach.' *Water Resources Management*, 19(5): 655-672.

- Mu, X.M. (2007), 'Impact of soil conservation measures on runoff and sediment in Hekou-Longmen region of the Yellow River.' *Journal of Sediment Research*, 2: 36-41.
- Mukherjee, S. (1987), 'Land use maps for conservation of ecosystems.' *Geog. Rev. India*, 3: 23-28.
- Murthy, Y.K. (1981), 'Water resource potentials of the Himalaya. In The Himalayas- Aspects of Change.' Lall, J.S., Moddi, A.D. (eds). *India International Centre: New Delhi*, 152-171.
- Musau, J., Sang, J. and Gathenya, J. (2013), 'General Circulation Models (GCMs) Downscaling Techniques and Uncertainty Modeling for Climate Change Impact Assessment.' *Proceedings of 2013 Mechanical Engineering Conference on Sustainable Research and Innovation*, 5, 24th - 26th April 2013.
- Mutlu, E., Chaubey, I., Hexmoor, H. and Bajwa, S.G. (2008), 'Comparison of Artificial Neural Network Models for Hydrologic Predictions at Multiple Gauging Stations in an Agricultural Watershed.' *Hydrological Processes*, 22: 5097- 5106.
- Muzein, B.S. (2006), 'Remote Sensing & GIS for Land Cover/ Land Use Change Detection and Analysis in the Semi-Natural Ecosystems and Agriculture Landscapes of the Central Ethiopian Rift Valley.' Technische Universitat Dresden Fakultat Forst-Geo- und Hydrowissenschaften Institut fur Photogrammetrie und Fernerkundung, *Thesis submitted for the degree of Doctor of Natural Science, Dresden, Germany*.
- Namias, J. (1985), 'Snow empirical evidence for the influence of snow cover on temperature and precipitation.' *Mon Wea Rev* , 113:1542-1553.
- Nandakumar, N. and Mein, R. G. (1997), 'Uncertainty in rainfall-runoff model simulations and the implications for predicting the hydrologic effects of land-use change.' *Journal of Hydrology*, 192: 211-232.
- NAS. (1979), 'Carbon Dioxide and Climate: A Scientific Assessment.' *National Academy Sciences*, National Academic Press, Washington, DC, USA.
- Nash, J.E. and Sutcliffe, J.V. (1970), 'River flow forecasting through conceptual models Part1- A discussion of principles.' *J. Hydrol.*, 10: 282-290.
- Nayak, T., Verma, M.K. and Hema B.S.(2012), 'SCS curve number method in Narmada Basin.' *International journal of Geomatics and Geosciences*, 3(1): 219-228.
- Nayak, T.R. and Jaiswal, R.K. (2003), 'Rainfall-runoff modelling using satellite data and GIS for Bebas river in Madhya Pradesh.' *IE (I) Journal*, 84: 47-50.
- Needham, J., Watkins, D., Lund, J.R., and Nanda, S.K. (2000). 'Linear Programming for Flood Control on the Iowa and Des Moines Rivers.' *Journal of Water Resources Planning and Management*, 126(3): 118-127.

- Negi, H.S. and Thakur, N.K. (2008), 'Operational Snow Cover Monitoring in NW-Himalaya using Terra and Aqua MODIS Imageries.' *Proc., International Workshop on Snow, Ice, Glacier and Avalanches, IIT Mumbai, India, 7–9 January*, pp.11–25.
- NEH-4 (1997), NEH-4 (National Engineering Handbook Section 4 Hydrology Part 630) (Washington, DC: US Department of Agriculture Natural Resources Conservation Service).
- Nesje, A., Bakke, J., Dahl, S.O., Lie, O. and Matthews, J.A. (2008), 'Norwegian mountain glaciers in the past, present and future.' *Global and Planetary Change*, 60 (1–2): 10–27.
- New, M., Hulme, M. and Jones, P.D. (1999), 'Representing Twentieth-Century Space- Time Variability. Part I: Development of a 1961-1990 Mean Monthly Terrestrial Climatology.' *J.Climate*, 12:829-856.
- Newson, D. (1997), 'Land, water and development: sustainable management of river basin systems.' *Routledge*, London.
- Niehoff, D., Fritsch, U. and Bronstert, A. (2002), 'Land-use impacts on storm-runoff generation: scenarios of land-use change and simulation of hydrological response in a meso-scale catchment in SW-Germany.' *Journal of Hydrology*, 267: 80–93.
- Niel, H., Paturel, J. E. and Servat, E. (2003), 'Study of parameter stability of a lumped hydrologic model in a context of climatic variability.' *Journal of Hydrology*, 278: 213–230.
- Nikolakopoulos, K. G., Kamaratakis, E. K. and Chrysoulakis, N. (2006), 'SRTM vs ASTER elevation products.Comparison for two regions in Crete, Greece.' *International Journal of Remote Sensing*, 27 (21). ISSN 0143-1161.
- Niu, J. and Sivakumar, B. (2013), 'Study of runoff response to land use change in the East River basin in South China.' *Stochastic Environmental Research and Risk Assessment*. doi:10.1007/s00477-013-0690-5.
- Nolin, A. and Liang, S. (2000), 'Progress in bidirectional reflectance modeling and applications for surface particulate media: Snow and soils.' *Remote Sensing Reviews*, 14: 307–342.
- Noorazuan, M. H., Rainis, R., Juahir, H., Sharifuddin, M. Z and Jaafar, N. (2003), 'GIS application in evaluating Land use-Land cover change and its impact on hydrological regime in Langat river basin, Malaysia.' *Map Asia Conference 2003*. www.gisdevelopment.net.
- Nori, W., Elssidig, N. and Niemeyer, I. (2008), 'Detection of land cover changes using multi-temporal satellite imagery.' *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. Vol. XXXVII. Part B7. Beijing 2008.

- Oerlemans, J., Anderson, B., Hubbard, A., Huybrechts, Ph., Johannesson, T., Knap, W.H., Schmeits, M., Stroeve, A.P., Wallinga, R.S.W., van de Wal, J. and Zuo, Z. (1998), 'Modeling the response of glaciers to climate warming.' *Climate Dynamics*, 14:267-274.
- Okkan, U. and Fistikoglu, O. (2013), 'Evaluating climate change effects on runoff by statistical downscaling and hydrological model GR2M.' *TheorApplClimatol*, doi: 10.1007/s00704-013-1005-y.
- Oliveira, R. and Loucks, D.P. (1997), 'Operating rules for multireservoir systems.' *Water Resour. Res.*, 33(4): 839-852.
- Olorunfemi J.F. (1983), 'Monitoring Urban Land – Use in Developed Countries – An aerial photographic approach.' *Environmental Int.*, 9:27 – 32.
- Olsson, J., Uvo, C.B., Jinno, K., Kawamura, A., Nishiyama, K., Koreeda, N., Nakashima, T. and Morita, O. (2004), 'Neural networks for rainfall forecasting by atmospheric downscaling.' *J. Hydrol. Eng.*, 9:1-12.
- Onstad, C. A. and Jamieson, D. G. (1970), 'Modelling the effects of land use modifications on runoff.' *Water Resources Research*, 6: 1287–1295.
- Ostrem, G., Andersen, T. and Odegaard, H. (1981), 'Operational use of satellite data for snow inventory and runoff forecast.' *Satellite Hydrology*, American Water Resources Association, Minneapolis, MN: 230-4.
- Ozturk, M., Coptu, N. K. and Saysel, A. K. (2013), 'Modeling the impact of land use change on the hydrology of a rural watershed.' *Journal of Hydrology*, 497: 97–109.
- Palmer, R.N., Smith, J.A., Cohon, J.L. and R Velle, C.S. (1982), 'Reservoir management in Potomac river basin.' *J. Water Resour. Plann. Manage.*, 108: 47-65.
- Pandey, A. and Sahu, A.K. (2002), 'Generation of curve number using remote sensing and Geographic Information System.' <http://www.GISdevelopment.net>.
- Pandy, A.C. and Nathawat, M.S. (2006), 'Land Use Land Cover Mapping Through Digital Image Processing of Satellite Data – A case study from Panchkula, Ambala and Yamunanagar Districts, Haryana State, India.'
- Panigrahi, P. and Majumdar, P.P. (2000), 'Reservoir Operation Modelling with Fuzzy Logic.' *Water Resources Management*, 14(2): 89–109.
- Parajka, J. and Blöschl, G. (2008), 'The value of MODIS snow-cover data in validating and calibrating conceptual hydrologic models.' *J. Hydrol.* 358: 240-258.
- Parajka, J. and Blöschl, G. (2012), 'MODIS-based Snow Cover Products, Validation, and Hydrologic Applications.' *Multiscale Hydrologic Remote Sensing Perspectives and*

Applications, edited by: Chang, Y. and Ni-Bin, H., CRC Press 2012, pp.185–212, Print ISBN 978-1-4398-7745-6, 2012.

- Parajka, J., Naeimi, V., Blöschl, G., Wagner, W., Merz, R. and Scipal, K. (2006), ‘Assimilating scatterometer soil moisture data into conceptual hydrologic models at the regional scale.’ *Hydrology and Earth System Sciences*, 10: 353–368.
- Parikh, S.C. (1966), ‘Linear decomposition programming of optimal long range operation of a multipurpose reservoir system.’ *Rep. ORC*, 66-68, Oper. Res. Cent., Univ. of Calif., Berkeley.
- Parmar, N., Parmar, A. and Raval, K. (2015), ‘Optimal reservoir operation for irrigation of crops using genetic algorithm: a case study of sukhi reservoir project.’ *International Journal of Civil Engineering and Technology (IJCIET)*, 6(5): 23-27.
- Paudel, K.P. and Andersen, P. (2011), ‘Monitoring snow cover variability in an agropastoral area in the Trans Himalayan region of Nepal using MODIS data with improved cloud removal methodology.’ *Remote Sensing of Environment*, 115: 1234-1246.
- Paul, F., Huggel, C. and Kaab, A. (2004), ‘Combining satellite multispectral image data and a digital elevation model for mapping debris-covered glaciers.’ *Remote Sensing of environment*, 89:510-518.
- Pearman, G.I. (1980), ‘The global carbon cycle and increased levels of atmospheric carbon dioxide.’ In: G.I. Pearman (Editor), *Carbon Dioxide and Climate: Australian Research. Australian Academy of science, Canberra, A.C.T.*, pp. 11-20.
- Peltier, W.R. (2004), ‘Global glacial Isostasy and the Surface of the Ice-age Earth: The ICE-5G(VM2) Model and GRACE.’ *Ann. Rev. Earth and Planet. Sci.*, 32: 111-149.
- Peng, C.S. and Buras, N.(2000), ‘Dynamic operation of a surface water resources system.’ *Water Resour. Res.* 36(9), 41–60.
- Petts, G.E. (1984), ‘Impounded rivers.’ *Willey, Chichester*.
- Petts, G.E. and Gurnell, A.M. (2005), ‘Dams and geomorphology: research progress and new directions.’ *Geomorphology*, 71: 27-47.
- Philip, G. and Sah, M.P. (2004), ‘Mapping repeated surges and retreat of glaciers using IRS-1C/1D data: a case study of Shaune Garang glacier, northwestern Himalaya.’ *International Journal of Applied Earth Observation and Geoinformation*, 6: 127-141.
- Pilon, P.G., Howarth, P.J. and Bullock, R.A.Q. (1988), ‘An enhanced classification approach to change detection in semi-arid environments.’ *Photogram Eng. Rem. Sens.*, 54:1709-1716.

- Pinto, J.G., Neuhaus, C.P., Leckebusch, G.C., Meyers, M. and Kerschgens, M. (2010), 'Estimation of wind storm impacts over Western Germany under future climate conditions using a statistical-dynamical downscaling approach.' *Tellus Series a-Dynamic Meteorology and Oceanography*, 62(2): 188-201.
- Pitman, A. J. and Perkins, S. E. (2008), 'Regional Projections of Future Seasonal and Annual Changes in Rainfall and Temperature over Australia Based on Skill-Selected AR4 Models.' *Earth Interact.*, 12: 1–50.
- Ponce V.M. and Hawkins, R.H. (1996), 'Runoff curve number: has it reached maturity?' *J. Hydr. Engrg.*, ASCE, 11-19.
- Pooja, K., Kumar, M. and Rawat, J.S. (2012), 'Application of remote sensing and GIS in land use and land cover change detection: a case study of Gagas Watershed, Kumaun Lesser Himalaya.' *India. Quest.*, 6 (2): 342–345.
- Postel, S. and Richter, B. (2003), 'Rivers for life- Managing water for people and nature.' *Island press*, Washington, USA, and London, United Kingdom.
- Postel, S.L., Daily, G.C. and Ehrlich, P.R. (1996), 'Human appropriation of renewable fresh water.' *Science*, 271: 785–788.
- Pour, S.H., Harun, S.B. and Shahid, S. (2014), 'Genetic Programming for the Downscaling of Extreme Rainfall Events on the East Coast of Peninsular Malaysia.' *Atmosphere*, 5: 914-936.
- Prasad, A.K., Yang, K.H.S., El-Askary, H.M. and Kafatos, M. (2009), 'Melting of major glaciers in the western Himalayas: evidence of climatic changes from long term MSU derived tropospheric temperature trend (1979–2008).' *Ann. Geophys.*, 27: 4505–4519.
- Prudhomme, C. and Davies, H. (2009), 'Assessing uncertainties in climate change impact analyses on the river flow regimes in the UK. Part 1: baseline climate.' *Climatic Change*, 93(1-2): 177-195.
- Rai, M.R. (2010), 'Reservoir operation considering downstream impact of a hydroelectric project.' *Ph.D. thesis, Indian Institute of Technology, Guwahati, India.*
- Raina, V.K. (2009), 'Himalayan Glaciers: A State-of-Art Review of Glacial Studies, Glacial Retreat, and Climate Change.' *Ministry of Environment and Forests, Government of India. Discussion Paper*, pp.56.
- Rajeevan, M., Bhate, J., Kale, J.D. and Lal, B. (2006), 'High resolution daily gridded rainfall data for the Indian region: Analysis of break and active monsoon spells.' *Current Science*, 91: 296 – 306.
- Rallison, R.E. (1980), 'Origin and evolution of the SCS runoff equation.' *Proc. Symposium on Watershed Management. ASCE, NY* 912–924.

- Raman, H. and Chandramouli, V. (1996), 'Deriving a general operating policy for reservoir using neural network.' *J. Water Resour. Plann. Manage.*, 122(5): 342-347.
- Ramsay, B.H. (1998), 'The interactive multi-sensor snow and ice mapping system.' *Hydrological Processes*, 12:1537-1546.
- Randall, D. A., Wood, R.A., Bony, S., Coleman, R., Fichet, T., Fyfe, J., Kattsov, V., Pitman, A., Shukla, J., Srinivasan, J., Stouffer, R.J., Sumi, A. and Taylor, K.E. (2007), 'Climate models and their evaluation, chapter of the book climate change 2007: the physical science basis. In: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K.B., Tignor, M., Miller, H.L.(eds) Contribution of working group I to the *fourth assessment report of the intergovernmental panel on climate change*. Cambridge University Press, Cambridge, pp 589–662.
- Rango, A. (1980), 'Operational applications of satellite snow cover observations.' *Water Res. Bul.*, 16: 1066-73.
- Rango, A., Martinec, J., Foster, J. and Marks, D. (1983), 'Resolution in operational remote sensing of snow cover.' *Hydrological Applications of Remote Sensing and Remote Data Transmission*, Proc. Hamburg Symp., August, 1983, IAHS Publ. No. 145: 371-82.
- Rango, A., Salomonson, V. V. and Foster, J. L. (1977), 'Seasonal streamflow estimation in the Himalayan region employing meteorological satellite snow cover observations.' *Water Resour. Res.*, 13: 109-12.
- Rao, D.P., Gautam, N.C., Nagaraja, R. and Ram Mohan, P. (1996), 'IRS-IC application in land use mapping and planning.' *Current Science*, 70(7): 575-581.
- Rao, K.L. (1979), 'India's Water Wealth.' New Delhi: *Orient Longman Limited*. 255 pp.
- Rawat, J.S. and Kumar, M. (2015), 'Monitoring land use/cover change using remote sensing and GIS techniques: A case study of Hawalbagh block, district Almora, Uttarakhand, India.' *The Egyptian Journal of Remote Sensing and Space Sciences*, 18: 77–84.
- Rawat, J.S., Biswas, V. and Kumar, M. (2013a), 'Changes in land use/cover using geospatial techniques-A case study of Ramnagar town area, district Nainital, Uttarakhand, India.' *Egypt. J. Rem. Sens. Space Sci.*, 16: 111–117.
- Rawat, J.S., Biswas, V. and Kumar, M. (2013b), 'Quantifying land use/cover dynamics of Nainital town (India) using remote sensing and GIS techniques.' *Asian J. Geoinf.*, 13 (2): 7–12.
- Rawat, J.S., Kumar, M. and Biswas, V. (2013c), 'An integrated approach of remote sensing and GIS for land use/cover change detection: a case study of Bhimtal Tourist Town (India).' *Bull. Envi. Sci. Res.*, 2 (2–3): 1–6.

- Rawat, J.S., Kumar, M. and Biswas, V. (2014), 'Land use/cover dynamics using multi-temporal satellite imagery: a case study of Haldwani Town area, district Nainital, Uttarakhand, India.' *Inter. J. Geom. Geosci.*, 4 (3): 536–543.
- Rawat, J.S., Kumar, M. and Pathak, R.N. (2013d), 'Spatio-temporal dynamics of Almora town area, India.' *Inter. J. Adv. Rem. Sens. GIS*, 2 (1): 425–432.
- Raymond, P.A., Oh, N.H., Turner, R.E. and Broussard, W. (2008), 'Anthropogenically enhanced fluxes of water and carbon from Mississippi River.' *Nature*, 451(24): 449-452.
- Raymond, P.A., Oh, N.H., Turner, R.E., Broussard, W.(2008), 'Anthropogenically enhanced fluxes of water and carbon from Mississippi River.' *Nature*, 451(24): 449-452.
- Reddy, G.P.O., Maji, A.K., Srinivas, C.V. and Velayutham, M. (2002), 'Geomorphological analysis for inventory of degraded lands in a river basin of basaltic terrain using remote sensing and GIS.' *Jour. Indian Soc. Remote Sensing*, 30(1–2):15–31.
- Reddy, J.M., Babu, S. and Mallikarjuna, P. (2008), 'Rainfall – Runoff Modeling: Comparison and Combination of Simple Time-Series, Linear Autoregressive and Artificial Neural Network Models.' *Wseas transactions on fluid mechanics*, 2(3): 126-136.
- Reddy, M.J. and Kumar, D.N. (2006), 'Optimal Reservoir Operation Using Multi-Objective Evolutionary Algorithm.' *Water Resources Management*, 20: 861–878.
- Rees, W.G. (2006), 'Remote Sensing of Snow and Ice.' *CRC Press, Taylor & Francis Group: Boca Rotan, FL, USA*, 99-117.
- Rezaei, Y. (2004), 'Investigation of Chale Khersan Glacier using Remote Sensing Data and GIS.' *M.S. Thesis, Khaje Nasire Toosi, Iran*.
- Riggs, G.A., Hall, D.K. and Salomonson, V.V.(2006), 'MODIS snow products user guide to collection5.' Available from http://modis-snow-ice.gsfc.nasa.gov/sug_c5.pdf.
- Robinson, D. A., Dewey, K.F. and Heim, R.R. (1993), 'Global snow cover monitoring: an update.' *Bull. Amer. Meteorol. Soc.*, 74: 1689-1696.
- Roefs, T.G. and Bodin, L.D.(1970), 'Multireservoir operation studies.' *Water Resou. Res.*, 6(2): 410-420.
- Roy, S. S. and Balling Jr R. C. (2005), 'Analysis of trends in maximum and minimum temperature, diurnal temperature range, and cloud cover over India.' *Geophysical Research Letters*, 32(12), L12702. doi:10.1029/ 2004GL022201.
- Ruiz-Luna, A. and Berlanga-Robles, C.A. (2003), 'Land use, land cover changes and costal lagoon surface reduction associated with urban growth in northwest Mexico.' *Land. Ecol.*, 18: 159–171.

- Russel, S.O. and Campbell, P.E. (1996), 'Reservoir operating rules with fuzzy logic programming.' *J. Water Resour. Plann. Manag.*, 122(3), 165–170.
- Saget, A. (1994), 'Base de donnees sur la qualite des rejets urbains de temps de pluie : distribution de la pollution rejetee, dimensions des ouvrages d'interception.' *PhD Thesis, Ecole Nationale des Ponts et Chaussees*, Paris (France), 333p.
- Sahu, R., Mishra, S. and Eldho, T. (2012), 'Performance evaluation of modified versions of SCS curve number method for two watersheds of Maharashtra, India.' *ISH Journal of Hydraulic Engineering*, 18: 27–36.
- Sailor, D.J., Hu, T., Li, X. and Rosen, J.N. (2000), 'A neural network approach to local downscaling of GCM output for assessing wind power implications of climate change.' *Renew Energy*, 19:359–378.
- Sajikumar, N. and Thandaveswara, B.S. (1999), 'A non-linear rainfall– runoff model using an artificial neural network.' *Journal of Hydrology*, 216: 32–55.
- Salomomson, V.V. and Appel, I. (2004), 'Estimating fractional snow cover from MODIS using the normalized difference snow index.' *Remote Sensing of Environment*, 89:351-360.
- Samadi, S. Carbone. G.J. ,Mahdavi, M., Sharifi, F. and Bihamta, M.R. (2012), Statistical downscaling of climate data to estimate streamflow in a semi-arid catchment.' *Hydrol. Earth Syst. Sci. Discuss.*, 9: 4869–4918.
- Sarkar, A. (2015), 'Impact of climate change on the runoff regime of an Eastern Himalayan river basin.' *Global NEST Journal*, 17(2): 323-333.
- Sarkar, A. and Kumar, R. (2012), 'Artificial neural networks for event based rainfall–runoff modeling.' *Journal of Water Resource and Protection*, 04: 891–897.
- Sarma K. and Kushwaha S.P.S.(2005), 'Coal mining impact on land use/land cover in Jaintia hills district of Meghalaya, India using Remote Sensing and GIS technique.' *University School of Environment Management*, Guru Gobind Singh Indraprastha University.
- Sausen, R., Schubert, S., Du menil, L.(1994), 'A model of river runoff for use in coupled atmosphere-ocean model.' *Journal of Hydrology*, 155: 337-352.
- Schanda, E., Matzler, C. and Kunzi, K. (1983), 'Microwave remote sensing of snow cover.' *International Journal of Remote Sensing*, 4(1): 149 - 158.
- Schilling, K.E. and Libra, R.D.(2003), 'Increased baseflow in Iowa over the second half of the 20th century.' *J. Am. Water Resour. Assoc.*, 39: 851-860.

- Schoof, J.T. and Pryor, S.C. (2001), 'Downscaling temperature and precipitation: a comparison of regression-based methods and Artificial Neural Networks.' *International Journal of Climatology*, 21(7): 773-790.
- Scilling, K.E. and Lutz, D.S. (2004), 'Relation of nitrate concentrations to baseflow in the Raccoon River, Iowa.' *J. Am. Water Resour. Assoc.*, 40: 889-900.
- SCS (1956), 'Hydrology. National Engineering Handbook.' Supplement A, Section 4. *Soil Conservation Service*, US Department of Agriculture: Washington, DC; Chapter 10.
- SCS (1985), 'National Engineering Handbook, Section 4: Hydrology, Chapter 4.' *Soil Conservation Service*, USDA, Washington, D.C.
- Seaby, L. P., Refsgaard, J. C., Sonnenborg, T. O., Stisen, S., Christensen, J. H. and Jensen, K.H. (2013), 'Assessment of robustness and significance of climate change signals for an ensemble of distribution-based scaled climate projections.' *Journal of Hydrology*, 486(0): 479-493.
- Segui, P.Q., Ribes, A., Martin, E., Habets, F. and Boe, J. (2010), 'Comparison of three downscaling methods in simulating the impact of climate change on the hydrology of Mediterranean basins.' *Journal of Hydrology*, 383(1-2): 111-124.
- Seko, K., Yakubi, H., Nakawo, M., Kadiota, T. and Yamada, Y. (1998), 'Changing surface features of Khumbu glacier, Nepal Himalayas revealed by SPOT images.' *Bulletin of Glacier Research*, 16: 33-41.
- Selcuk, R., Nisanci, R., Uzun, B., Yalcin, A., Inan, H. and Yomralioglu, T. (2003), 'Monitoring land-use changes by GIS and remote sensing techniques: case study of Trabzon.' http://www.fig.net/pub/morocco/proceedings/TS18/TS18_6_reis_el_al.pdf f 5.
- Shafer, B. A. and Leaf, C. F. (1979), 'Landsat derived snowcover as an input variable for snowmelt runoff forecasting in Central Colorado.' *Proc. Final Workshop on Operational Applications of Satellite Snow Cover Observations*, NASA CP-2116: 151-69.
- Shamsudheen, M., Dasog, G.S. and Tejaswini, N.B. (2005), 'Land use/Land cover mapping in the coastal area of north Karnataka using remote sensing data.' *J. Indian Society of Remote Sensing*, 33(2): 253-257.
- Sharda, R. and Patil, R. (1990), 'Neural Networks as forecasting experts: an empirical test.' *Proceedings of the 1990 International Joint Conference on Neural Networks*, Washington DC, USA.; 1: 491-494.
- Sharif, M., Hamid, A.T. and Husain, A. (2013), 'Simulation of Karangkates reservoir operation.' *International Journal of Innovative Research in Science, Engineering and Technology*, 2(5): 1850-1857.

- Sharma, L.K., Pandey, P.C. and Nathawat, M.S. (2012), 'Assessment of land consumption rate with urban dynamic changes using Geospatial approach.' *J. Land Use Sci.*, 7 (2): 131–148.
- Sharma, T., Kiran, P.V.S., Singh, T.P., Trivedi, A.V. and Navalgund, R.R.(2001), 'Hydrological response of a watershed to land use changes: a remote sensing and GIS approach.' *International Journal of Remote Sensing*, 22(11): 2095-2108.
- Sheail, J. (1988), 'River regulation in the United Kingdom: A historical perspective.' *Regulated Rivers: Research and Management*, 6: 53-70.
- Shetty, A., Nandagiri, L., Thokchom, S. and Rajesh, M.V.S. (2005), 'Land use-Land cover mapping using satellite data for a forested watershed, Udupi district, Karnataka state, India.' *J. Indian Society of Remote Sensing*, 33(2): 233-238.
- Shindell, D. and Faluvegi, G. (2009), 'Climate response to regional radiative forcing during the twentieth century.' *Nature Geoscience*, 2 (4): 294–300.
- Shirke, Y., Kawitkar, R. and Balan, S. (2012), 'Artificial neural network based runoff prediction model for a reservoir.' *International Journal of Engineering Research and Technology*, 1(3): 1–4.
- Shoshany, M. (1994), 'Monitoring Temporal Vegetation Cover Changes in Mediterranean and Arid Ecosystems Using a Remote Sensing Technique: case study of the Judean Mountain and the Judean Desert.' *Journal of Arid Environments*, 33: 9 – 21.
- Shrestha, B. P., Duckstein, L. and Stakhiv, E. Z. (1996), 'Fuzzy rule based modeling of reservoir operation.' *J. Water Resour. Plann. Manag.*, 122(4), 262–269.
- Siderius, C., Biemans, H., Wiltshire, A., Rao, S., Franssen W.H.P., Kumar, P., Gosain, A.K., Vliet, M.T.H. and Collins, D.N.(2013), 'Snowmelt contribution to the discharge of the Ganges.' *Science of the total environment*, 468-469: \$93-\$101.
- Simonovic, S.P. and Marino, M.A. (1982), 'Reliability programming in reservoir management, system of multipurpose reservoir.' *Water Resources Res.*, 18(4): 735-743.
- Singh, P., Jain, S.K. and Kumar, N. (1997a), 'Snow and Glacier melt runoff contribution in the Chenab river at Akhnour.' *Mountain Research development*, 17:49-56.
- Singh, P. and Bengtsson, L. (2003), 'Effect of warmer climate on depletion of snow covered area in the Satluj basin in the Western Himalayan region.' *Hydrological Sciences Journal*, 48(3): 413-425.
- Singh, P. and Bengtsson, L. (2004), 'Impact of warmer climate on melt and evaporation for the rainfed, snowfed and glacierfed basins in the Himalayan region.' *Journal of Hydrology*, 300: 140-154.

- Singh, P. and Jain, S.K. (2002), 'Snow and glacier contribution in the satluj river at Bhakra Dam in the Western Himalayan region.' *Hydrological Sciences Journal*, 47: 93-106.
- Singh, P., Gupta, P. and Singh, M. (2014), 'Hydrological inferences from watershed analysis for water resource management using remote sensing and GIS techniques.' *Egypt. J. Rem. Sens. Space Sci.*, 17: 111–121.
- Singh, P., Jain, S.K., Kumar, N. and Singh, U.K. (1994a), 'Snow and Glacier Contribution in the Chenab Rriver at Akhnoor', CS (AR)-131, *National Institute of Hydrology, Roorkee, India*.
- Singh, V.P., Sharma, B., Shekhar, C. and Ojha, P. (2004), 'The Brahmaputra Basin Water Resources.' *Kluwer Academic Publishers*, ISBN 1-4020-1737-5.
- Sohail,A., Watanabe, K.and Takeuchi, S. (2006), 'Stream flow forecasting by artificial neural network (ANN) model trained by real coded genetic algorithm (GA).' *Journal of Groundwater Hydrology Japan*, 48 (4): 233–262.
- Solecki, W.D. and Oliveri, C. (2004), 'Downscaling climate change scenarios in an urban land use change model.' *Journal of Environmental Management*, 72 (1–2): 105–115.
- Song, X., Kong, F., Zhan, C.,and Han, J. (2012), 'Hybrid Optimization Rainfall-Runoff Simulation Based on Xinanjiang Model and Artificial Neural Network.' *J. Hydrol. Eng.*, 10: 1033-1041.
- Soulis, K.X., Valiantzas, J.D., Dercas, N. and Londra, P.A. (2009), 'Investigation of the direct runoff generation mechanism for the analysis of the SCS-CN method applicability to a partial area experimental watershed.' *Hydrology and Earth System Sciences*, 13: 605-615.
- Srivastava, D.K. and Patel, I.A. (1992), 'Optimization simulation model for the design of irrigation project.' *J. Water Resour. Mgt. (The Netherlands)*, 6: 315.
- Stahl, K., Moore, R. D., Shea, J. M., Hutchinson, D., and Cannon, A. J. (2008), 'Coupled modelling of glacier and streamflow response to future climate scenarios.' *Water Resour. Res.*, 44, W02422, doi:10.1029/2007WR005956, 2008.
- Stern, N. (2006), 'The Stern Review: Economics of Climate Change.' *Cambridge University Press*. ISBN- 13: 9780521700801. 700pp.
- Stocker, T. F., Clarke, G. K. C., Le Treut, H., Lindzen, R. S., Meleshko, V. P., Mugara, R. K., Palmer, T. N., Pierrehumbert, R. T., Sellers, P. J., Trenberth, K. E., and Willebrand, J.(2004), 'Physical climate processes and feedbacks.' in: *Climate Change 2001: The Scientific Basis*, edited by: Houghton, J. T., et al., Cambridge University Press, Cambridge, 417-470, 2001.

- Streenhuis, T.S., Winchell, M., Rossing, J., Zollweg, J.A. and Walter, M.F. (1995), 'SCS runoff equation revisited for variable-source runoff areas.' *Journal of Irrigation and Drainage Engineering*, 121(3): 234-38.
- Sudheer, K. P., Gosain, A. K. and Ramasastri, K. S. (2002), 'A data-driven algorithm for constructing artificial neural network rainfall-runoff models.' *Hydrological Processes*, 16: 1325-1330.
- Tanasienko, A.A. and Chumbaev, A.S. (2008), 'Features of snowmelt runoff waters in the Cis-Salair region in an extremely snow-rich hydrological year.' *Contemporary Problems of Ecology*, 1(6): 687-696.
- Tarble, R.D. (1963), 'Areal Distribution of Snow as Determined from Satellite Photographs.' *International Association of Scientific Hydrologists*, 65: 373-375.
- Tatli, H., Dalfes, H.N. and Menten, S. (2004), 'A statistical downscaling method for monthly total precipitation over Turkey.' *International Journal of Climatology*, 24 (2): 161-180.
- Tekeli, A.E. (2005), 'Operational hydrological forecasting of snowmelt runoff by remote sensing and geographic information systems integration.' *Ph.D. thesis*, The Graduate School of Natural and Applied Sciences of Middle East Technical University.
- Thair, S.K., Ayad, S.M. and Hasan, H.M. (2015), 'Reservoir Operation by Artificial Neural Network Model (Mosul Dam -Iraq, as a Case Study).' *Eng. &Tech.Journal*, 33(7): 1697-1714.
- Thanapakpawin, P., Richey, J., Thomas, D., Rodda, S., Campbell, B. and Logsdon, M. (2006), 'Effects of landuse change on the hydrologic regime of the Mae Chaem river basin, NW Thailand.' *Journal of Hydrology*, 334: 215-230.
- Thomson, M.C., Doblas-Reyes, F.J., Mason, S.J., Hagedorn, R., Connor, S.J., Phindela, T., Morse, A.P. and Palmer, T.N. (2006), 'Malaria early warnings based on seasonal climate forecasts from multi-model ensembles.' *Nature*, 439:576-579. Doi: 10.1038/nature04503.
- Tollan, A.(2002), 'Land use change and floods: what do we need most research or management?' *Water Science and technology*, 45: 183-190.
- Tripathi, S., Srinivas, V.V. and Nanjundiah, R.S. (2006), 'Downscaling of precipitation for climate change scenarios: A support vector machine approach.' *Journal of Hydrology*, 330: 621-640.
- Turner II, B.L., Skole, D.L., Sanderson, S., Fischer, G., Fresco, L.O. and Leemans, R. (1995), 'Land-use and land-cover change.' *Science/Research Plan*. Stockholm and Geneva: IGBP Report No. 35 and HDP Report No. 7, 132 pp.

- Turner, M.G. and Ruscher, C.L. (2004), 'Change in landscape patterns in Georgia. USA Land.' *Ecol.*, 1 (4): 251–421.
- Umadevi, P.P., James, E.J. and Jegathambal, P. (2014), 'Evolving reservoir operation rules using fuzzy logic inference system for irrigation management in a sub-basin scale.' *International Journal of Engineering Research & Technology (IJERT)*, 3(3): 221-227.
- USDA (1986), 'Urban Hydrology for Small Watersheds.' *Technical Release 55*, 2nd edn (Springfield, VA: United States Department of Agriculture Natural Resources Conservation Service).
- USGS (2014), 'Landsat 8 thermal infrared sensor geometric characterization and calibration.' *Remote Sensing*, 6: 11153-11181.
- Usman, M., Liedl, R., Shahid, M.A. and Abbas, A. (2015), 'Land use/land cover classification and its change detection using multi-temporal MODIS NDVI data.' *J. Geogr. Sci.*, 25(12): 1479-1506.
- Valent, P., Szolgay, J. and Rivero, C. (2012), 'Assessment of the uncertainties of a conceptual hydrologic model by using artificially generated flows.' *Slovak Journal of Civil Engineering*, 20: 35–43.
- Van Mullem, J.A. (1989), 'Runoff and peak discharge using GreenAmpt Infiltration model.' *J. Hydr. Engrg.*, ASCE, 117(3): 354-370.
- Vapnik, V.N. (1995), 'The Nature of Statistical Learning Theory.' *Springer Verlag*, New York.
- Vapnik, V.N. (1998), 'Statistical Learning Theory.' *Wiley*, New York.
- Vedula, S. and Majumdar, P.P. (2005), 'Water Resources Systems: Modeling techniques and analysis.' *TATA McGraw Hill Education Pvt. Ltd.*, New Delhi.
- Vermeer, M. and Rahmstorf, S. (2009), 'Global sea level linked to global temperature.' *Proceedings of the National Academy of Sciences December 22, 2009*, 106(51): 21527-21532.
- Viji, R., Prasanna, P.R. and Ilango, R. (2015), 'GIS based SCS - CN method for estimating runoff in Kundahpalam watershed, Nilgiris district, Tamilnadu.' *Earth Sciences Research Journal*, DOI: <https://doi.org/10.15446/esrj.v19n1.44714>.
- Viviroli, D., Archer, D.R., Buytaert, W., Fowler, G., Greenwood, G.B., Hamlet, A.F., Huang, Y., Koboltschnig, G., Litaor, M.I., Lopez-Moreno, J.I., Lorentz, S., Schädler, B., Schreier, H., Schwaiger, K., Vuille, M. and Woods, R. (2011), 'Climate change and mountain water resources: overview and recommendations for research, management and policy.' *Hydrol. Earth Syst. Sci.*, 15: 471–504.

- Viviroli, D., Durr, H.H., Messerli, B., Meybeck, M. and Weingartner, R. (2007), 'Mountains of the world, water towers for humanity: Typology, mapping, and global significance.' *Water Resour. Res.*, 43, W07447, doi:10.1029/2006WR005653.
- Viviroli, D., Zappa, M., Gurtz, J. and Weingartner, R. (2009), 'An introduction to the hydrological modelling system PREVAH and its pre- and post-processing-tools.' *Environmental Modelling and Software*, 24: 1209–1222.
- Vu, M.T., Aribarg, T., Supratid, S., Raghavan, S.V. and Liong, S.Y.(2016), 'Statistical downscaling rainfall using artificial neural network: significantly wetter Bangkok?' *Theoretical and Applied Climatology*, 1-15.
- Walcher, J. (1773), 'Nachrichten von den Eisbergen in Tyrol.' *Wien*, 99 pp.
- Wang, Y., Guo, S., Xiong, L., Liu, P. and Liu, D. (2015), 'Daily Runoff Forecasting Model Based on ANN and Data Preprocessing Techniques.' *Water*, 7: 4144-4160.
- Wang, G.X., Zhang, Y., Liu, G.W. and Chen, L. (2006), 'Impact of land-use change on hydrological processes in the Maying River basin, China.' *Science in China Series D: Earth Sciences*, 49 (10): 1098-1110.
- Wang, X., Xie, H. and Liang, T. (2008), 'Evaluation of MODIS snow cover and cloud mask and its application in Northern Xinjiang, China.' *Remote Sensing of Environment*, 112(4):1947-1513.
- Warburton, M. L., Schulze, R. E. and Jewitt, P. G. (2012), 'Hydrological impacts of land use change in three diverse South African catchments.' *Journal of Hydrology*, 414–415: 118–135.
- WASA (1998), 'Changing waves and storms in the Northeast Atlantic?' *Bull. Amer. Met. Soc.*, 79: 741–760.
- Watterson, I.G. and Whetton, P.H. (2011), 'Distributions of decadal means of temperature and precipitation change under global warming.' *J. Geophys. Res.*, 116: D07101, doi:10.1029/2010JD014502.
- Weisse, R. and Oestreicher, R. (2001), 'Reconstruction of potential evaporation for water balance studies.' *Climate Research*, 16 (2): 123–131.
- Wessels, R.L., Kargel, J.S. and Kieffer, H.H. (2002), 'ASTER measurement of supraglacial lakes in the Mount Everest region of the Himalaya.' *Annals of Glaciology*, 34: 399-408.
- Wijesekara, G. N., Gupta, A., Valeo, C., Hasbani, J. G., Qiao, Y., Delaney, P. and Marceau, D. J. (2012), 'Assessing the impact of future land-use changes on hydrological processes in the Elbow River watershed in southern Alberta, Canada.' *Journal of Hydrology*, 412–413: 220–232.

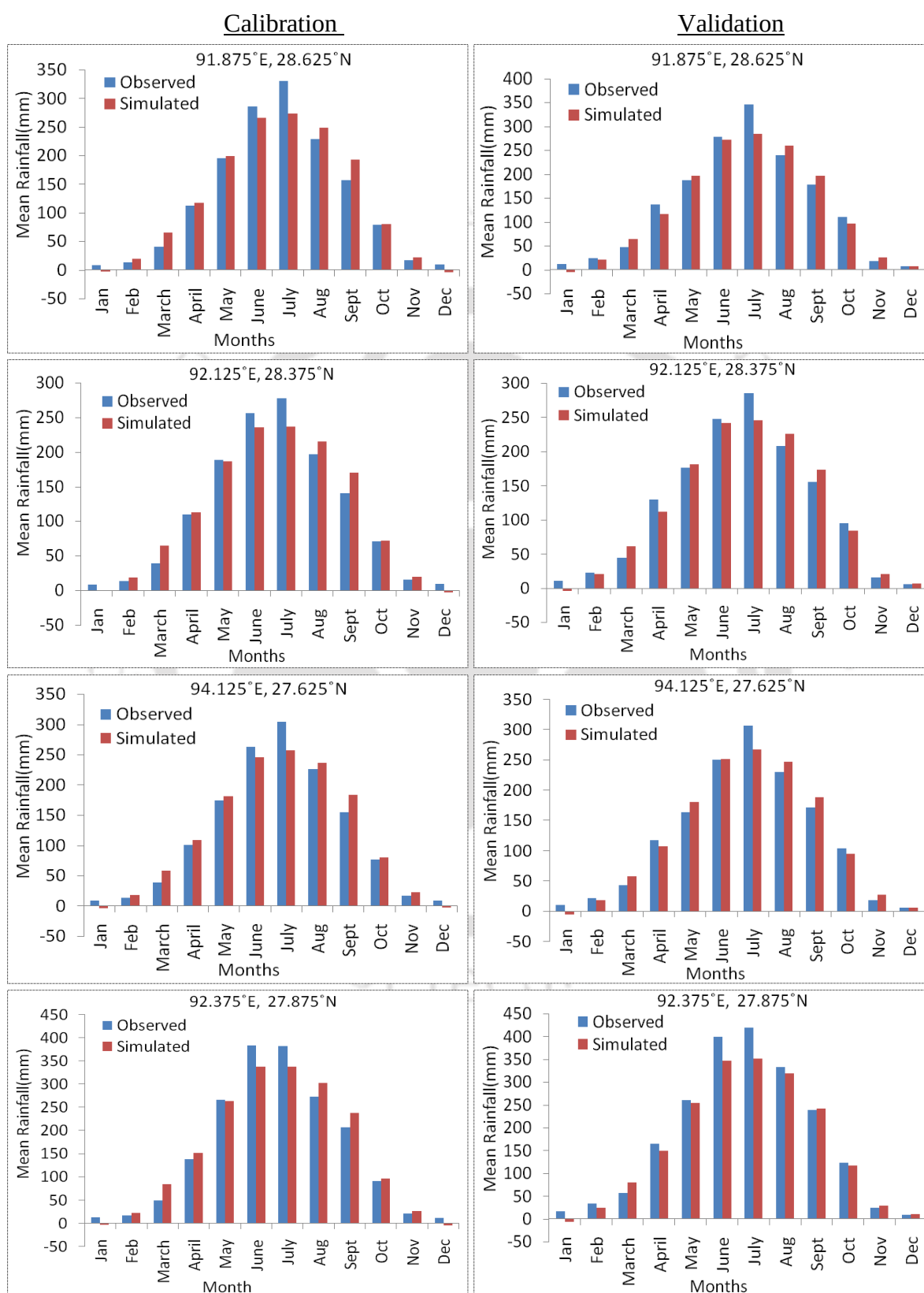
- Wilby, R. L., and Harris, I. (2006), 'A framework for assessing uncertainties in climate change impacts: low-flow scenarios for the River Thames, UK.' *Water Resour. Res.*, 42, W02419, doi:02410.01029/02005WR004065, 2006.
- Wilby, R. L., Troni, J., Biot, Y., Tedd, L., Hewitson, B. C., Smith, D. M. and Sutton, R. T. (2009), 'A review of climate risk information for adaptation and development planning.' *International Journal of Climatology*, 29(9): 1193-1215.
- Wilby, R.L., Wigley, T.M.L., Conway, D., Jones, P.D., Hewitson, B.C., Main, J. and Wilks, D.S. (1998), 'Statistical downscaling of general circulation model output: a comparison of methods.' *Water Resources Research*, 34: 2995-3008.
- Wilcox, B.P., Rawls, W.J., Brakensiek, D.L. and Wight, J.R. (1990), 'Predicting runoff from rangeland catchments: A comparison of two models.' *Water Resour. Research*, 26(10): 2401-2410.
- Wilks, D. S. (1999), 'Multisite downscaling of daily precipitation with a stochastic weather generator.' *Clim. Res.*, 11: 125-136.
- Williams, G.P. and Wolman, M.G. (1984), 'Downstream effects of dams on alluvial rivers. U.S. Geological Survey Professional Paper. 1286.
- Williams, J., Kannan, N., Wang, X., Santhi, C., and Arnold, J. (2012), 'Evolution of the SCS Runoff Curve Number Method and Its Application to Continuous Runoff Simulation.' *J. Hydrol. Eng.*, 10.1061/(ASCE)HE.1943-5584.0000529: 1221-1229.
- Williams, J.R. and LaSeur, V. (1976), 'Water yield model using SCS curve numbers.' *Journal of Hydraulic Engineering*, 102(HY9): 1241-1253.
- Winkler, J.A., Palutikof, J.P., Andresen, J.A. and Goodess, C.M. (1997), 'The simulation of daily temperature time series from GCM output: Part II: Sensitivity analysis of an empirical transfer function methodology.' *J. Climate*, 10: 2514-2535.
- Winkler, S., Chinn, T., Gartner-Roer, I., Nussbaumer, S.U., Zemp, M. and Zumbuhl, H.J. (2010), 'An Introduction to Mountain Glaciers as Climate Indicators with Spatial and Temporal Diversity.' *Erdkunde*, 64(2): 97-118.
- WMO, 2006(a), 'Environmental Aspects of Integrated flood Management.' *APFM Technical Document No.3, Flood Management Policy Series.*, WMO-No. 1009, Geneva.
- WMO.(2015), 'Reservoir operation and managed flows.' *Integrated flood management tools series*, 5(2.1).
- Wu, K. and Johnston, C. A. (2007), 'Hydrologic response to climatic variability in a Great Lakes Watershed: A case study with the SWAT model.' *Journal of Hydrology*, 337: 187-199.

- WWF (2005). 'An overview of glaciers, glacier retreat, and subsequent impacts in Nepal, India and China.' WWF Nepal Program, 2005.
- Xiao, X., Shen, Z. and Qin, X. (2001), 'Assessing the potential of VEGETATION sensor data for mapping snow and ice cover: A normalized difference snow and ice index.' *Int. J. Remote Sens.*, 22:2479–2487.
- Xiaoling, C., Xiaobin, C. and Hui, L. (2006), 'Expert classification method based on patch-based neighborhood searching algorithm.' *Geo-Spatial Info. Sci.*, 1 10(1): 37-43.
- Xie, H., Wang, X. and Liang, T. (2009), 'Development and assessment of combined Terra and Aqua snow cover products in Colorado Plateau, USA and northern Xinjiang, China.' *Journal of Applied Remote Sensing*, 3(033559).
- Xie, P., Yatagai, A., Chen, M., Hayasaka, T., Fukushima, Y., Liu, C. and Yang, S. (2007), 'A gauge-based analysis of daily precipitation over East Asia.' *Journal of Hydrometeorology*, 8: 607-627.
- Xu, J., Grumbine, R.E., Shrestha, A., Eriksson, M., Yang, X., Wang, Y. and Wilkes, A. (2008), 'The Melting Himalayas: Cascading Effects of Climate Change on Water, Biodiversity, and Livelihoods.' *Conservation Biology*, 23 (3): 520-530.
- Xu, J., Shrestha, A. and Eriksson, M. (2009), 'Climate change and its impacts on glaciers and water resource management in the Himalayan Region. Assessment of Snow, Glacier and Water Resources in Asia.' *International Hydrological Programme of UNESCO and Hydrology and Water Resources Programme of WMO*.
- Yadav, R. R., Park, W. K., Singh, J. and Dubey, B. (2004), 'Do the western Himalayas defy global warming?' *Geophysical Research Letters*, 31(17).
- Yang, C., Chandler, R.E. and Isham, V. S.. (2005), 'Wheater, Spatial-temporal rainfall simulation using generalized linear models.' *Wat. Resour. Res.*, 41. doi: 10.1029/2004WR003,739.
- Yao, T.D., Guo, X.J., Lonnie, T., Duan, K.Q., Wang, N.L., Pu, J.C., Xu, B.Q., Yang, X.X. and Sun, W.Z. (2006), 'Record of temperature change over the past 100 years in ice cores on the Tibetan Plateau'. *Science in China, Series D Earth Science*, 49(1): 1-9.
- Yatagai, A., Xie, P. and Kitoh, A. (2005), 'Utilization of a new gauge-based daily precipitation dataset over monsoon Asia for validation of the daily precipitation climatology simulated by the MRI/JMA 20-km-mesh AGCM.' *SOLA*, 1, 193-196, doi:10.2151/sola.2005-050.
- Yeh, W. (1985), 'Reservoir management and operation models: A state of the art review.' *Water Resour. Res.*, 21(12): 1797-1818.

- Young, G.K. (1967), 'Finding reservoir operation rules.' *J. Hydraulic Div., ASCE*, 93 (HYC): 297-321.
- Yuan, F., Sawaya, K.E., Loeffelholz, B. and Bauer, M.E. (2005), 'Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing.' *Rem. Sen. Envi.*, 98: 317–328.
- Zadeh, L.A. (1965), 'Fuzzy sets.' *Information and Control*, 8(3): 38-53.
- Zhan, X. and Huang, M.L. (2004), 'ArcCN-Runoff: an ArcGIS tool for generating curve number and runoff maps.' *Environmental Modelling & Software*, 19: 875-879.
- Zhan, X., Sohlberg, R.A., Townshend, J.R.G., DiMiceli, C., Carroll, M.L., Eastman, J.C., Hansen, M.C. and DeFries, R.S. (2002), 'Detection of land cover changes using MODIS 250 m data.' *Remote sensing of Environment*, 83: 336-350.
- Zhang, X. (2007), 'A comparison of explicit and implicit spatial downscaling of GCM output for soil erosion and crop production assessments.' *Climatic Change*, 84(3-4): 337-363.
- Zhang, X.C., Nearing, M.A., Garbrecht, J.D. and Steiner, J.L. (2004), 'Downscaling monthly forecasts to simulate impacts of climate change on soil erosion and wheat production.' *Soil Sci Soc Am J*, 68:1376–1385.
- Zhang, Y., Yan, S. and Lu, Y. (2010), 'Snow Cover Monitoring Using MODIS Data in Liaoning Province, Northeastern China.' *Remote Sens.*, 2: 777-793;
- Zhang, Y.K. and Schilling, K.E. (2006), 'Increasing streamflow and baseflow in the Mississippi River since the 1940s: effect of land use change.' *J. Hydrol.*, 324: 412-422.
- Zhao, H. and Fernandes, R. (2009), 'Daily snow cover estimation from Advanced Very High Resolution radiometer Polar Path finder data over Northern Hemisphere land surfaces during 1982-2004.' *Journal of Geophysical Research*, 114(D5).
- Zhao, T., Cai, X., Lei, X. and Wang, H. (2012), 'Improved dynamic programming for reservoir operation optimization with a concave objective function.' *J. Water Resour. Plann. Manage.*, 138:590-596.

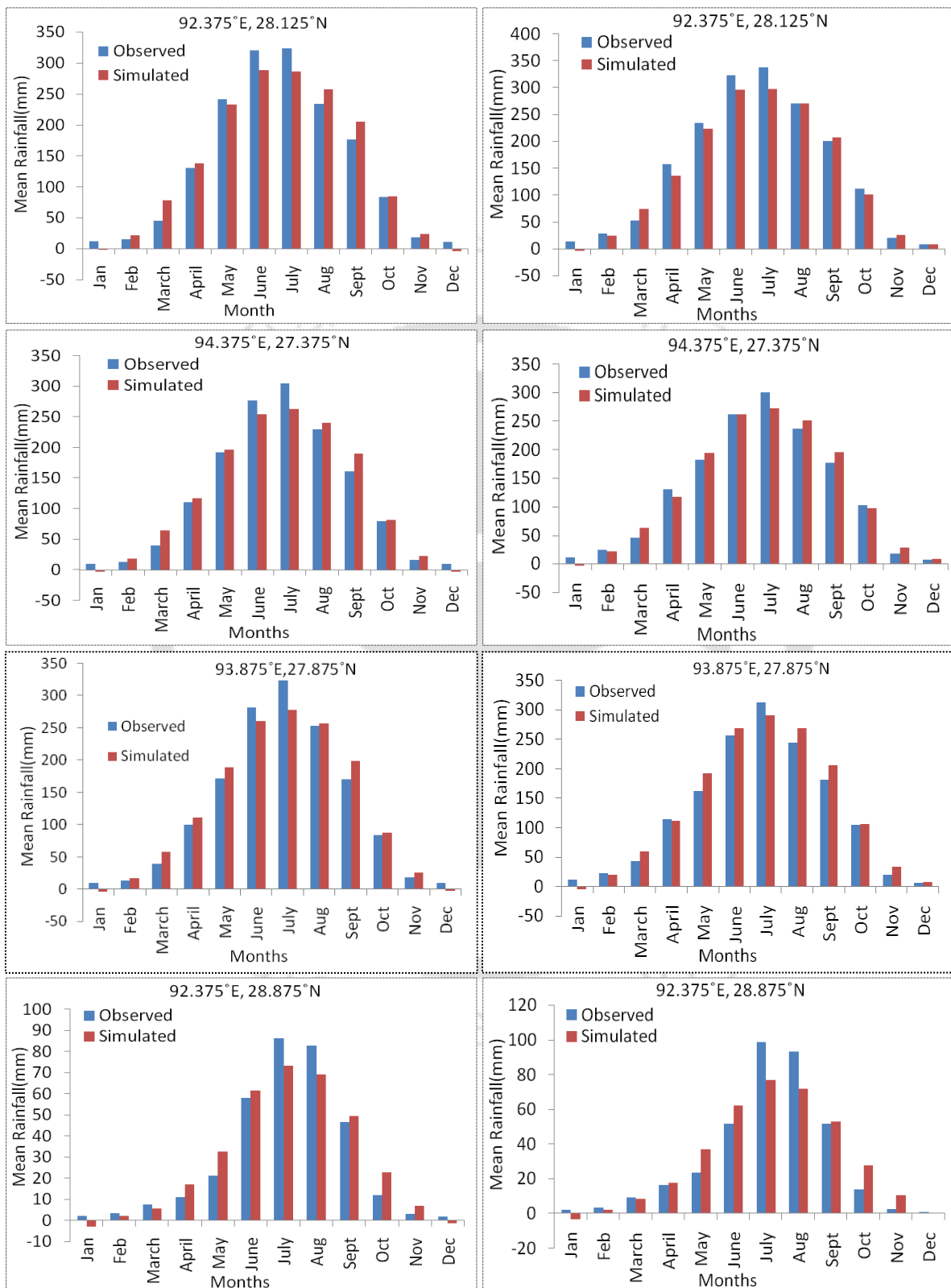
Annexure 1

Calibration and Validation graphs for multiple linear regression performed by taking climatic parameters of one HadCM3 GCM point



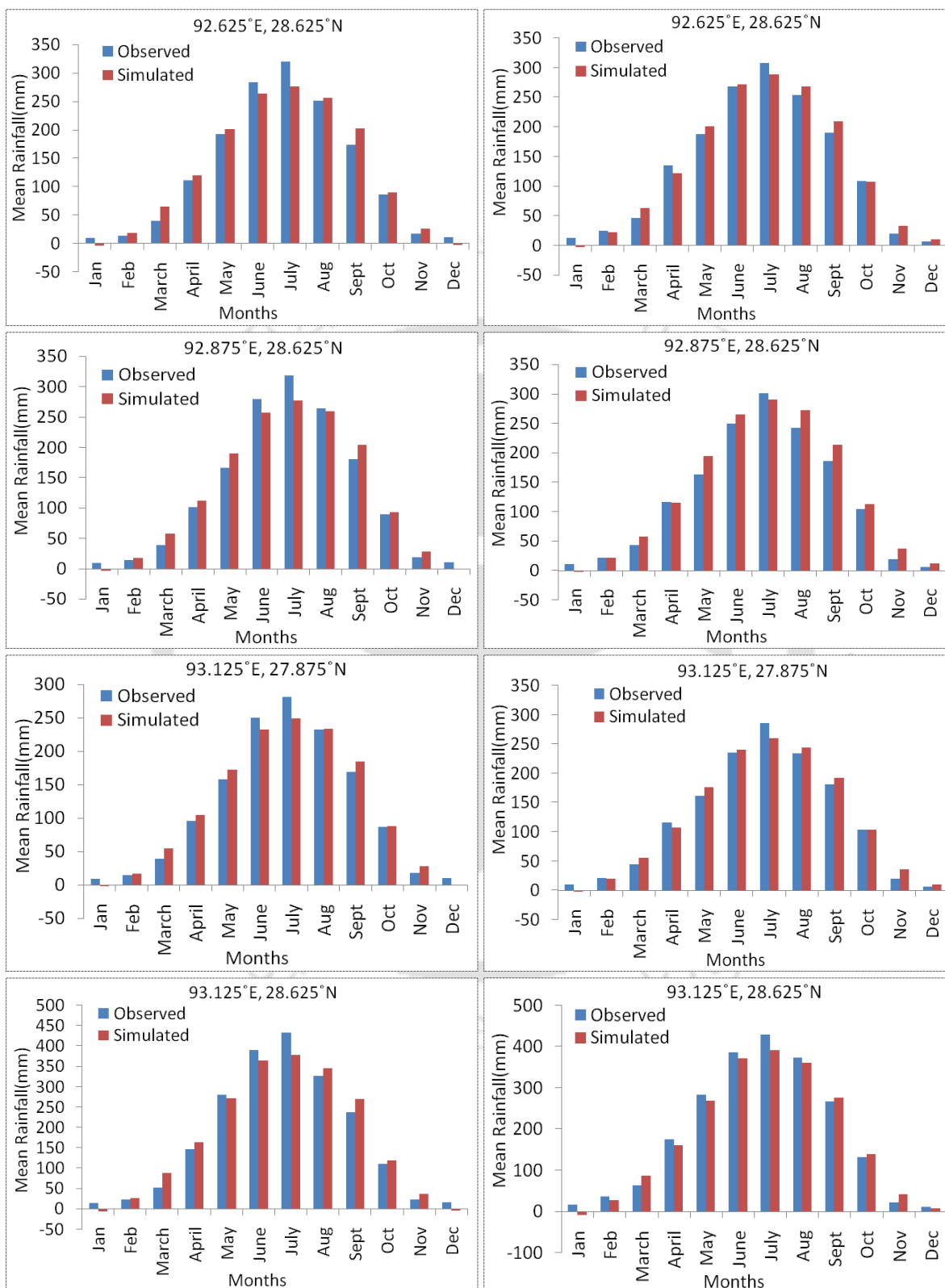
Calibration

Validation

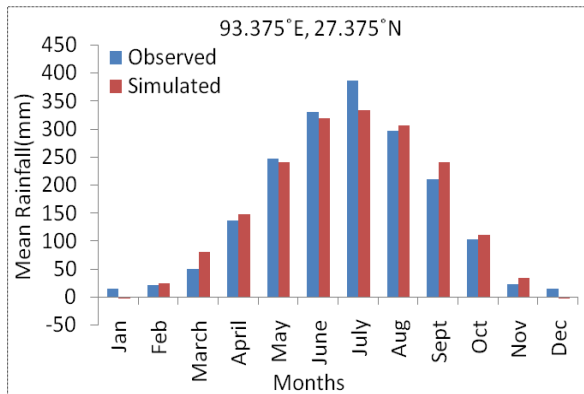


Calibration

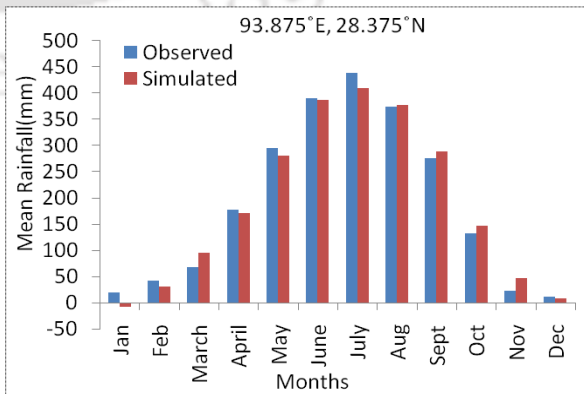
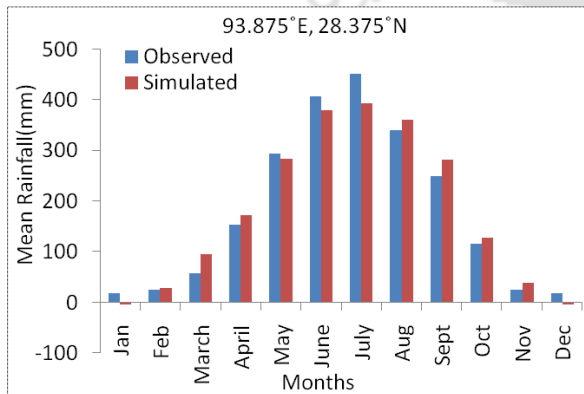
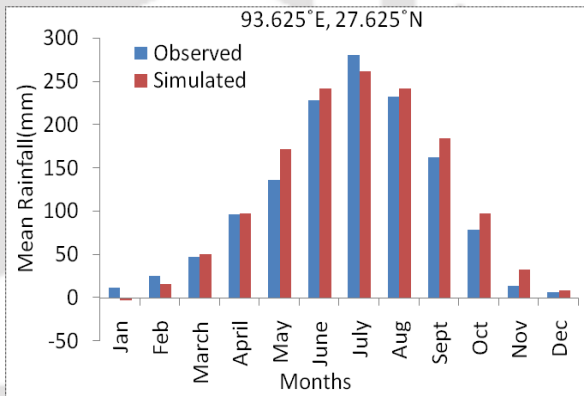
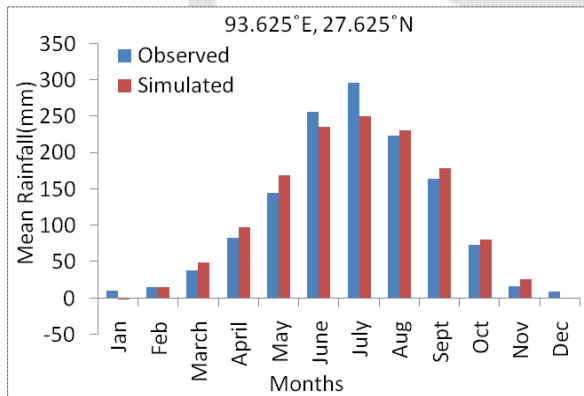
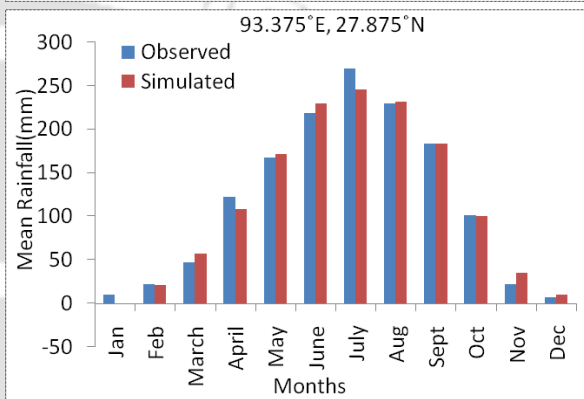
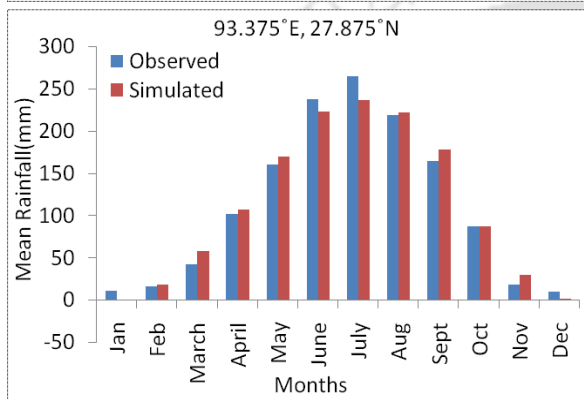
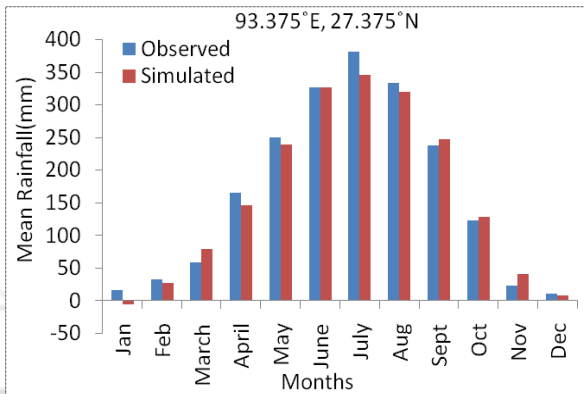
Validation



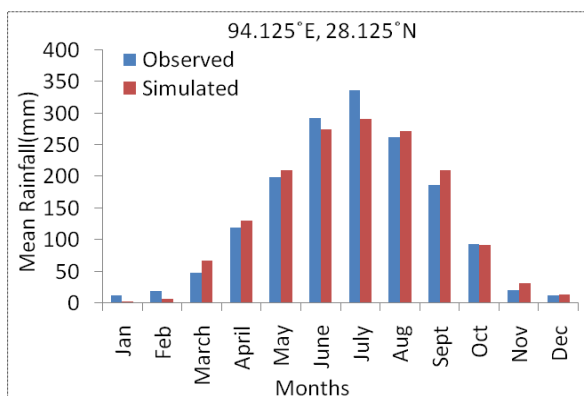
Calibration



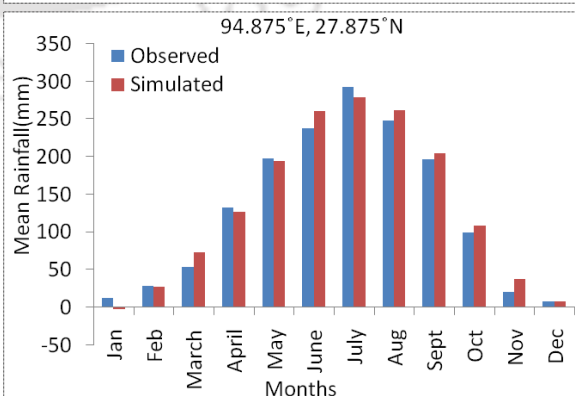
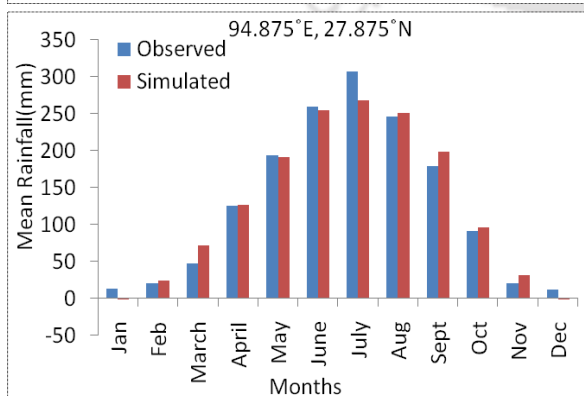
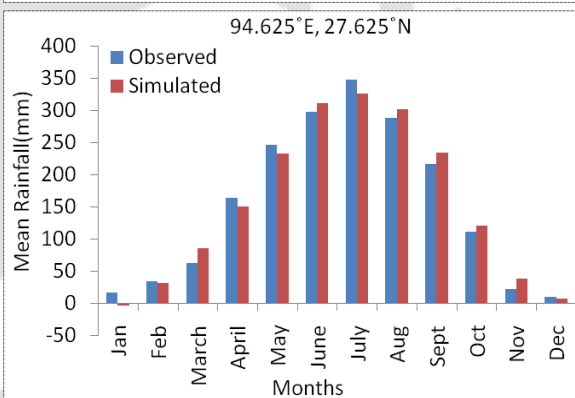
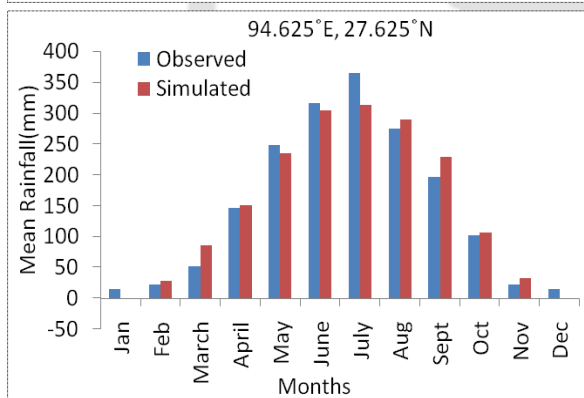
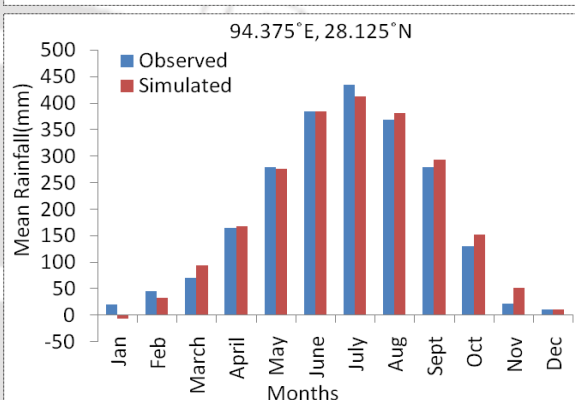
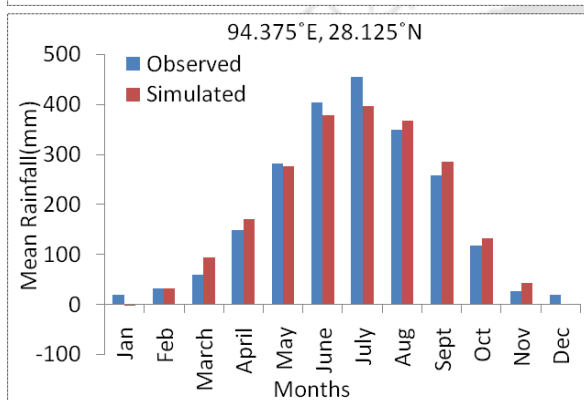
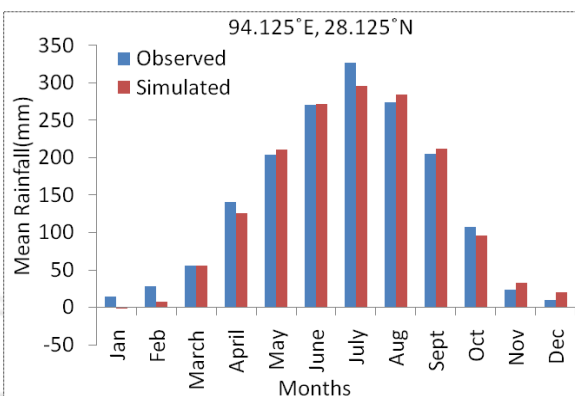
Validation



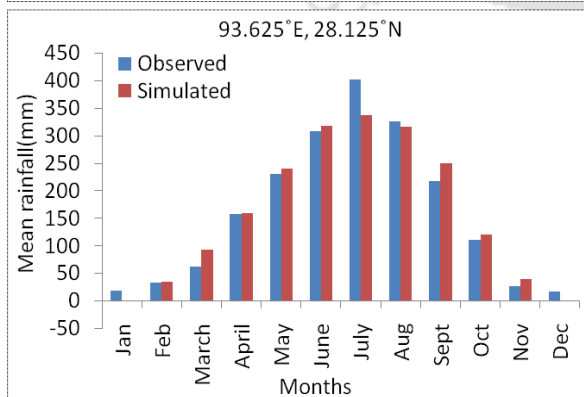
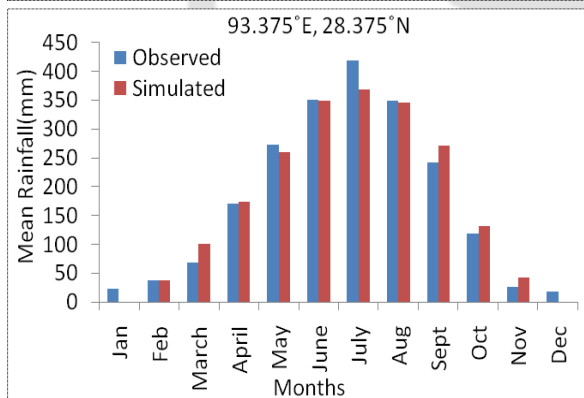
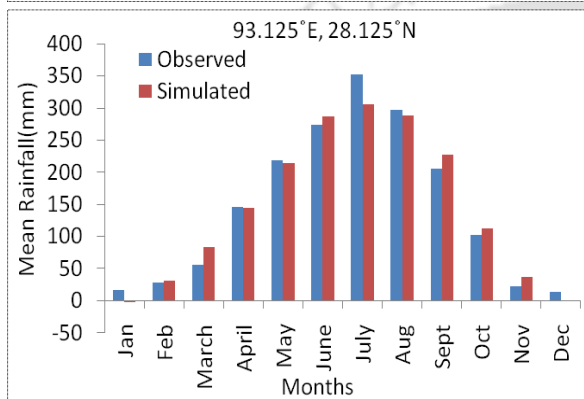
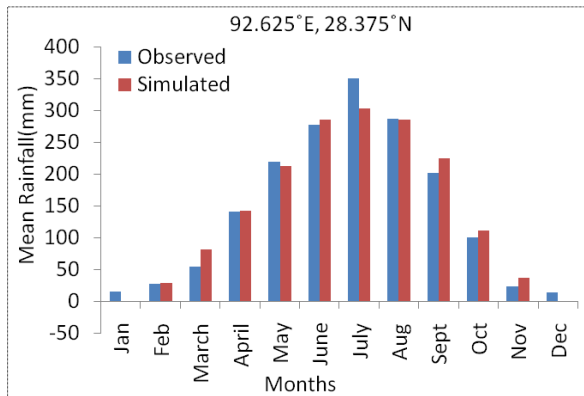
Calibration



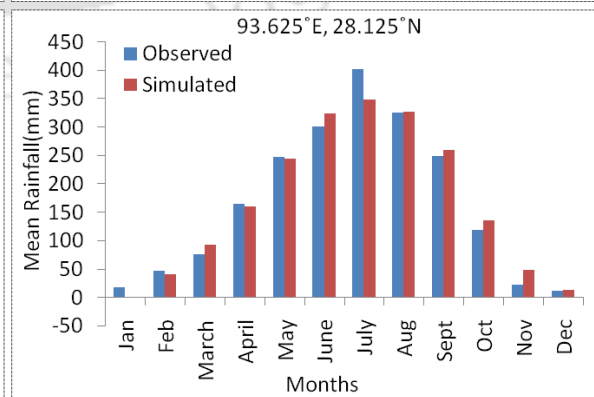
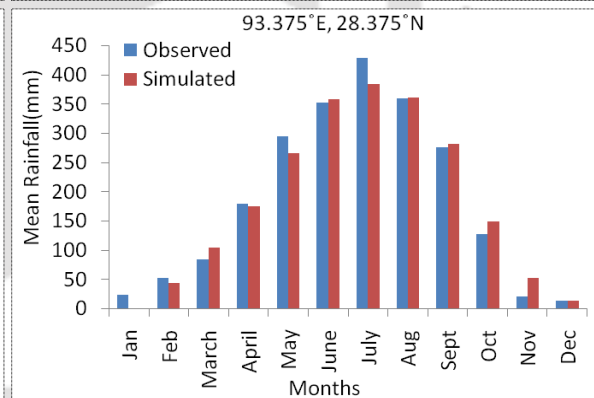
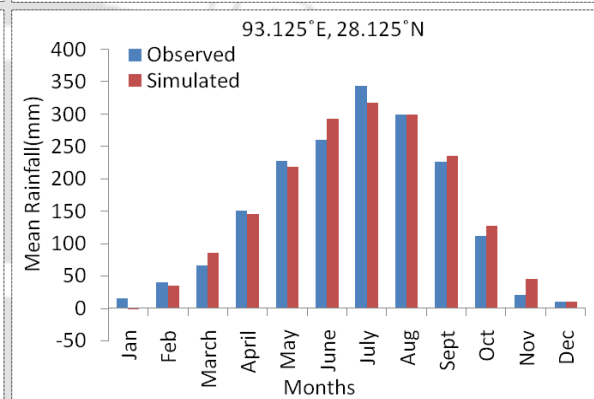
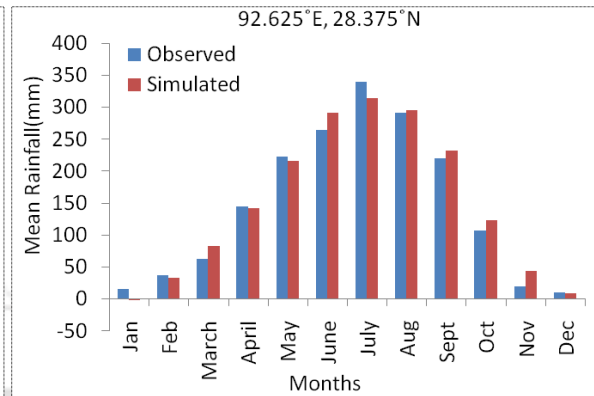
Validation



Calibration



Validation

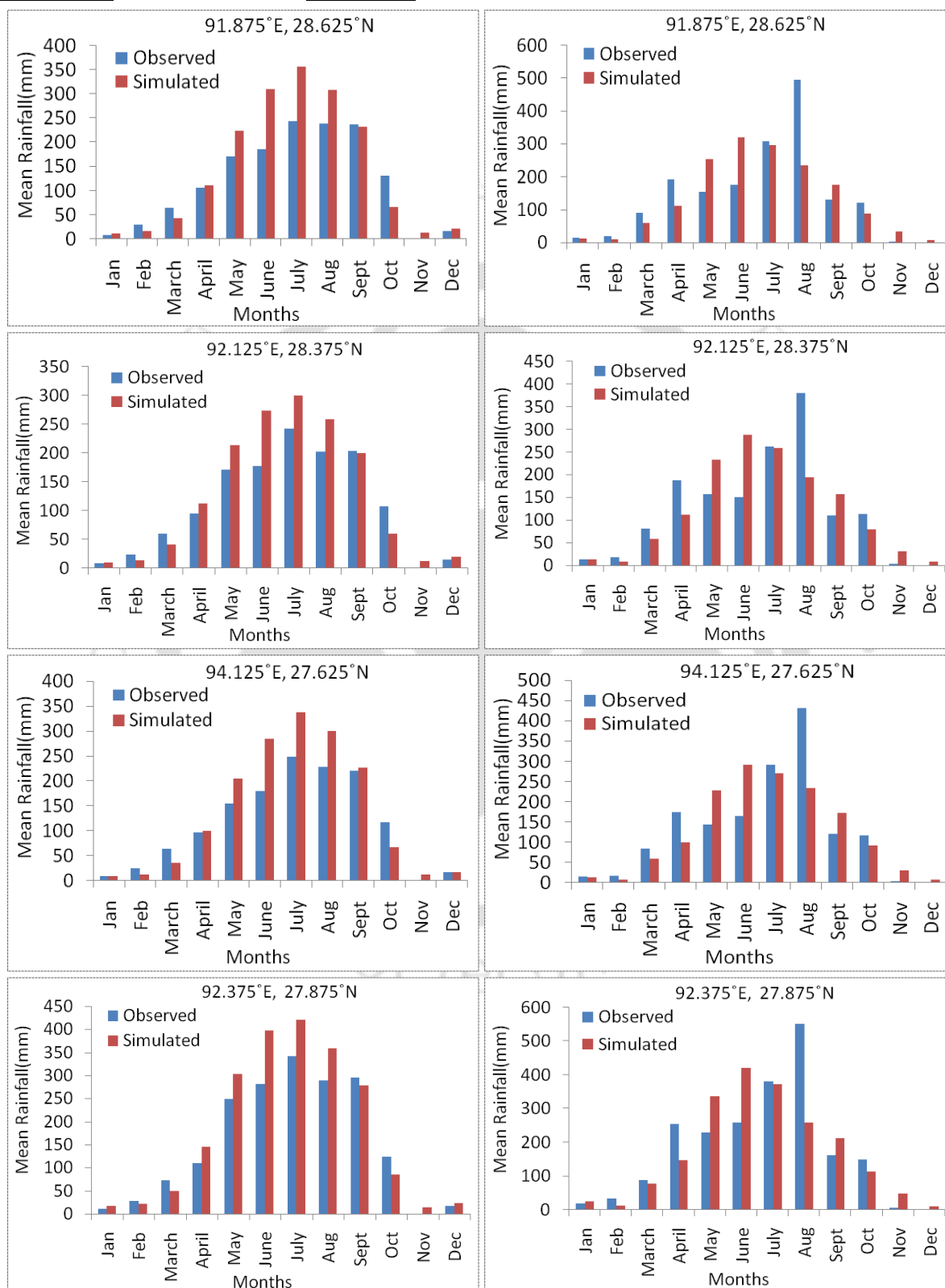


Annexure 2

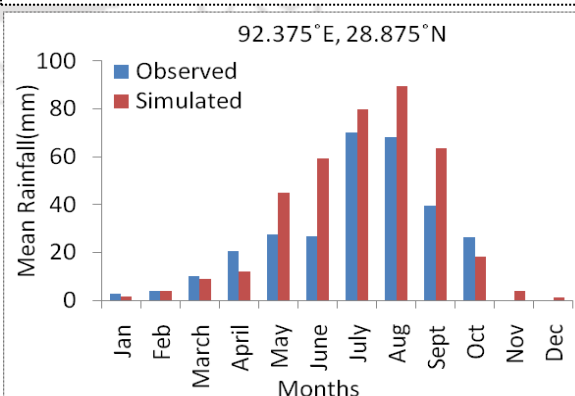
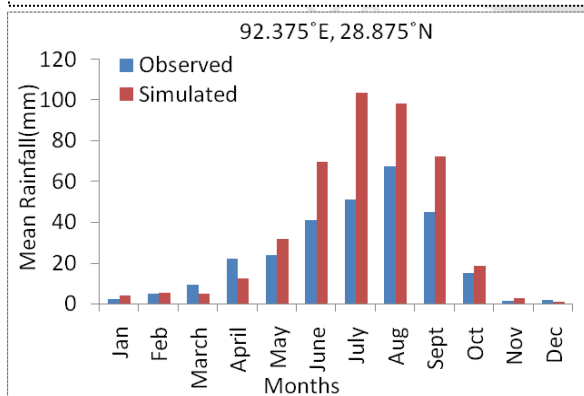
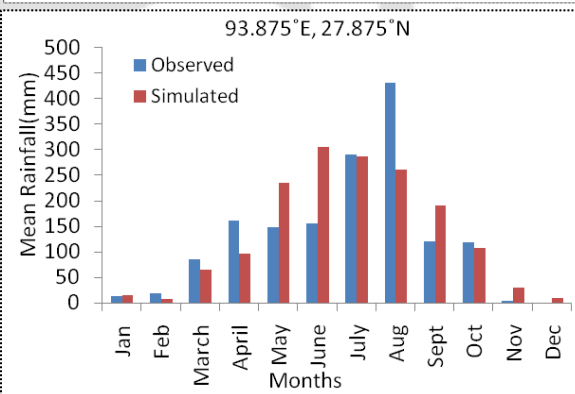
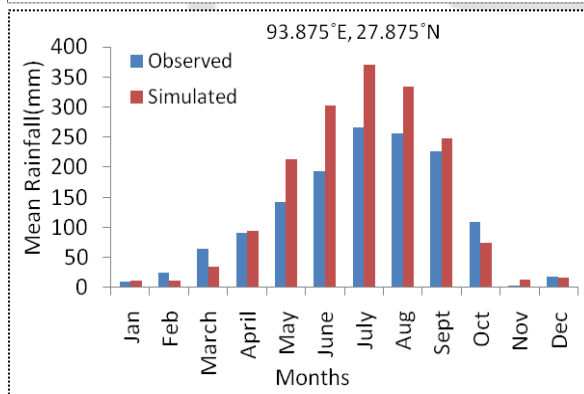
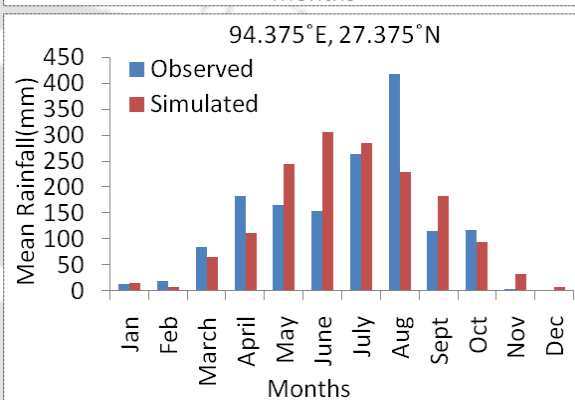
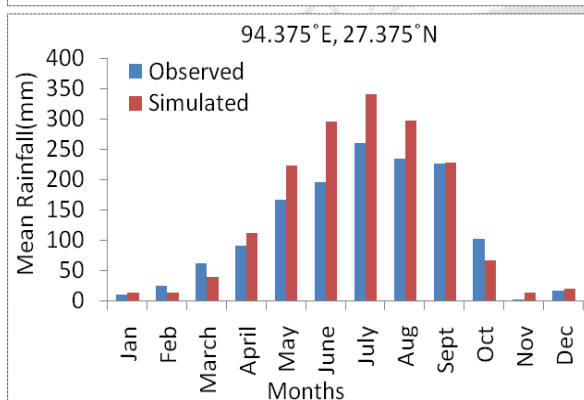
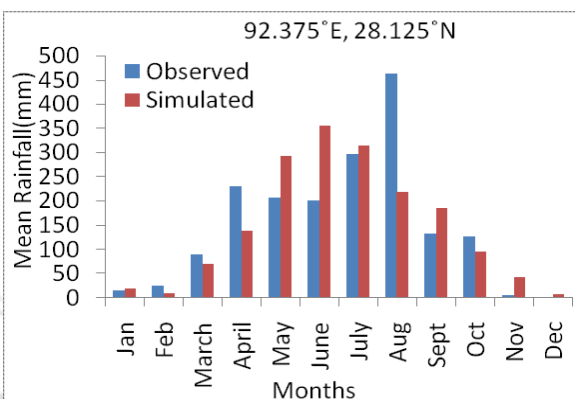
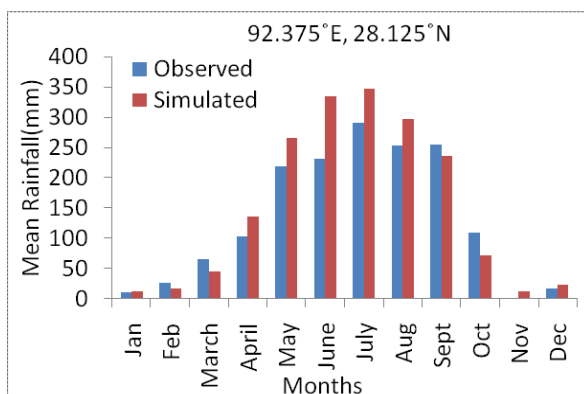
Calibration and Validation graphs for multiple non-linear regression analysis performed by taking the climating parameters of one HadCM3 GCM point

Calibration

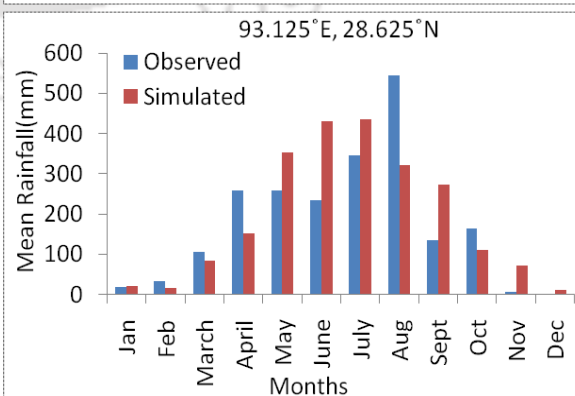
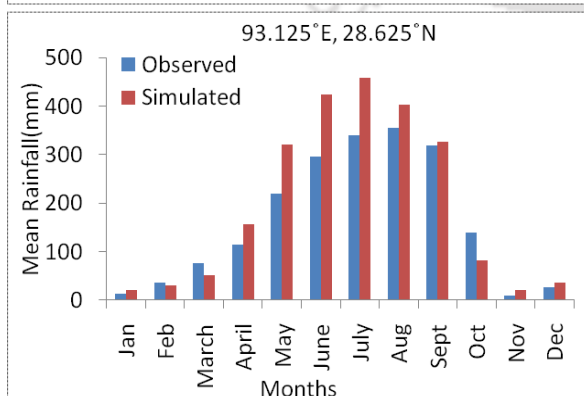
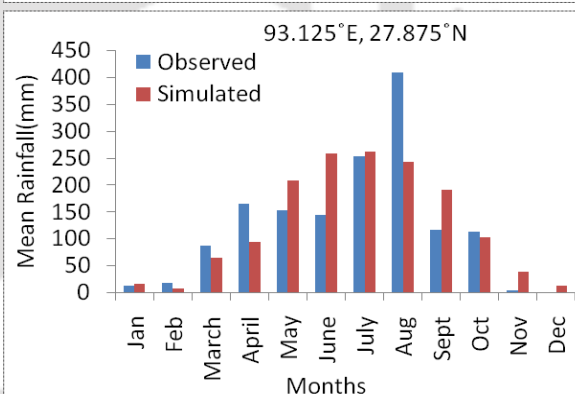
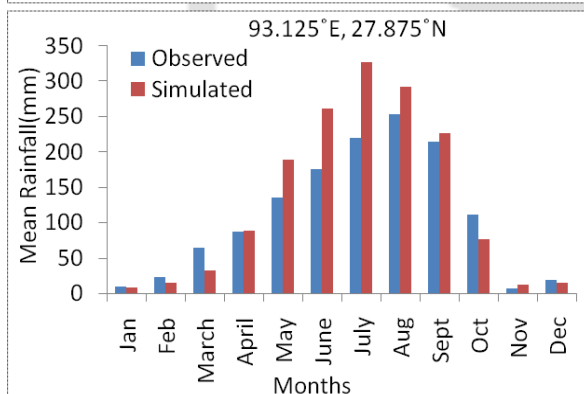
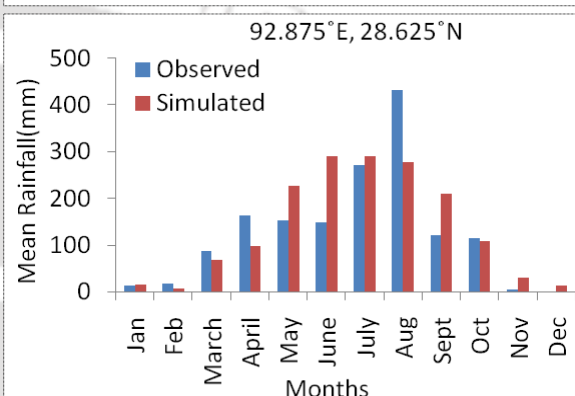
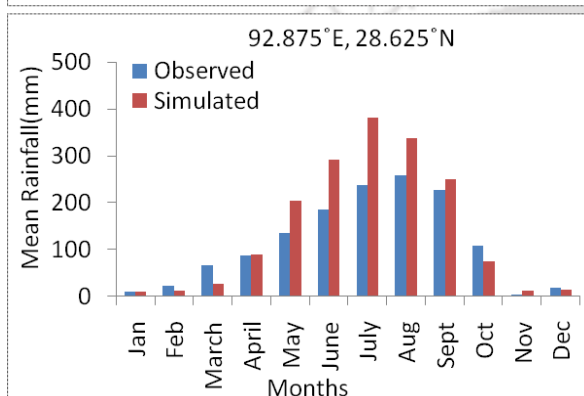
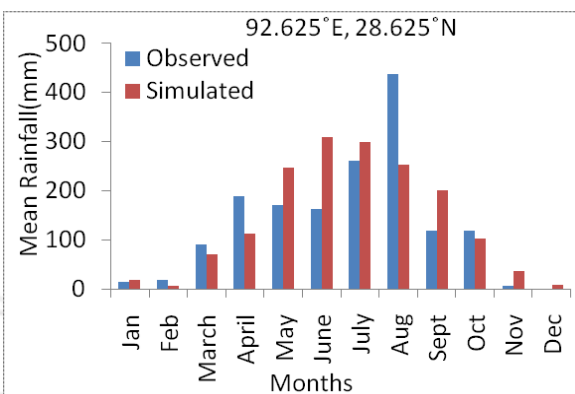
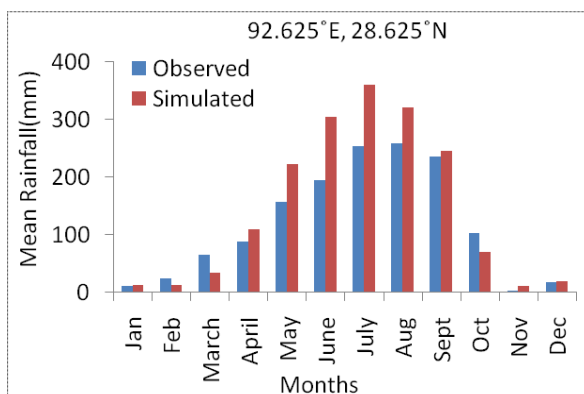
Validation



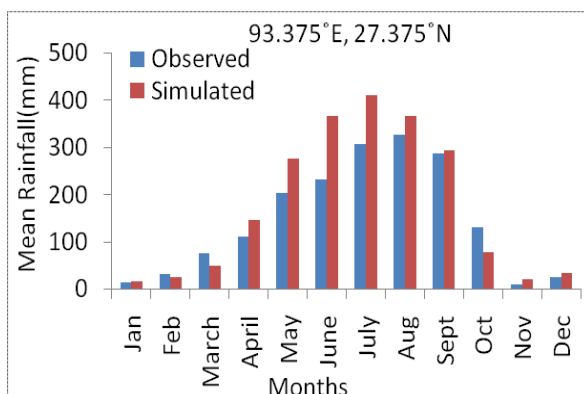
Calibration



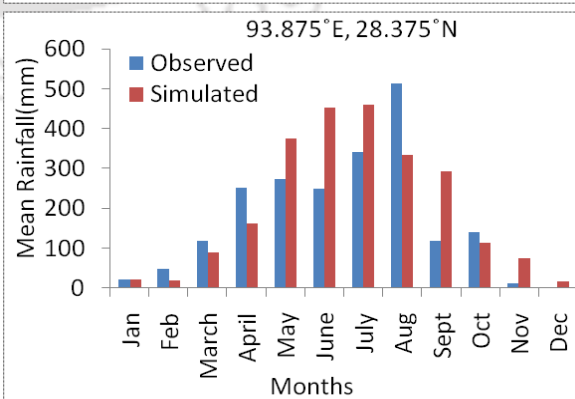
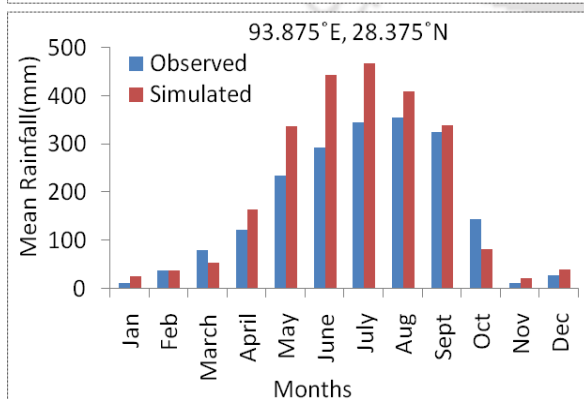
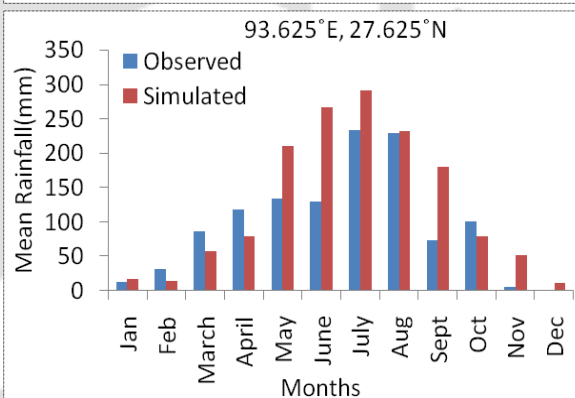
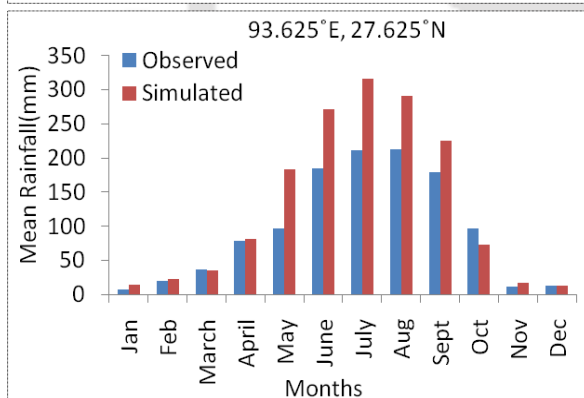
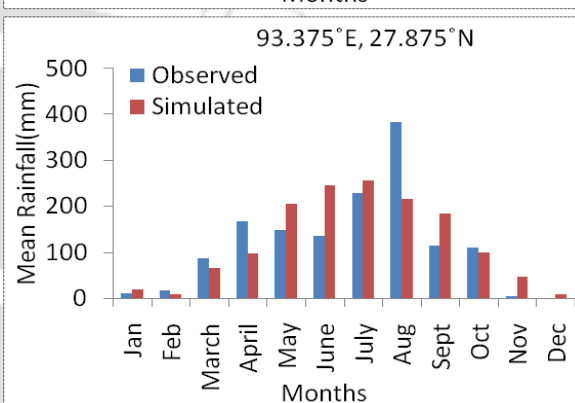
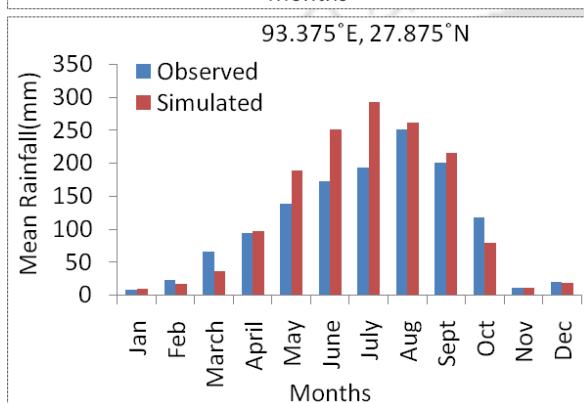
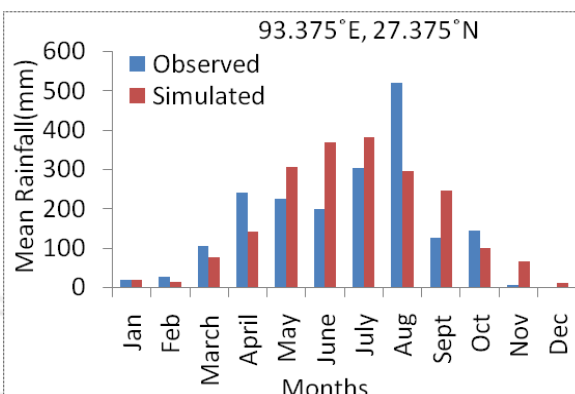
Calibration



Calibration

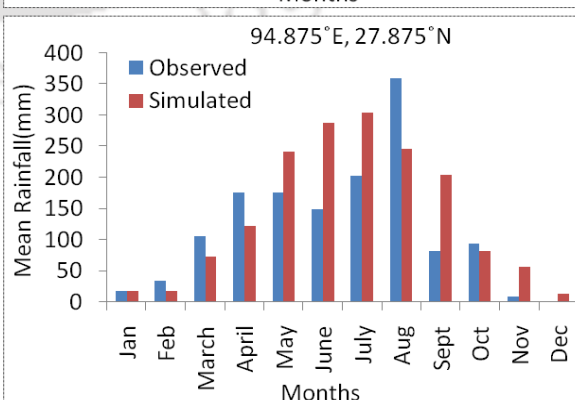
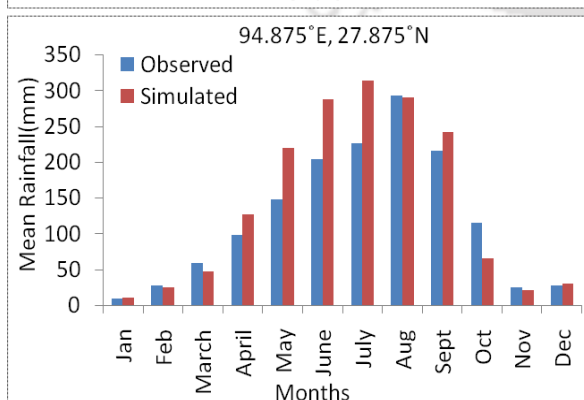
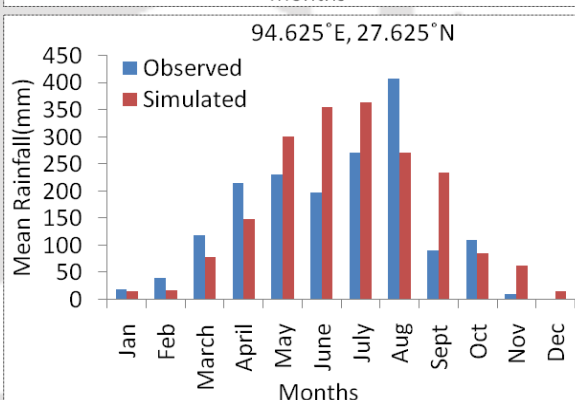
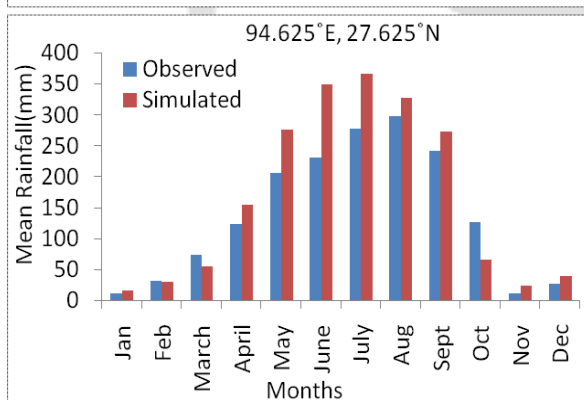
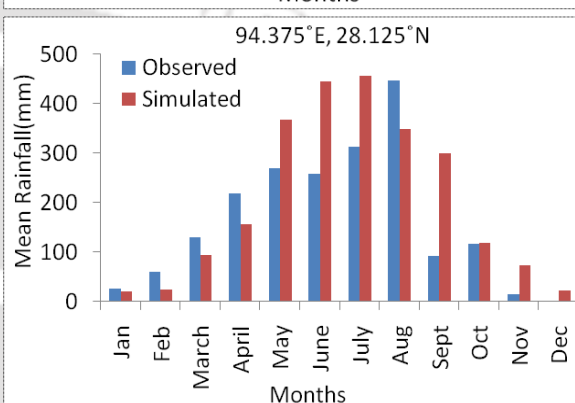
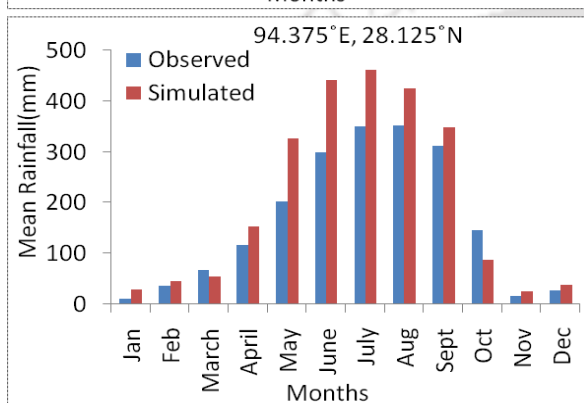
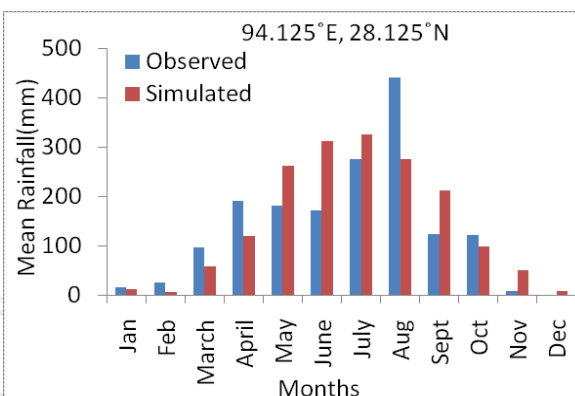
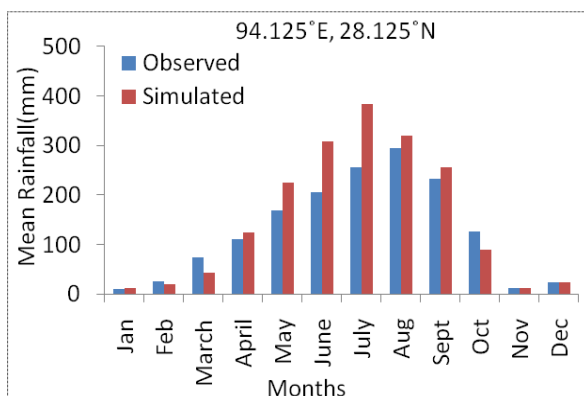


Validation

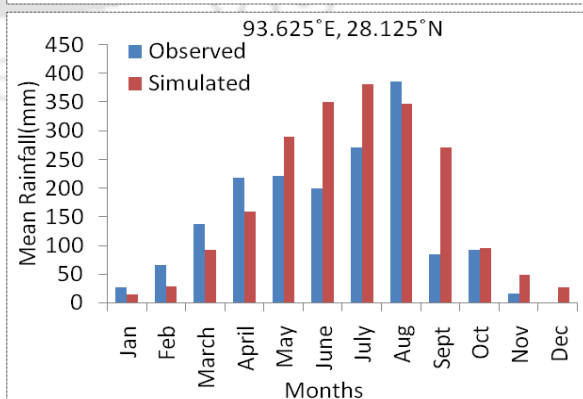
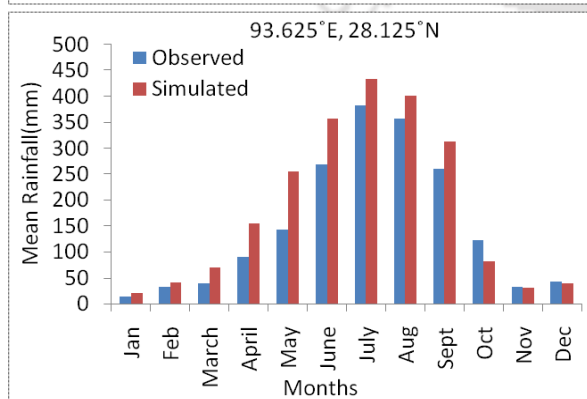
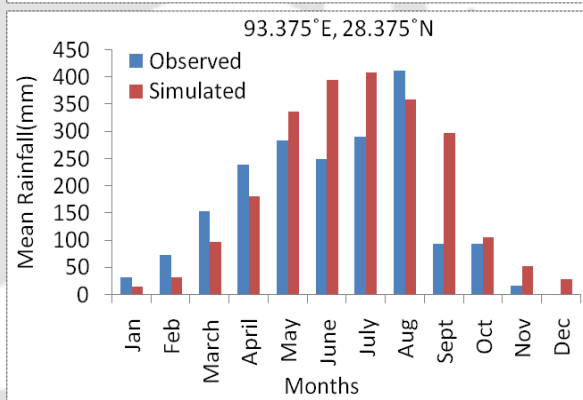
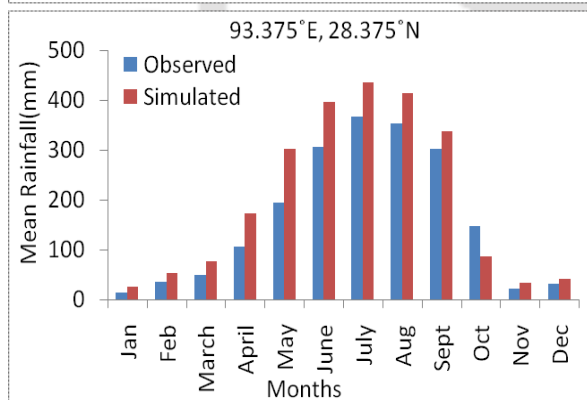
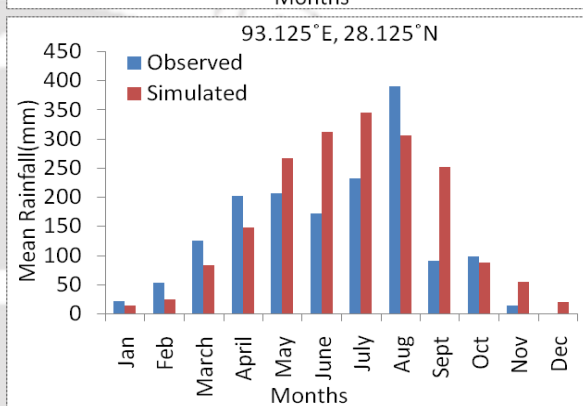
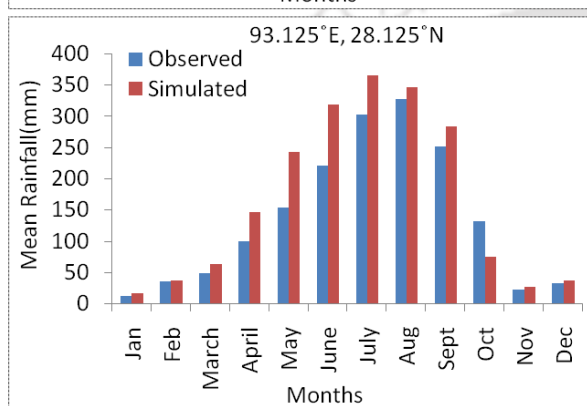
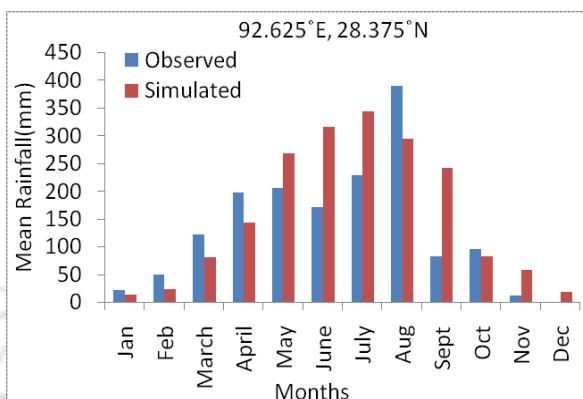
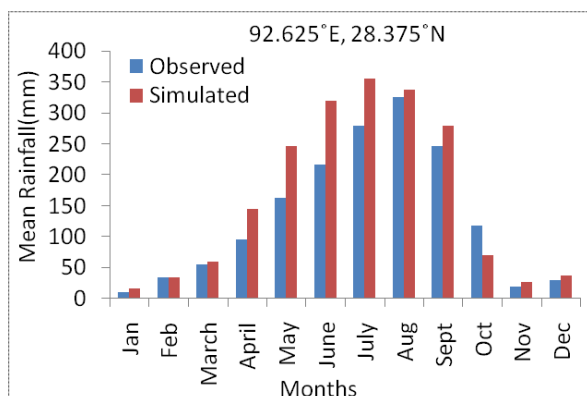


Calibration

Validation

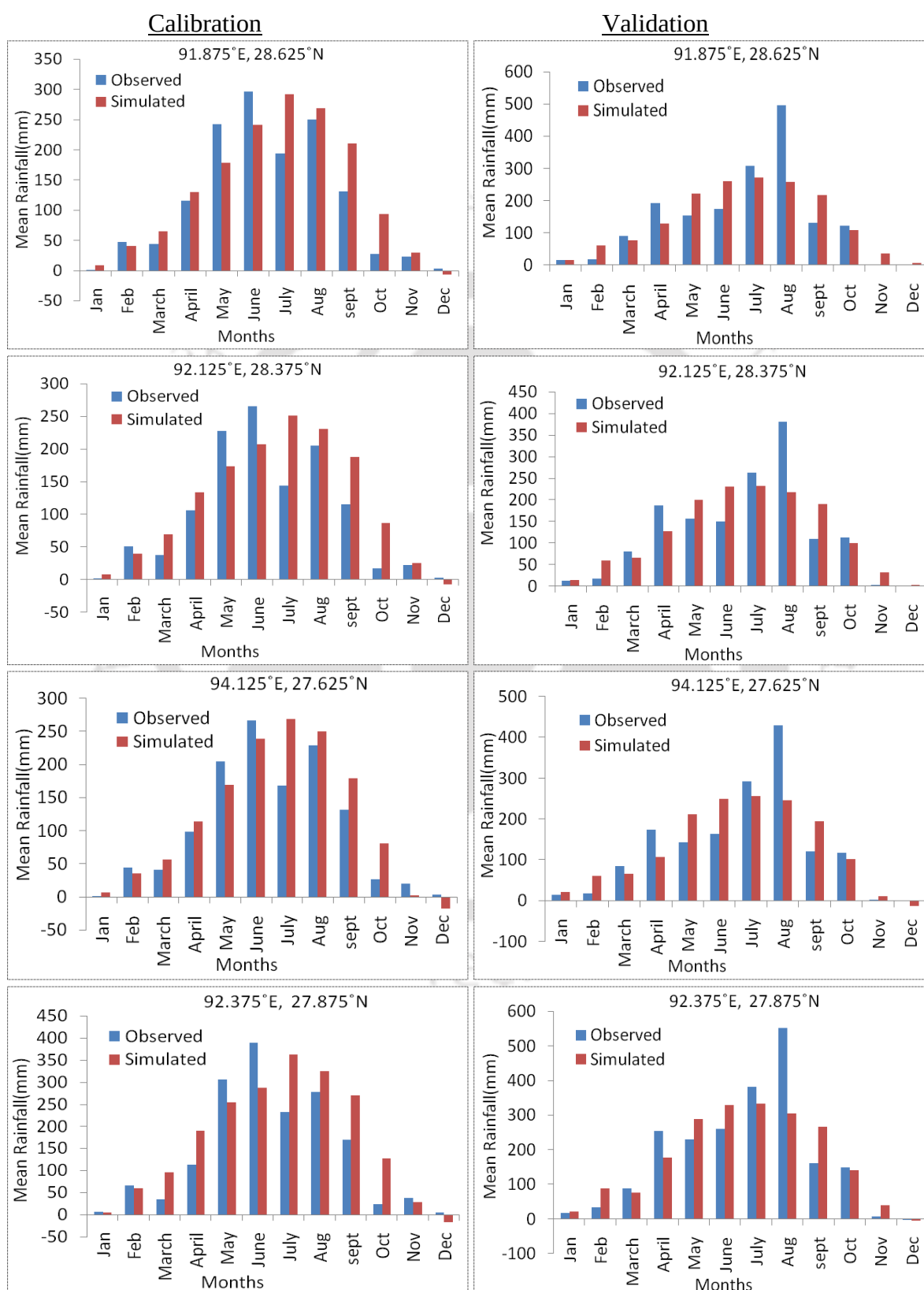


Calibration

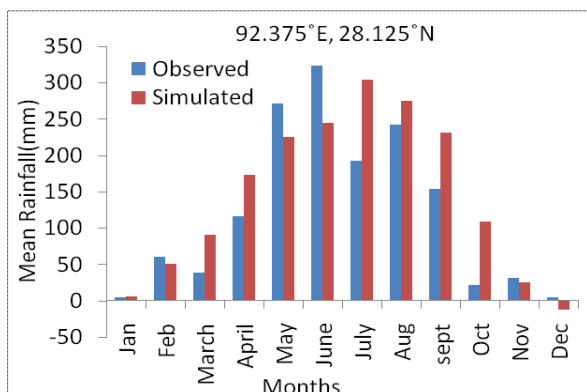


Annexure 3

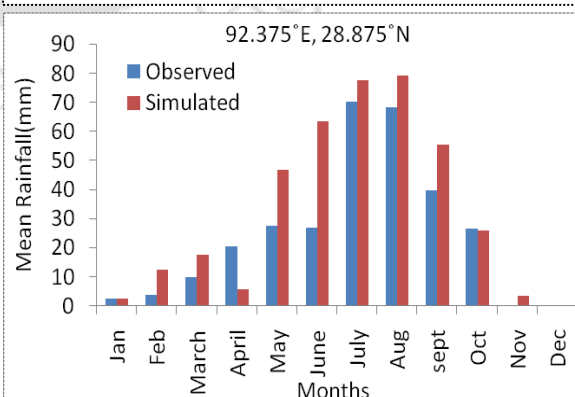
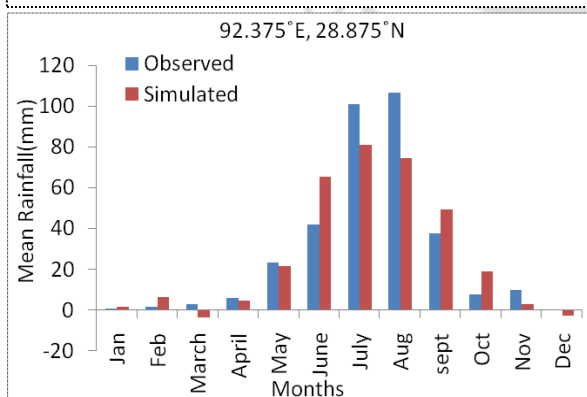
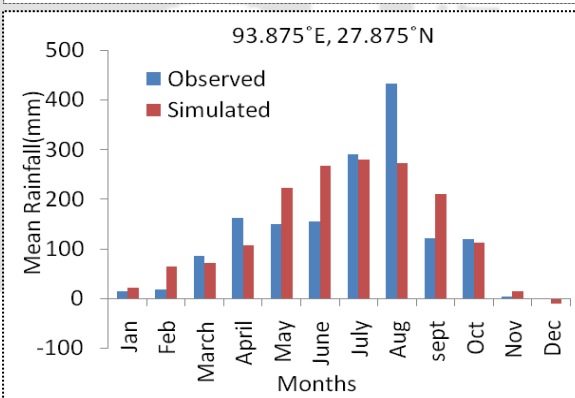
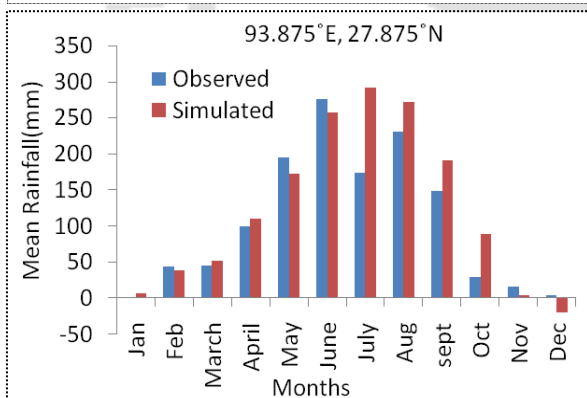
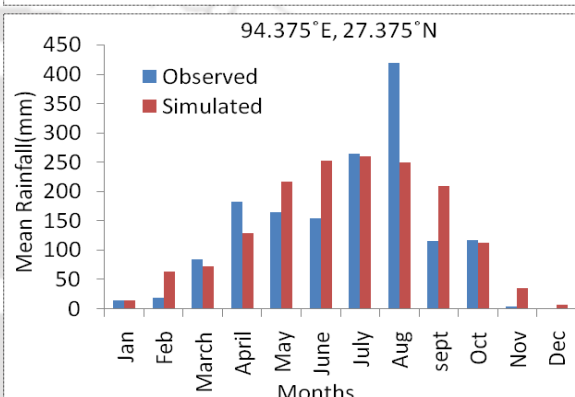
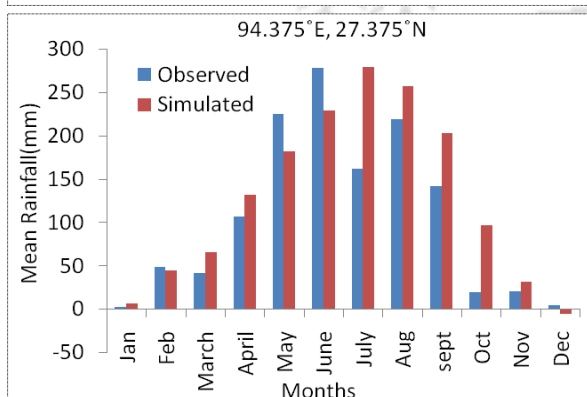
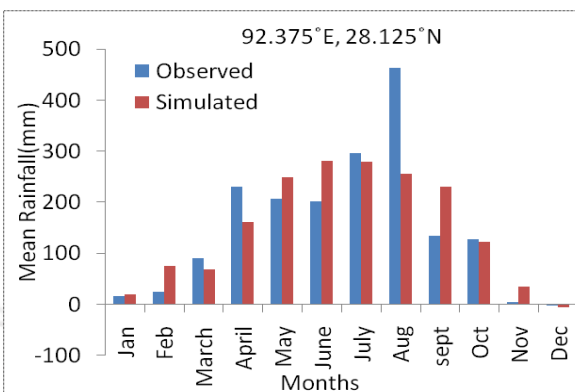
Calibration and validation graphs for multiple linear regression analysis performed by taking the weighted average of the climatic parameters of four HadCM3 GCM points



Calibration

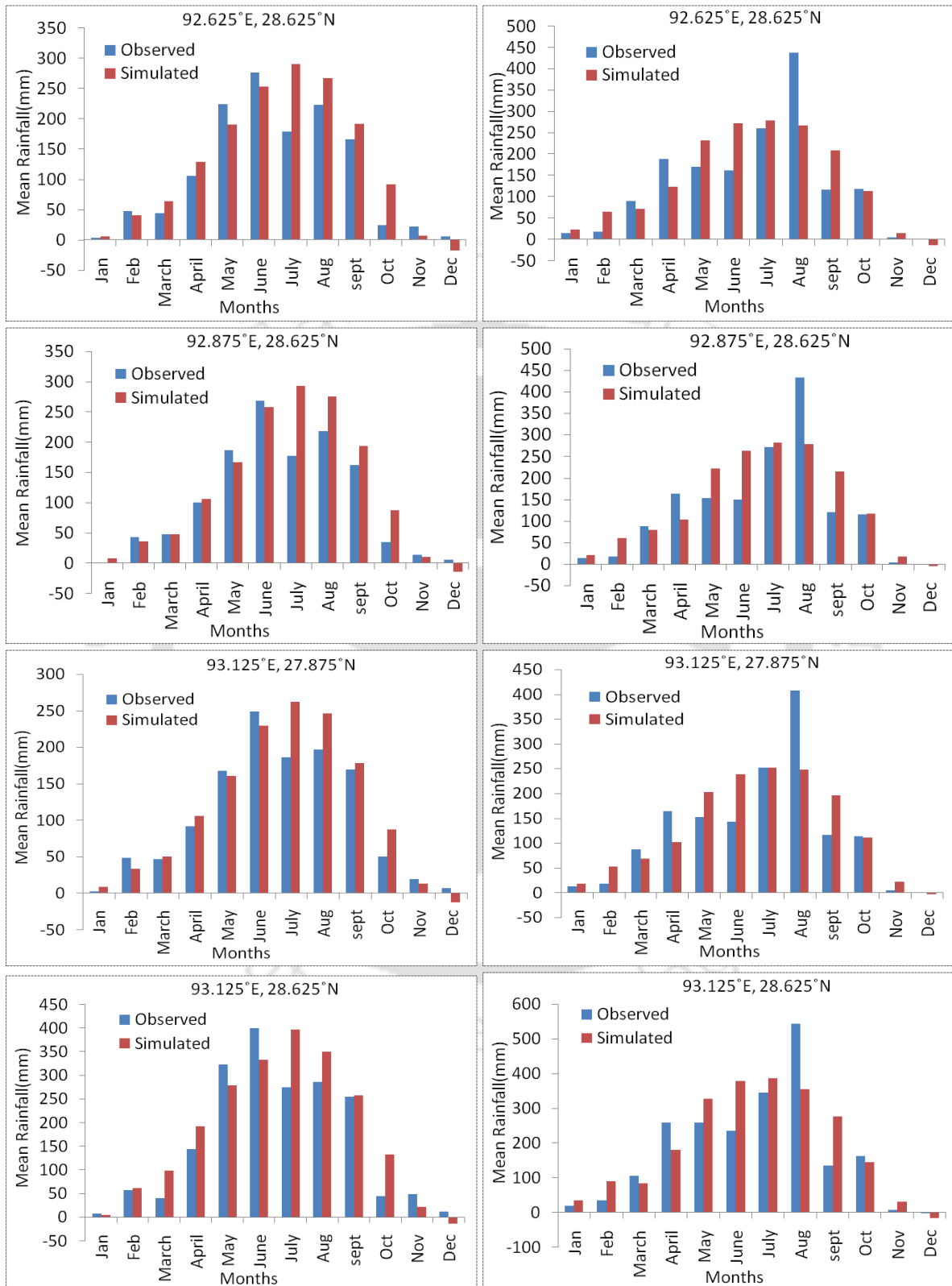


Validation

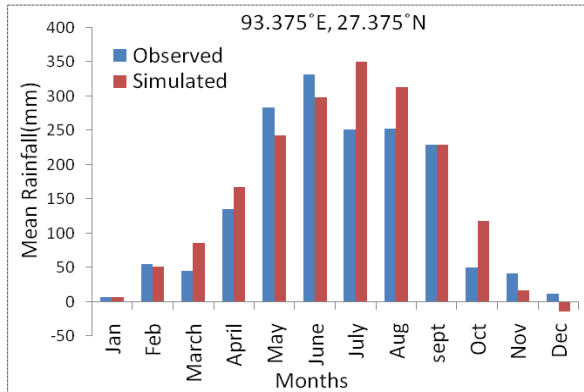


Calibration

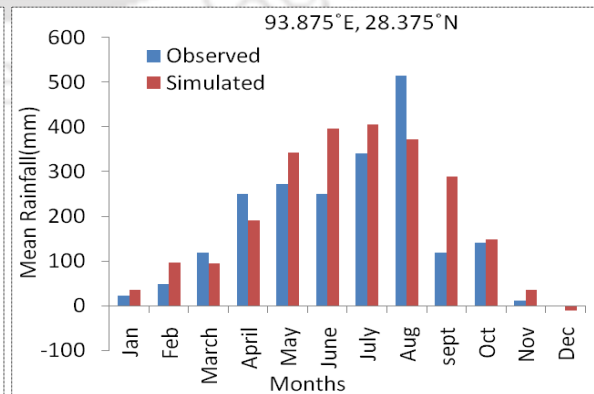
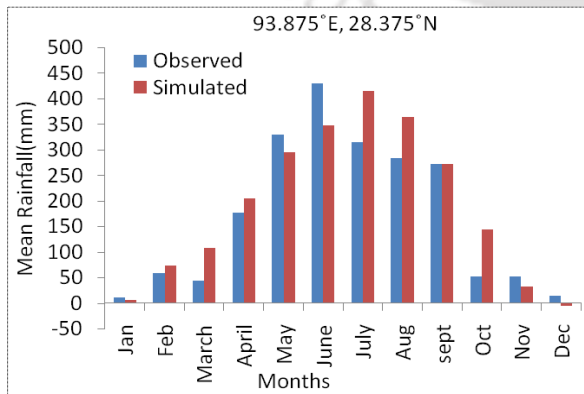
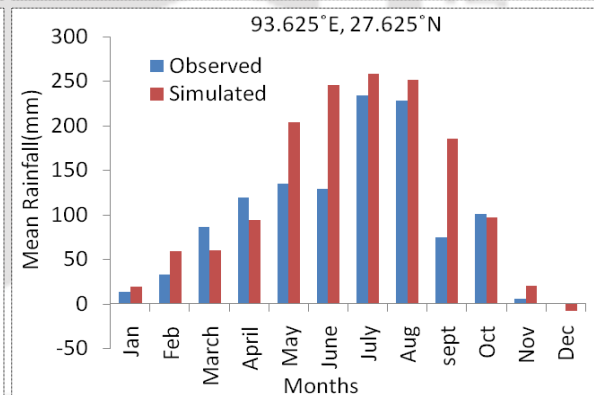
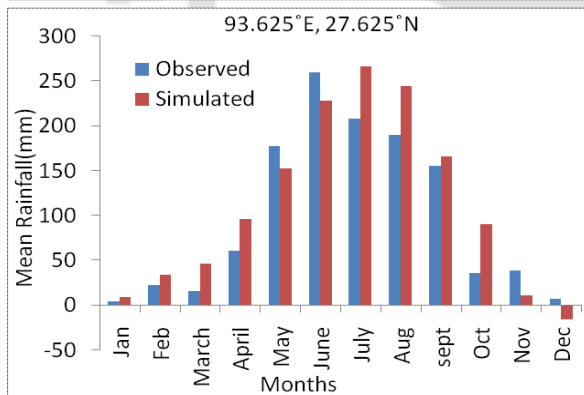
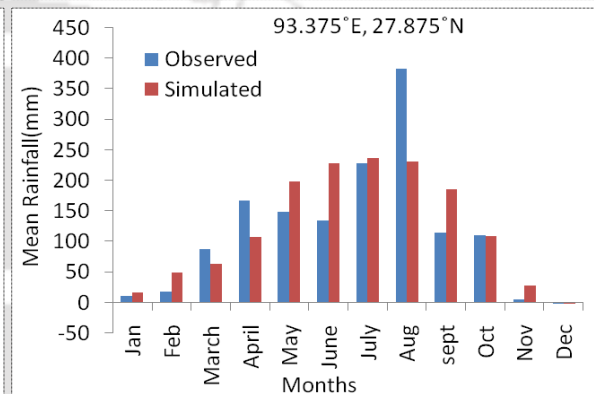
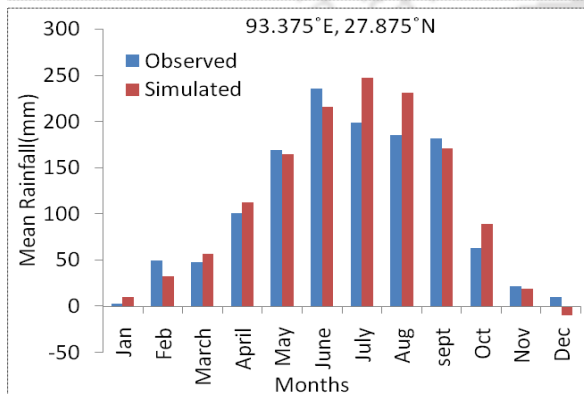
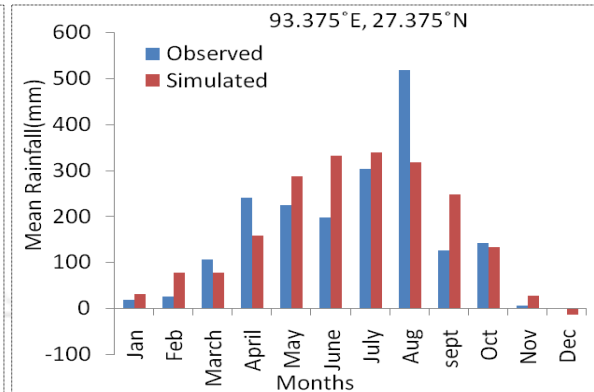
Validation



Calibration

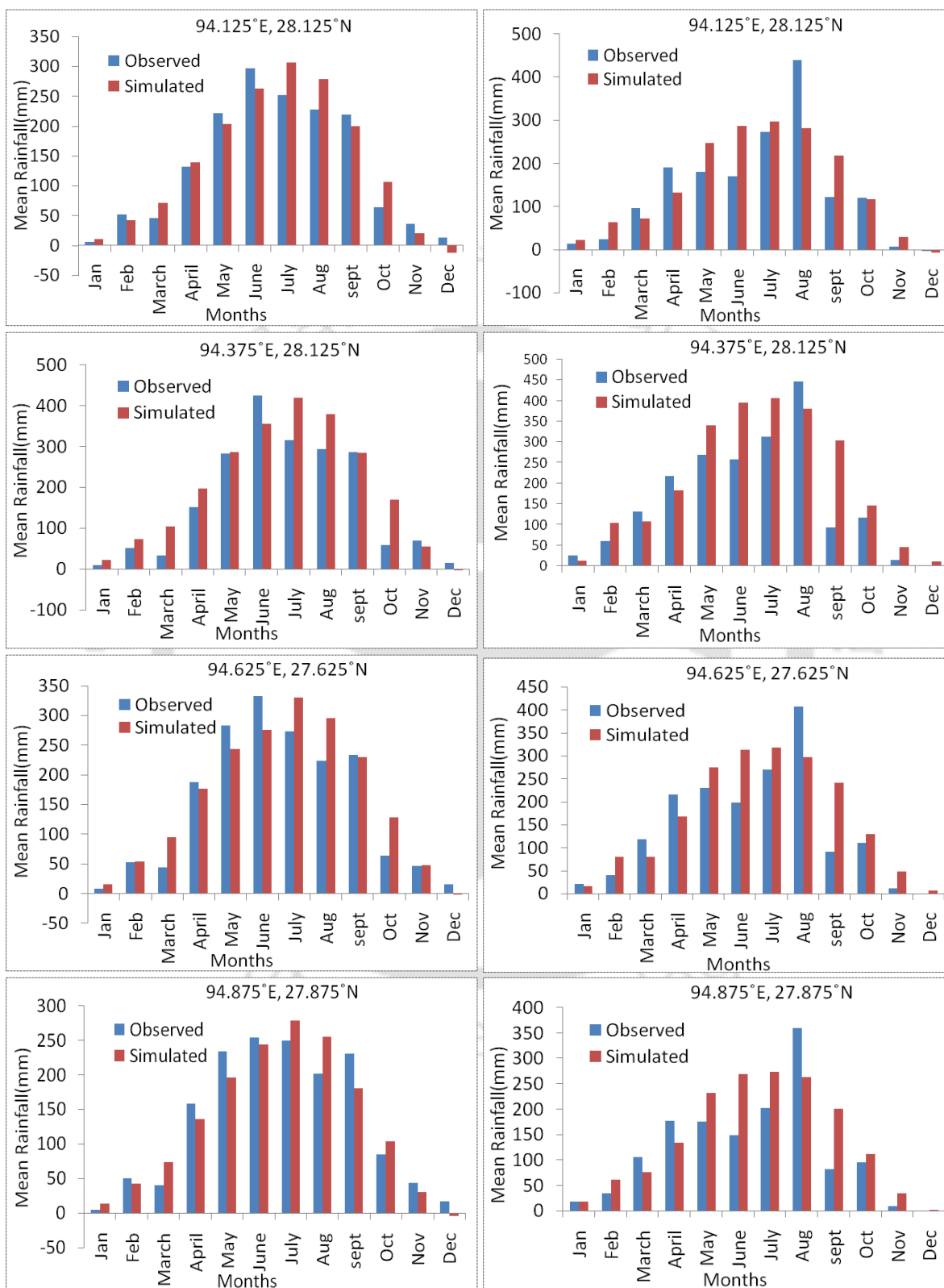


Validation



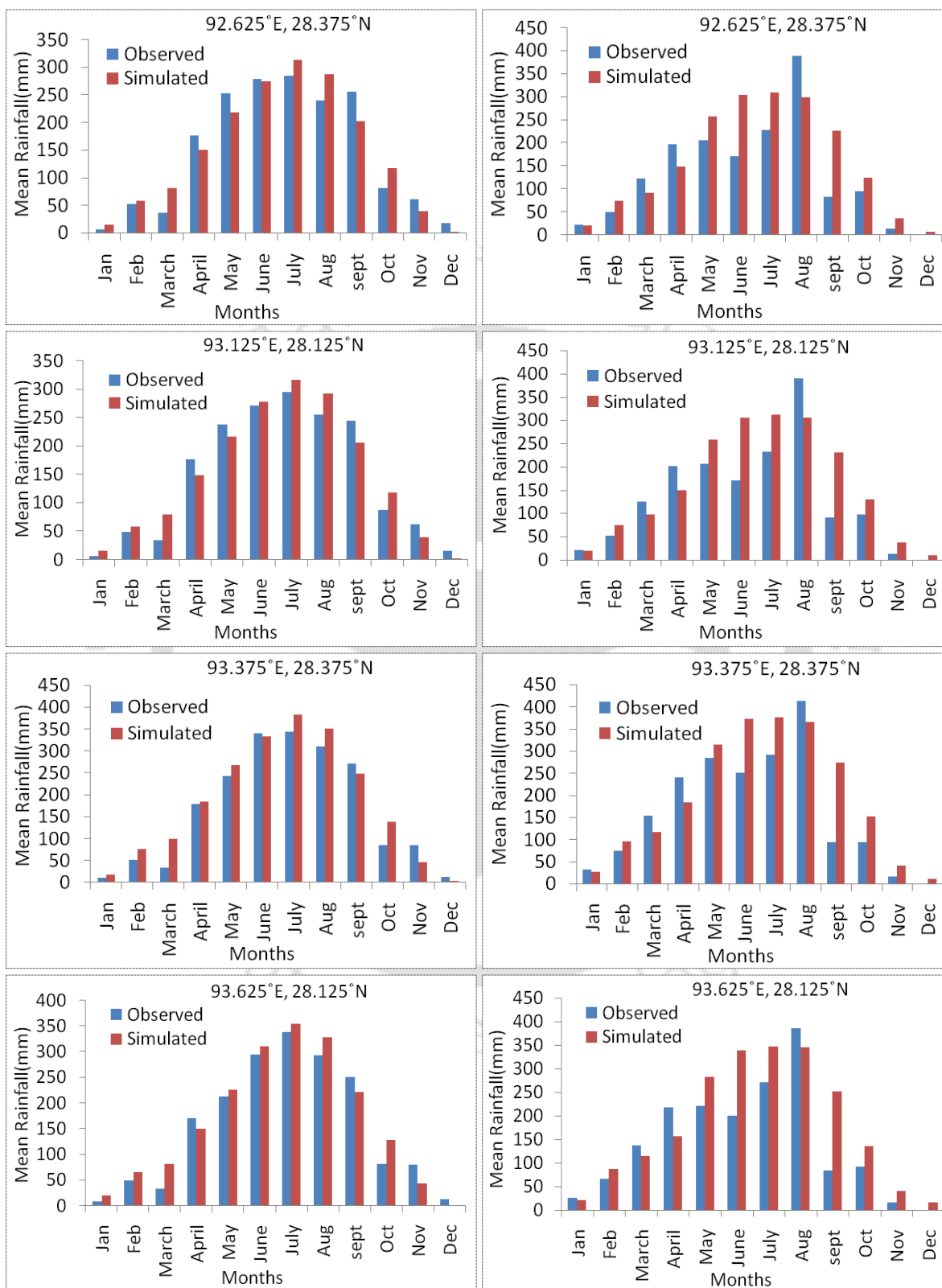
Calibration

Validation



Calibration

Validation

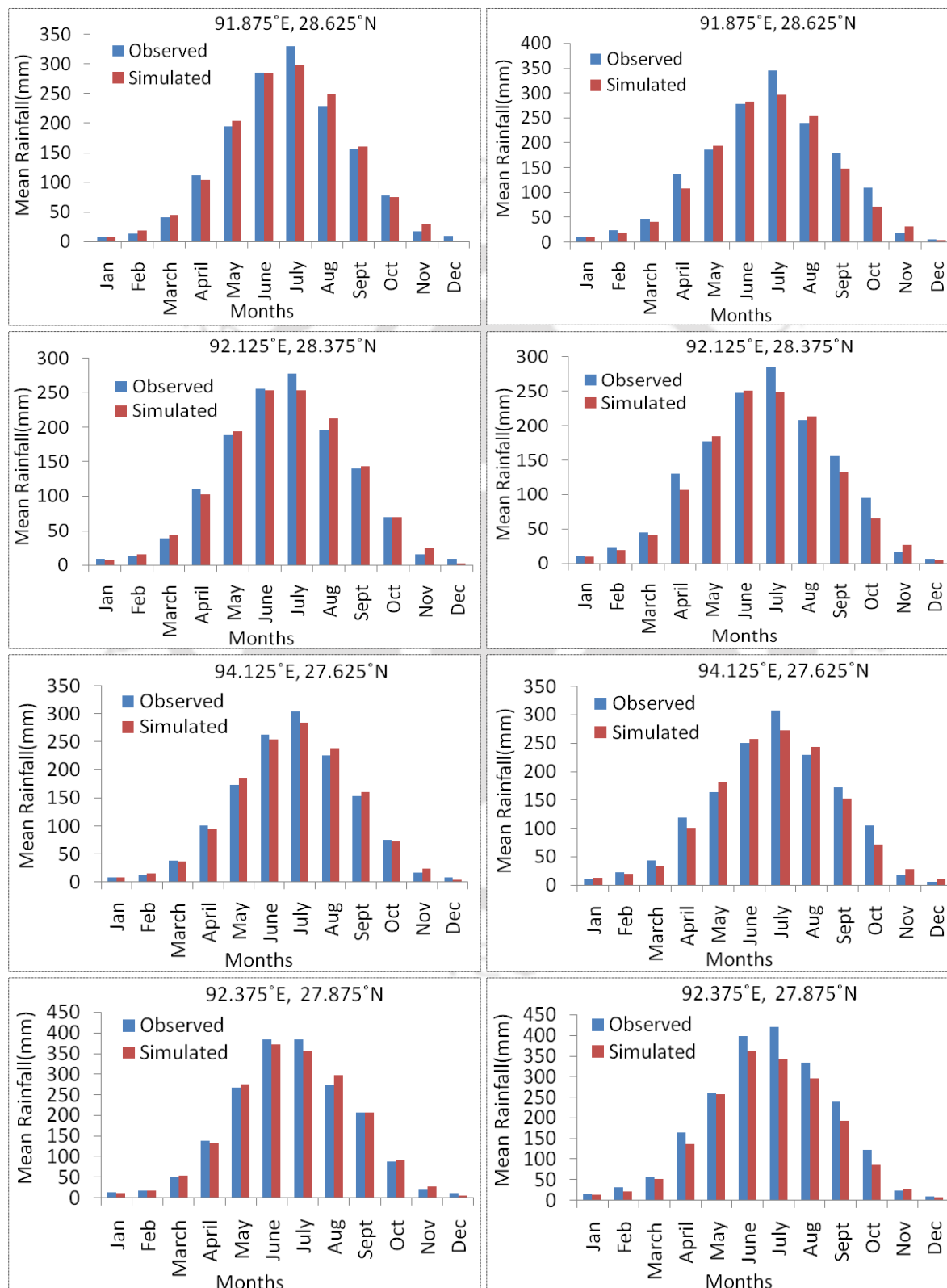


Annexure 4

Calibration and Validation graphs for multiple non-linear regression analysis performed by taking the weighted average of the climatic parametrs of the four HadCM3 GCM points

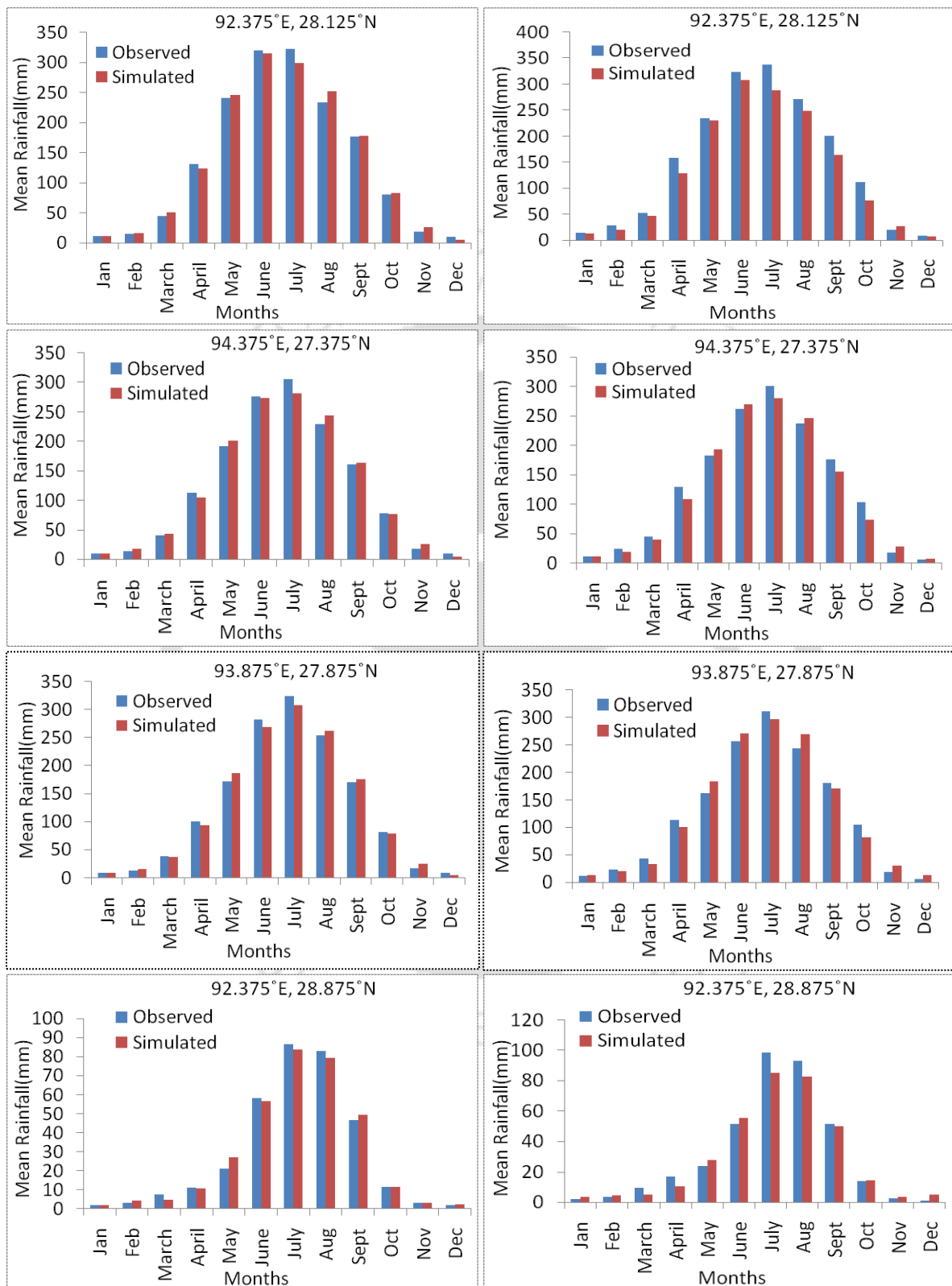
Calibration

Validation

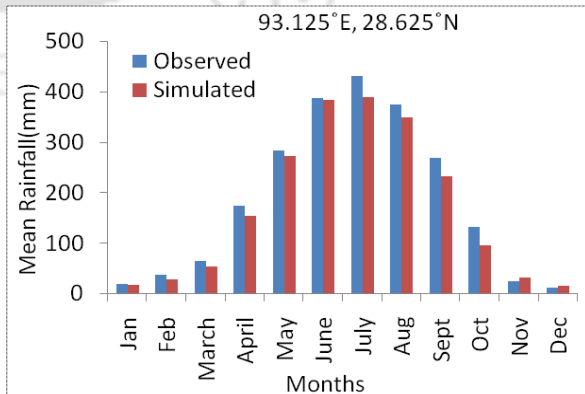
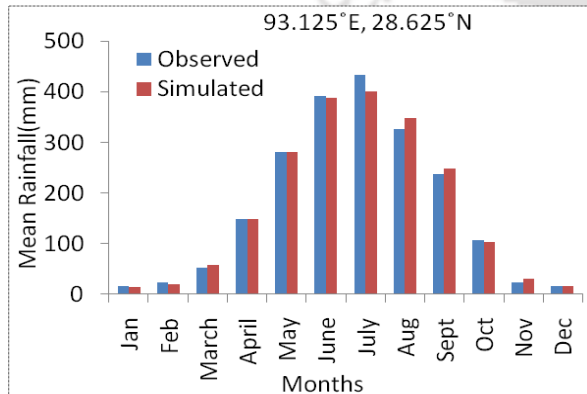
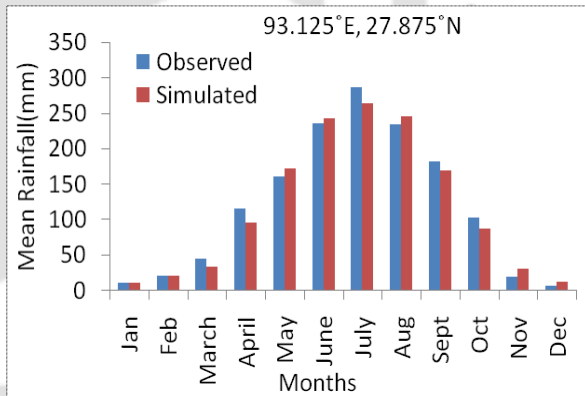
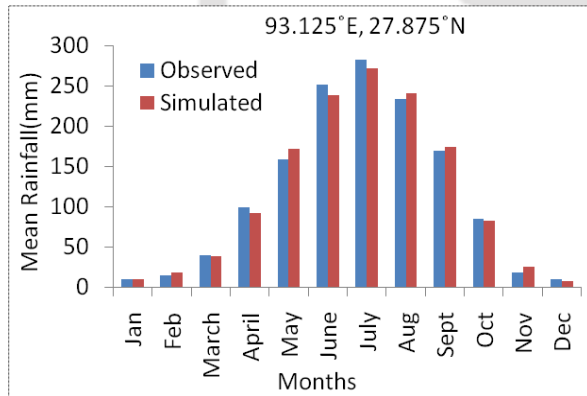
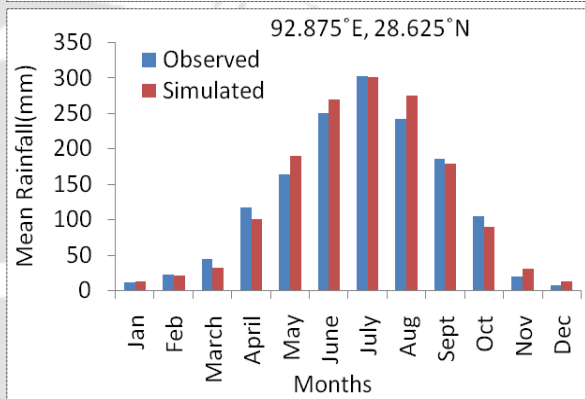
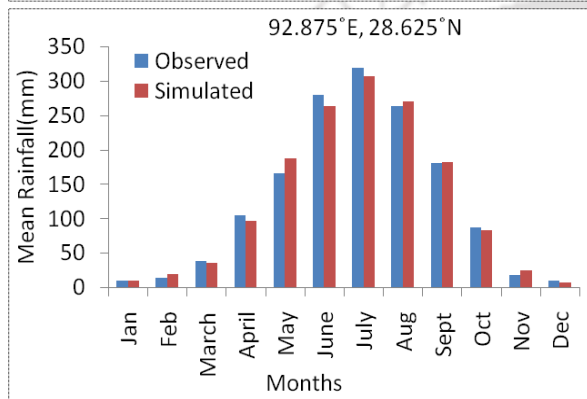
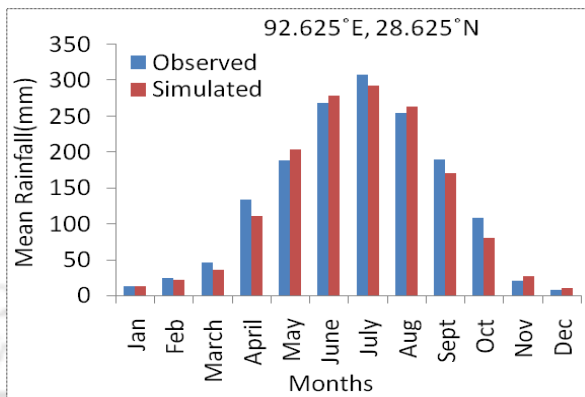
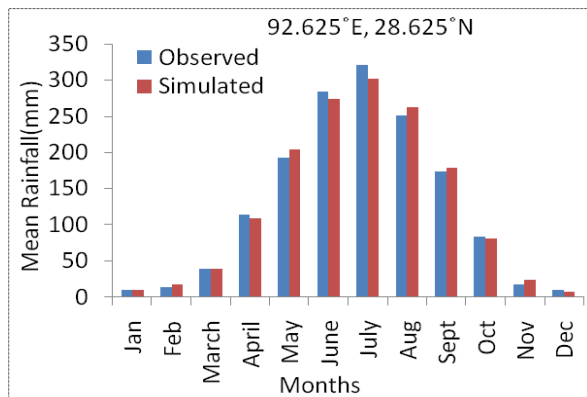


Calibration

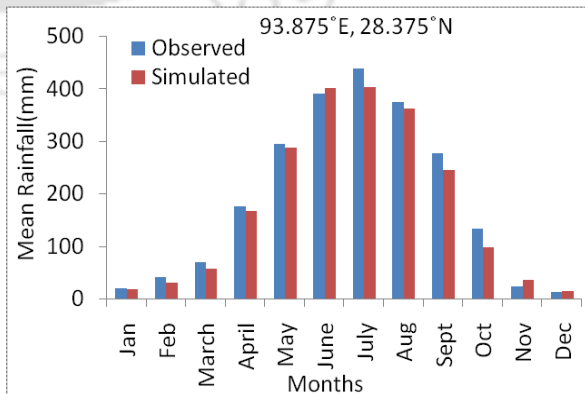
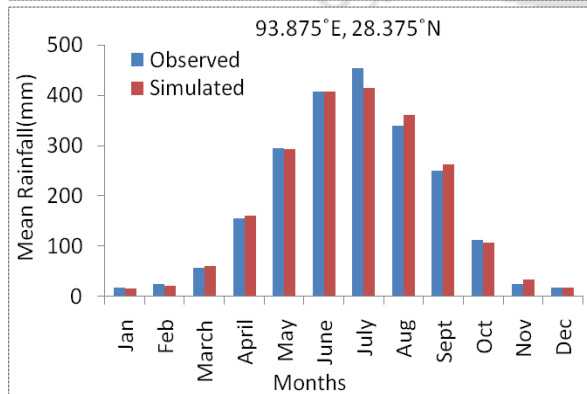
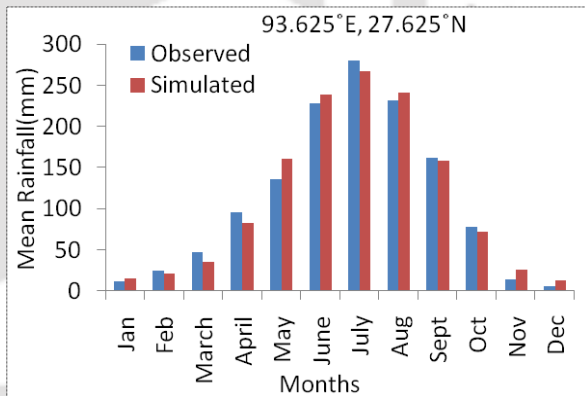
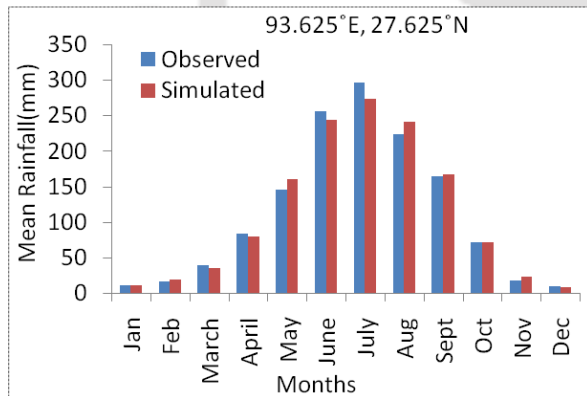
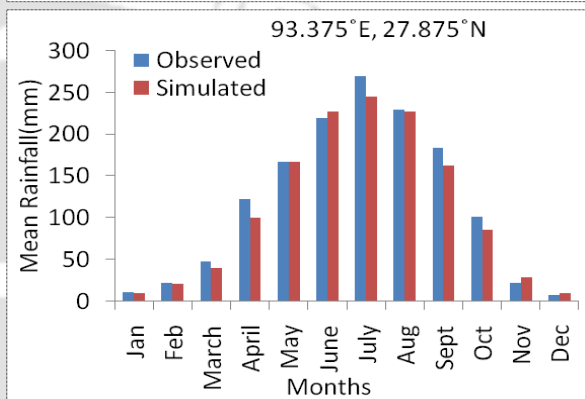
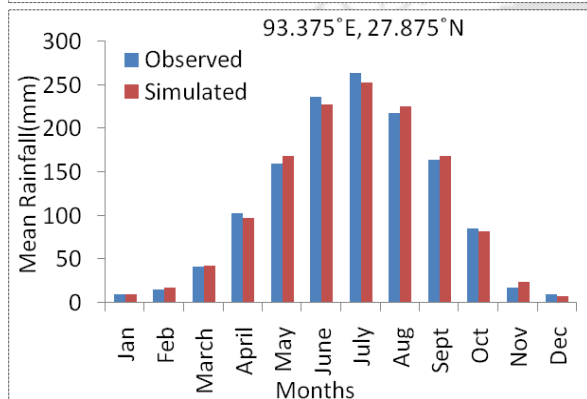
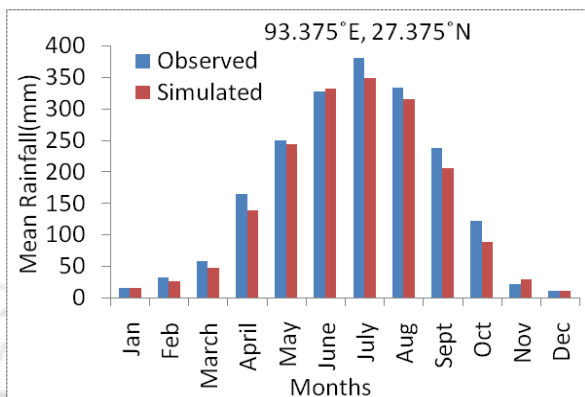
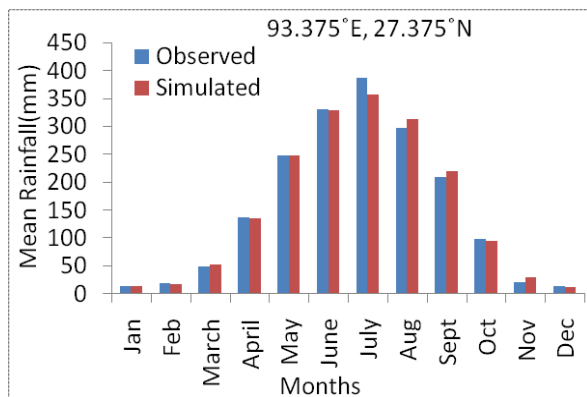
Validation



Calibration

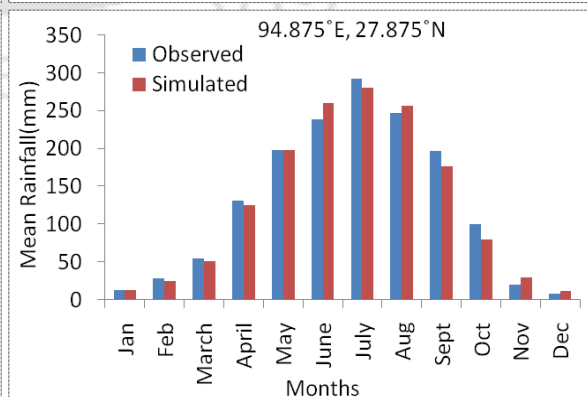
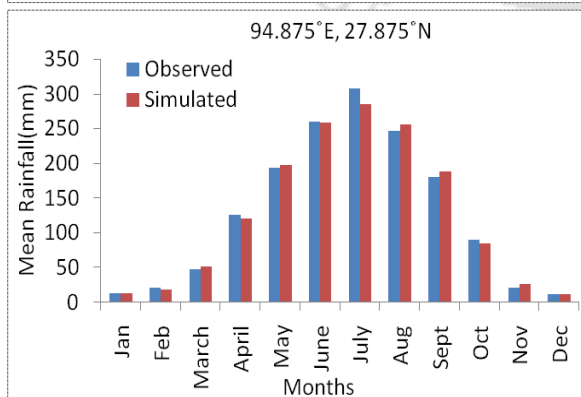
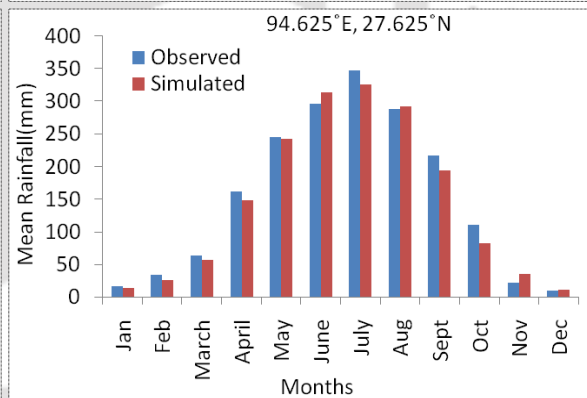
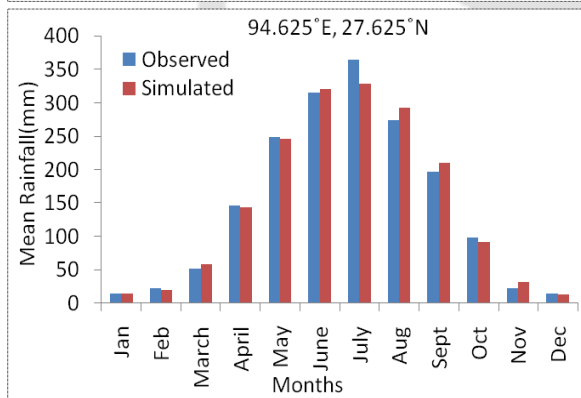
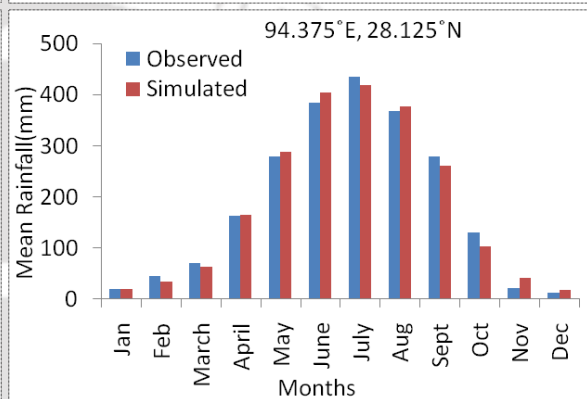
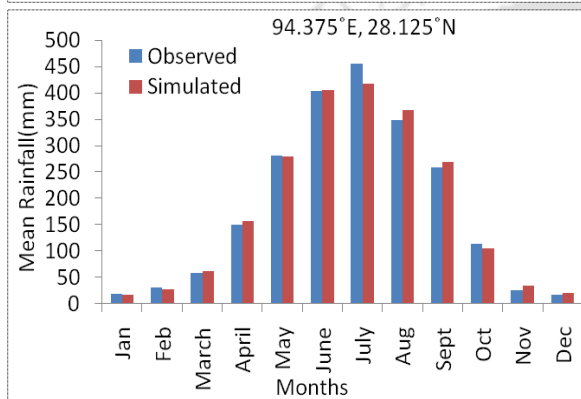
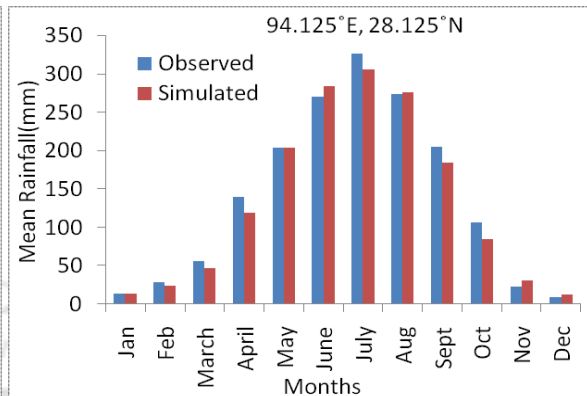
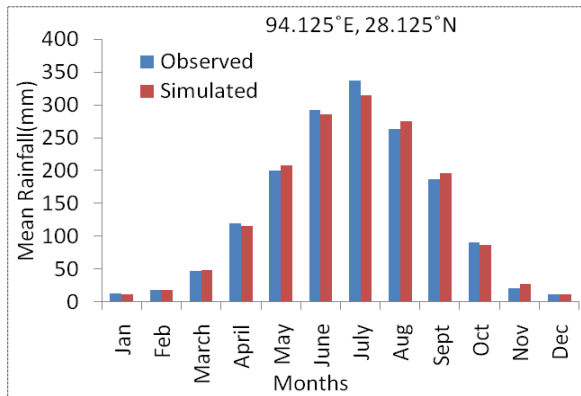


Calibration

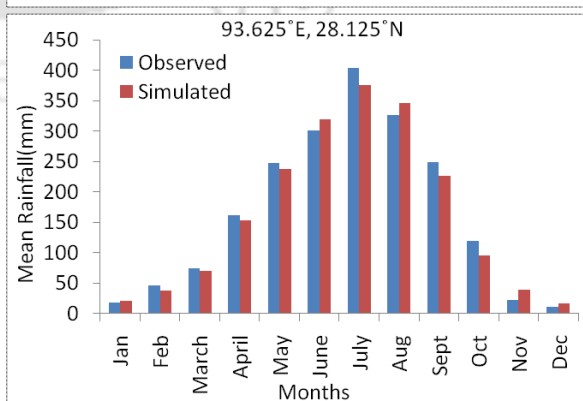
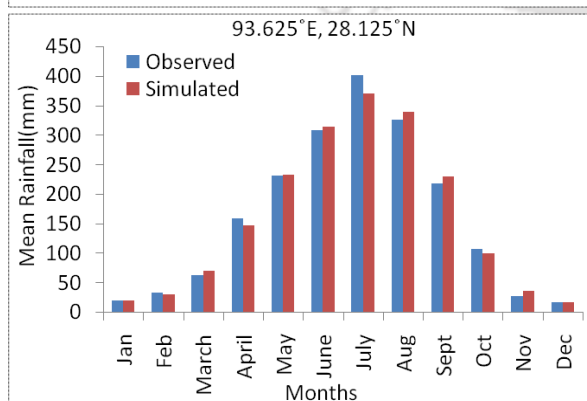
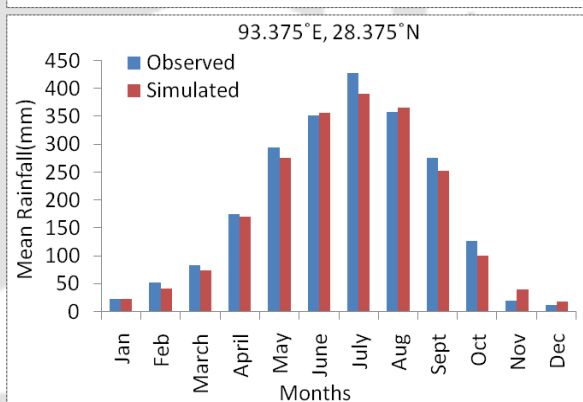
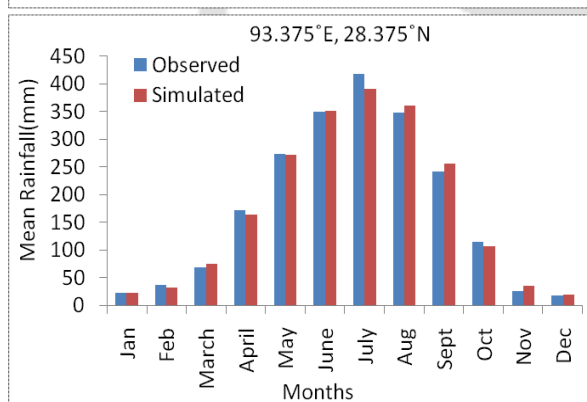
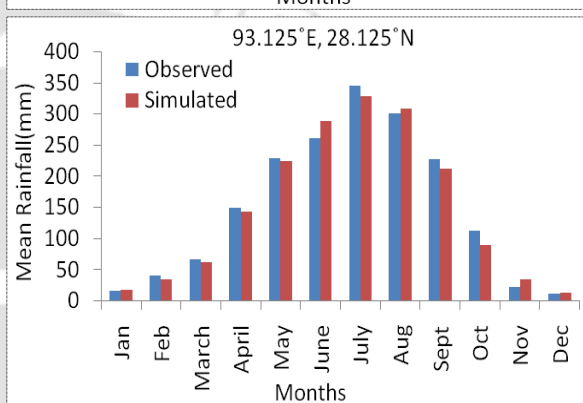
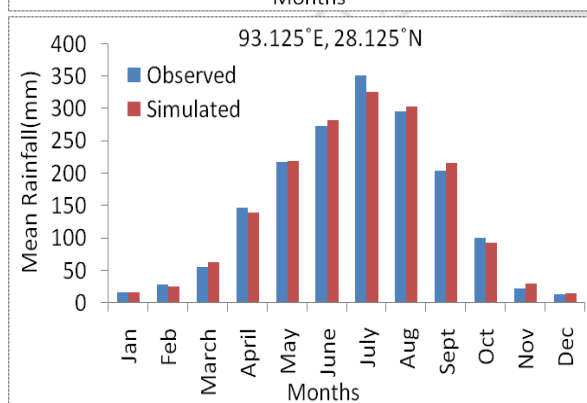
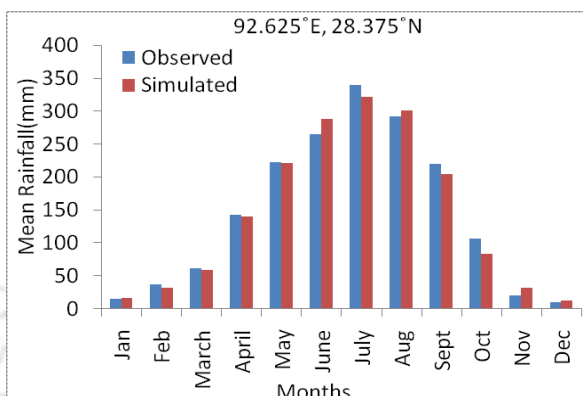
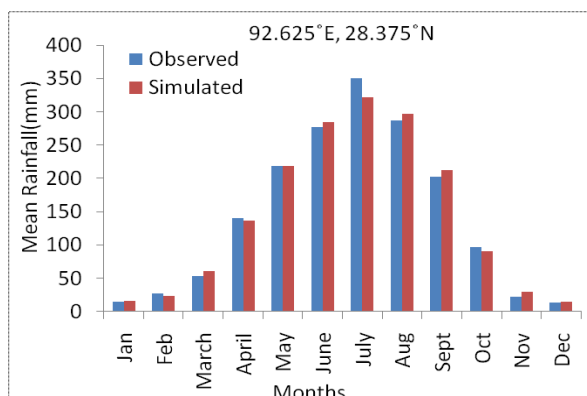


Calibration

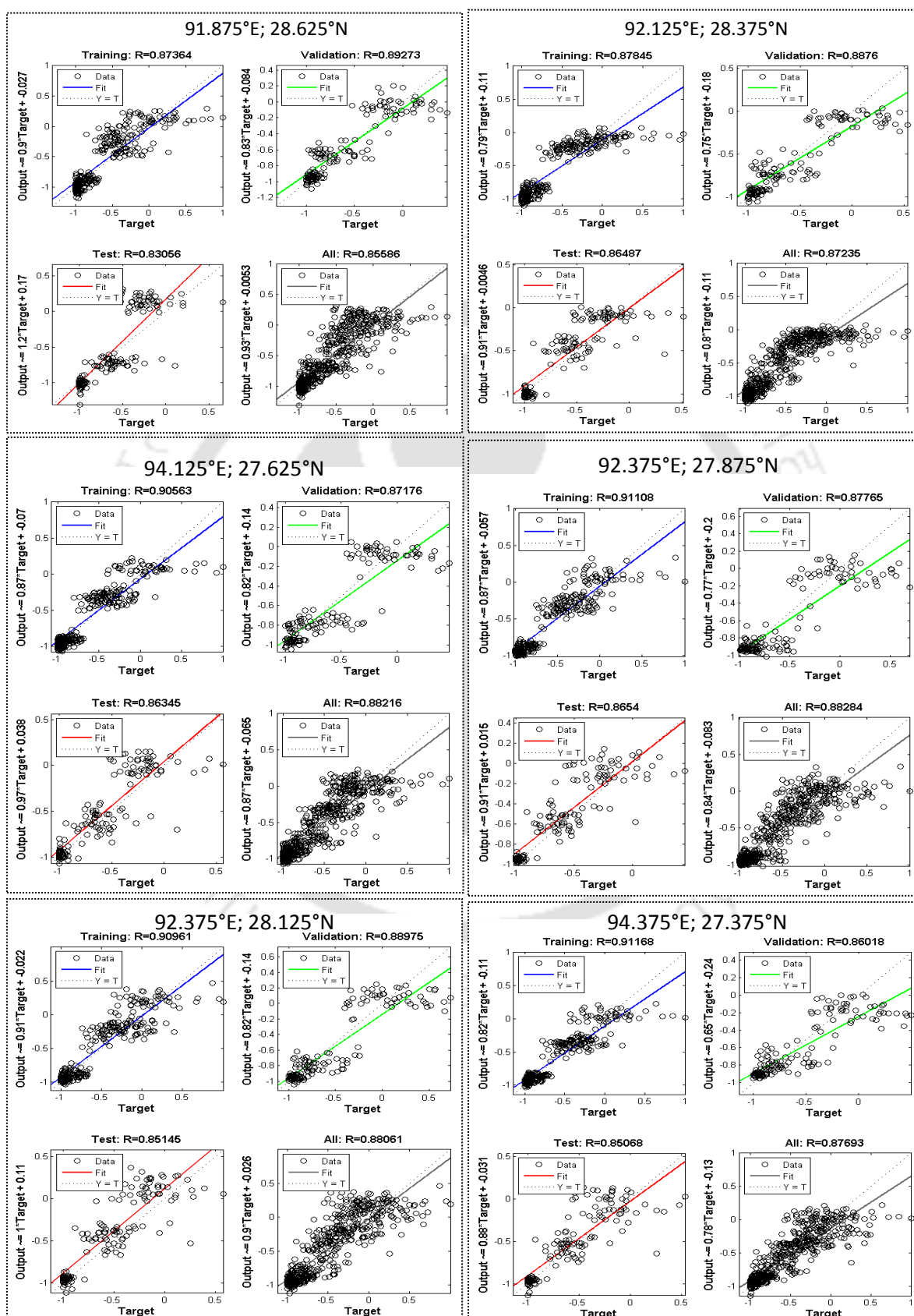
Validation

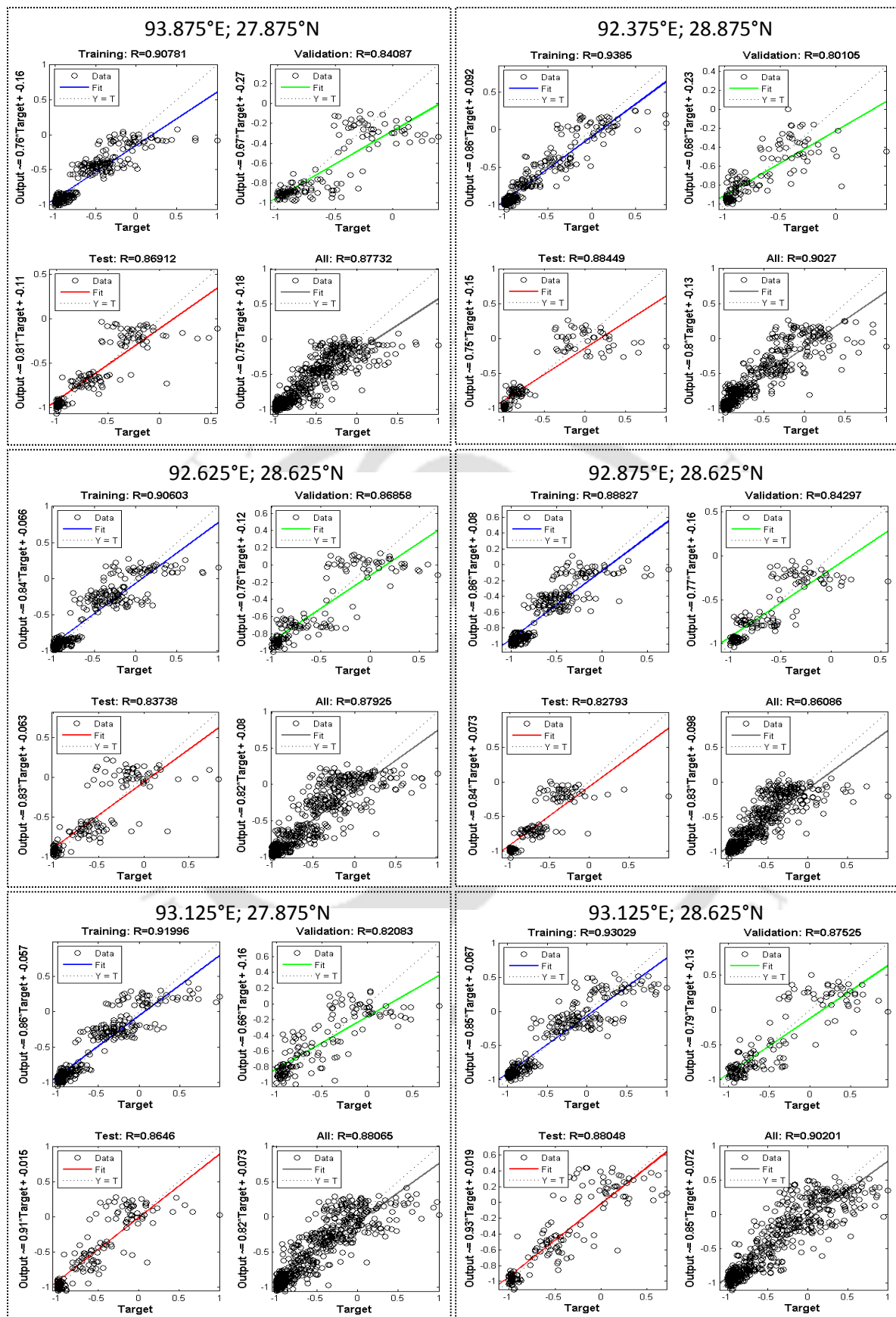


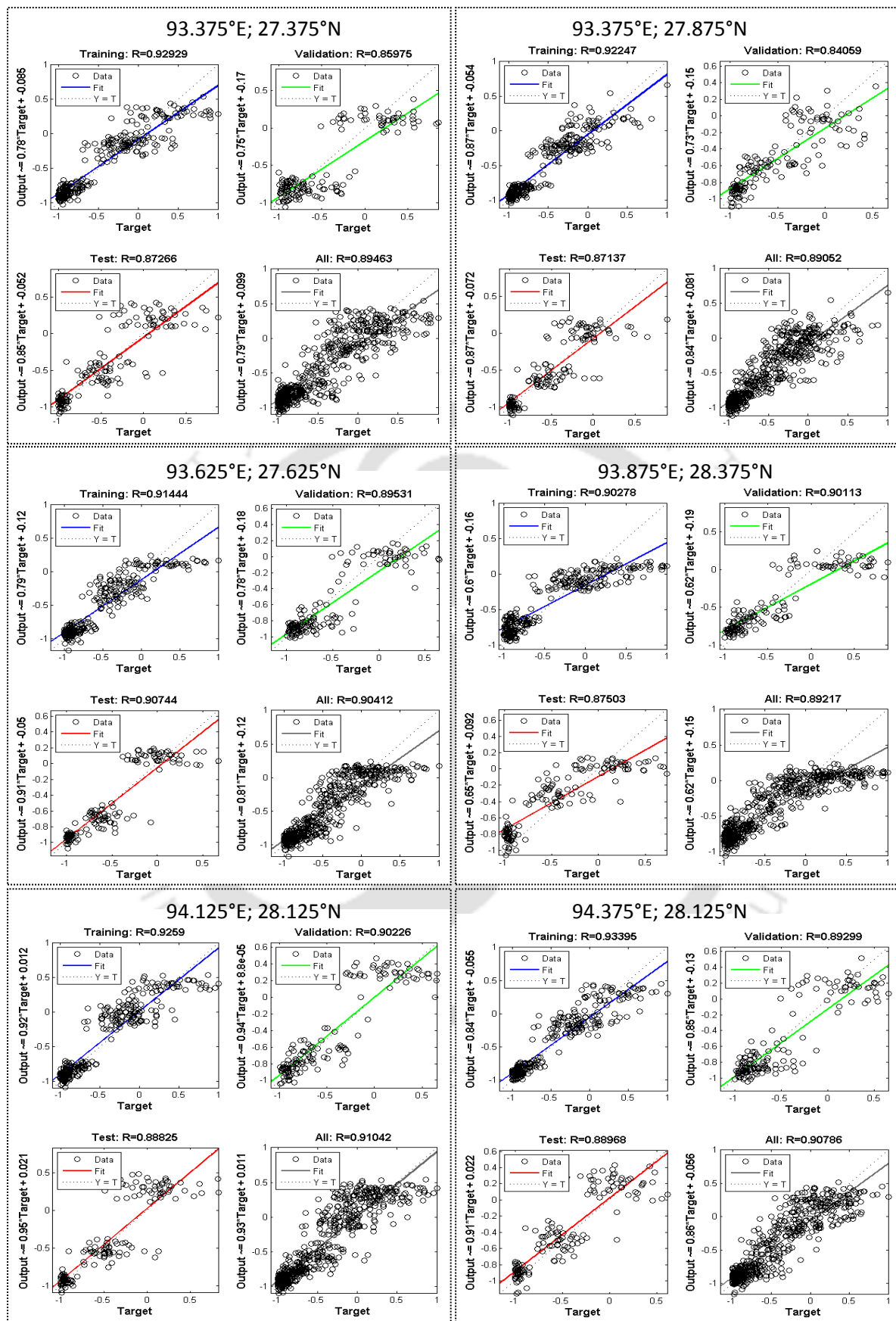
Calibration

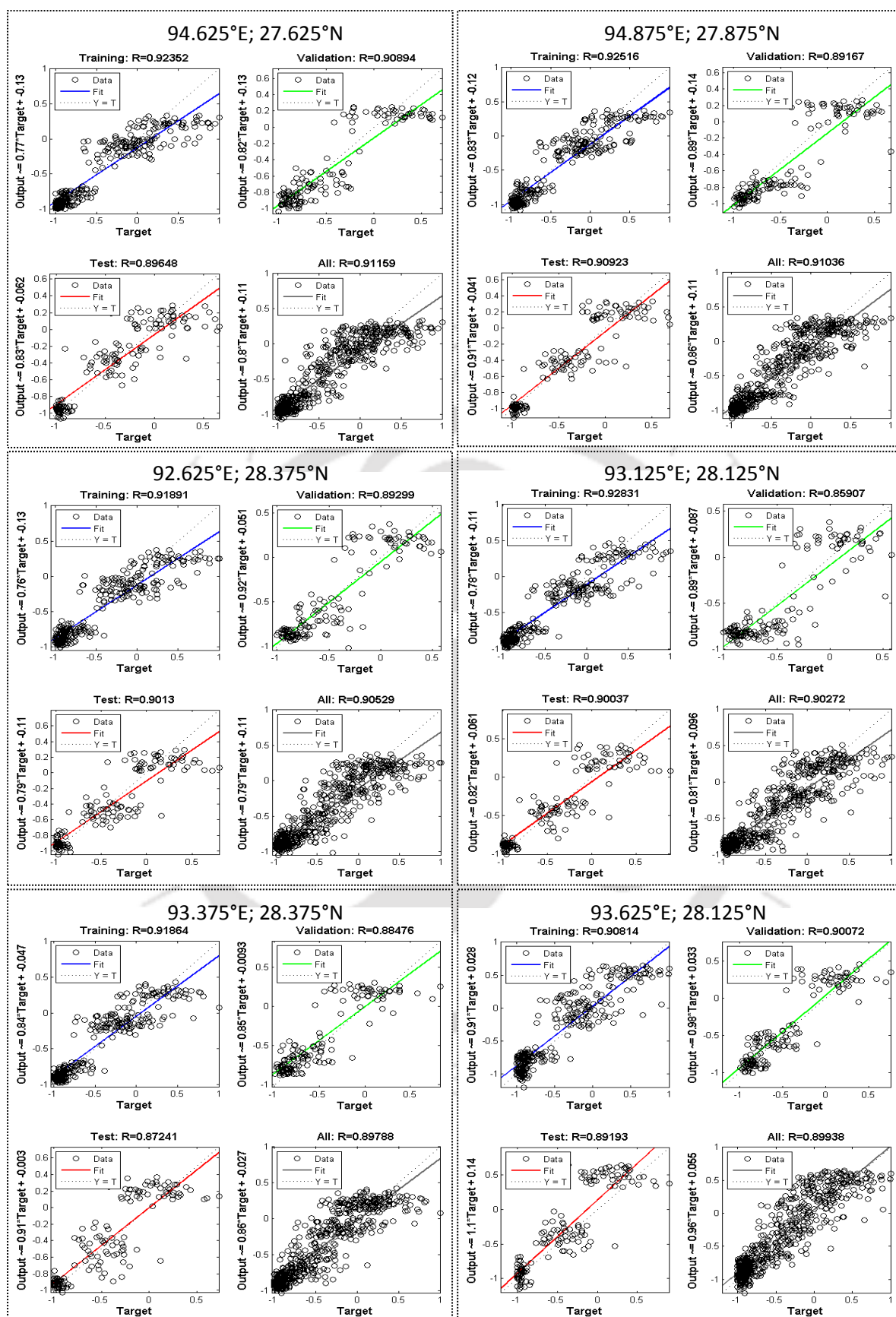


Regression plots for downscaling by ANN at different APHRODITE points



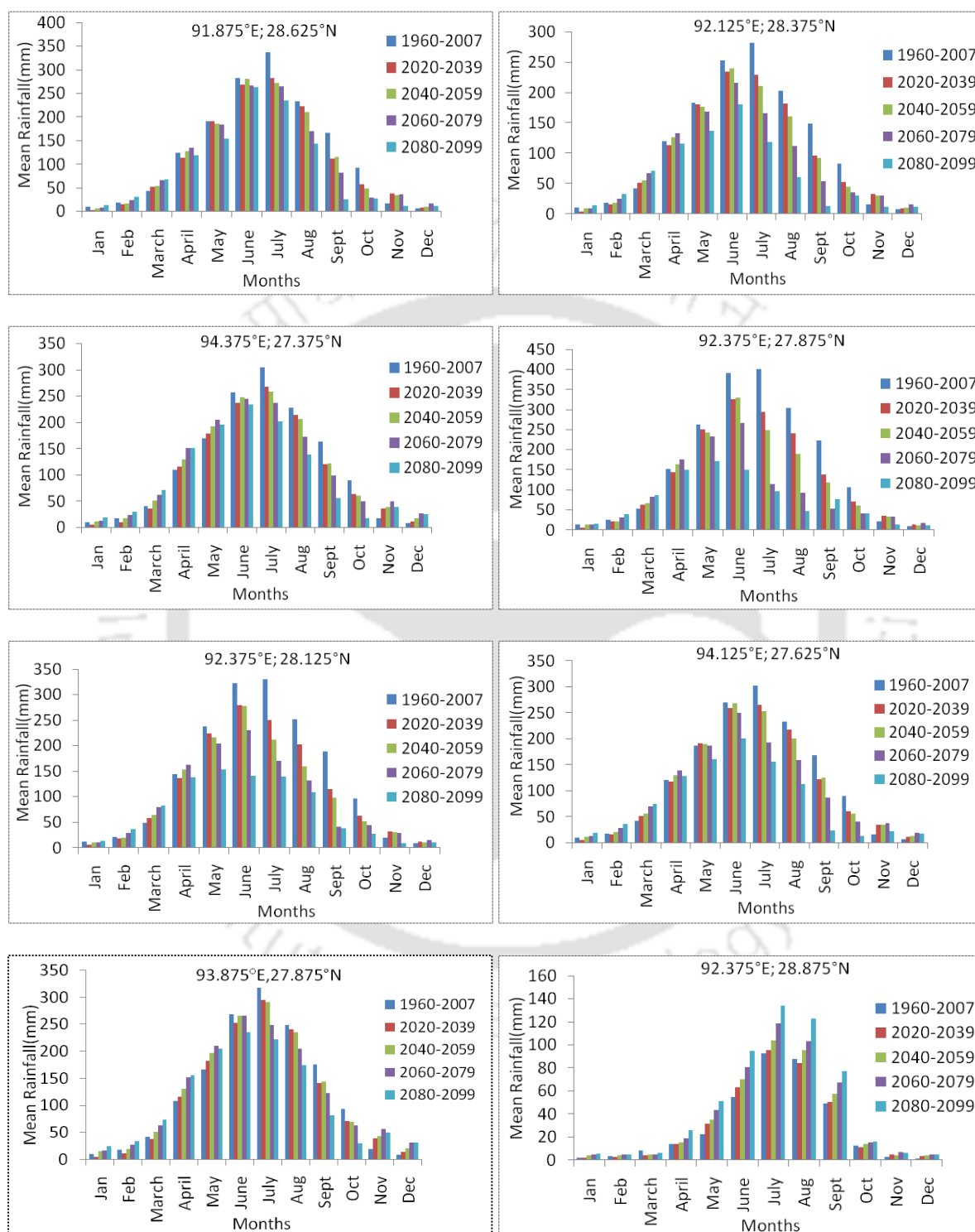


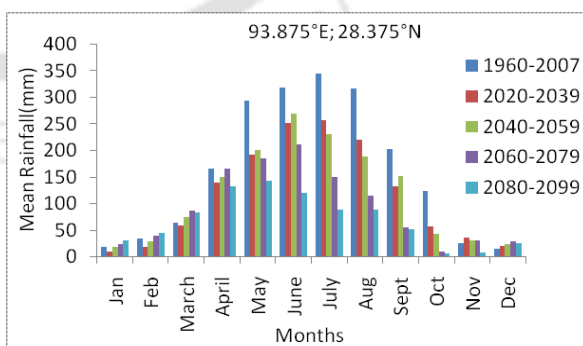
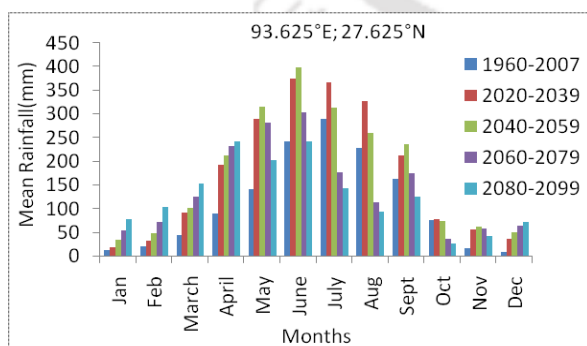
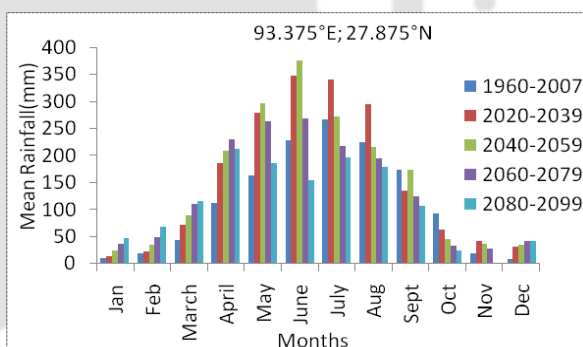
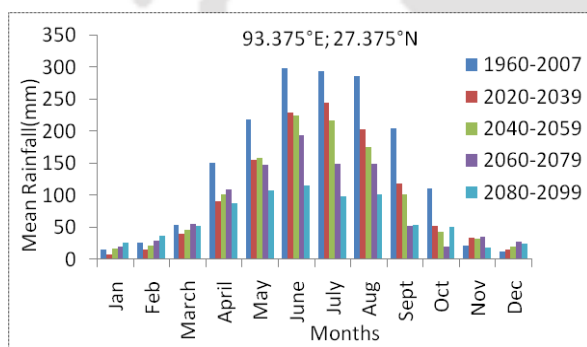
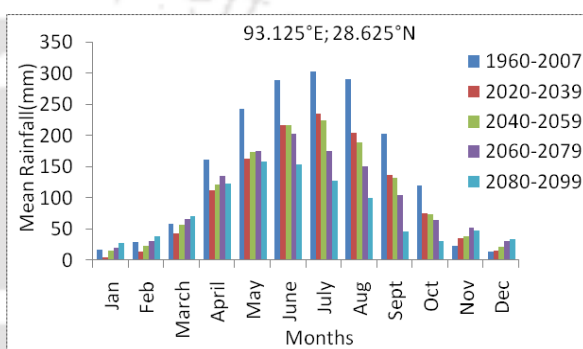
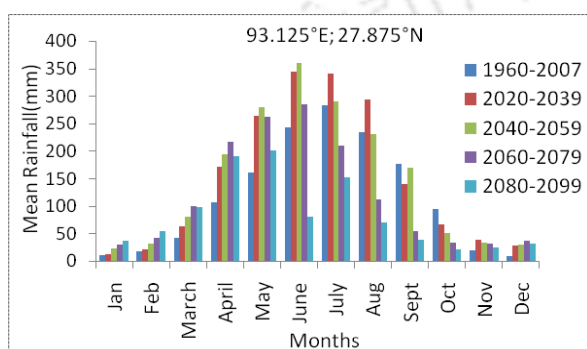
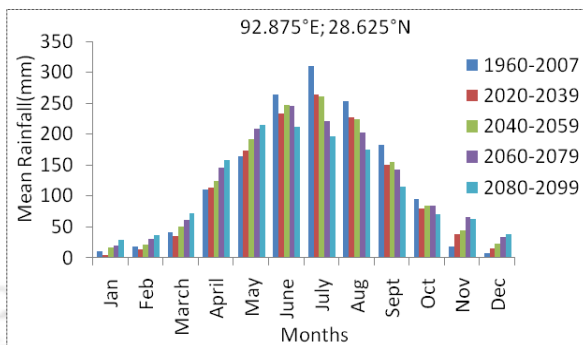
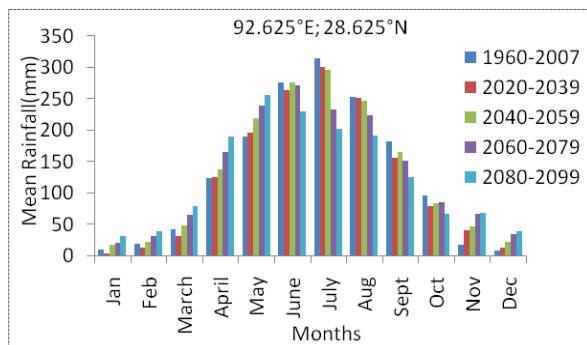


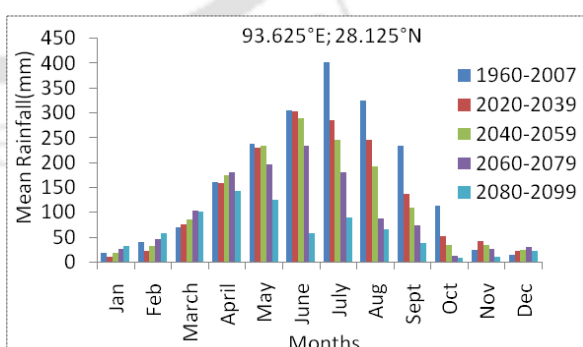
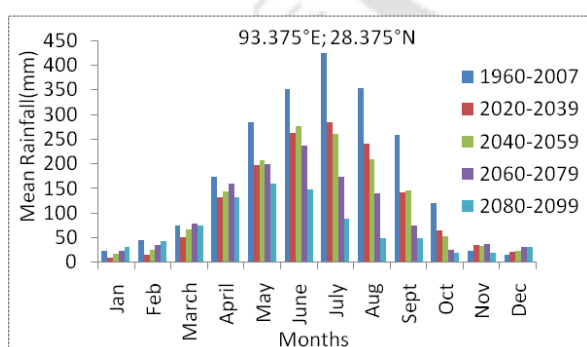
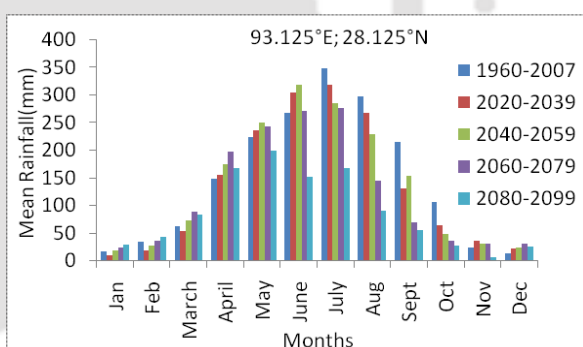
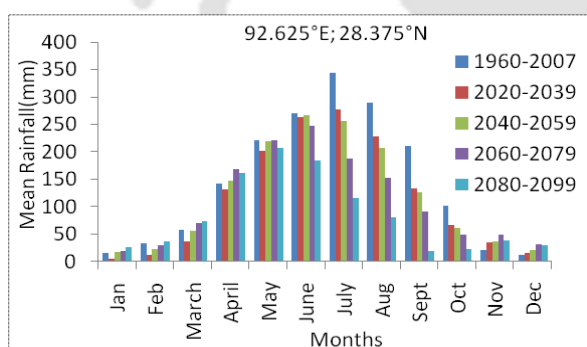
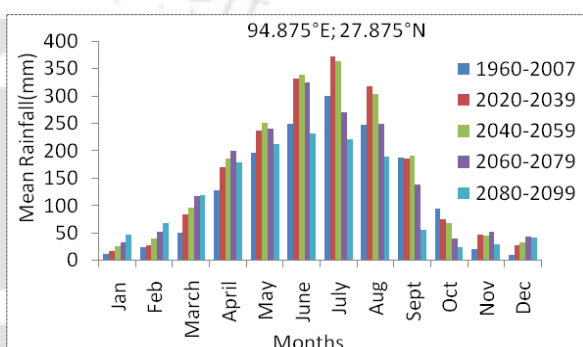
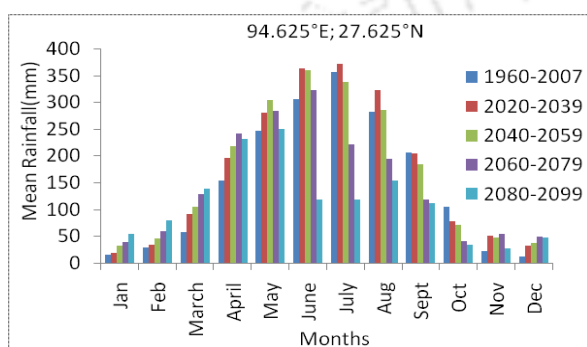
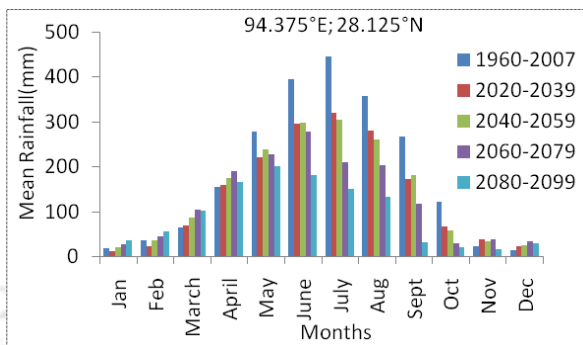
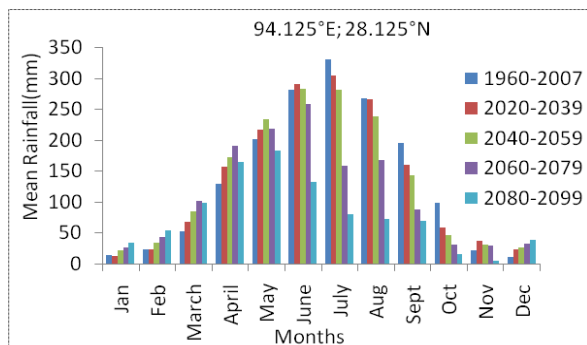


Annexure 6

Graphs showing the future rainfall of Subansiri basin at 24 different APHRODITE's rainfall points









List of Publications

Journal Publications:

1. Barman, S. and Bhattacharjya, R.K. (2015), ‘Comparison of linear regression, non linear regression and artificial neural network model for downscaling of rainfall at Subansiri river basin, Assam, India.’ *European Water*. 51: 51-62.
2. Barman, S. and Bhattacharjya, R.K.(2015), ‘Change in snow cover area of Brahmaputra river basin and its sensitivity to temperature.’ *Environmental System Research*, 4:16, DOI: 10.1186/s40068-015-0043-0.
3. Barman, S. and Bhattacharjya, R.K. (2016), ‘ANN-SCS based hybrid model in conjunction with GCM to evaluate the impact of climate change on the flow scenario of river Subansiri.’ *Journal of Irrigation and Hydraulic Engineering (ASCE)* (Under review).

Conference Publications:

1. Barman, S. and Bhattacharjya, R.K. (2016), “Delineation of Subansiri river basin of Assam and a case study of the change detection of its land use/land cover using MODIS satellite data”, *8th International Perspective on Water Resources and the Environment (IPWE 2016), held at Cinnamon Grand Hotel, Colombo, Sri Lanka from 4-6 January, 2016.*
2. Barman, S. and Bhattacharjya, R.K. (2015), “Comparison of linear regression, non linear regression and artificial neural network model for downscaling of rainfall at Subansiri river basin, Assam, India”, *EWRA 9th World Congress- Water Resources Management in a Changing World: Challenges and Opportunities, held at Grand Cevahir Hotel & Convention Center, Turkey, Istanbul from 10-13 June, 2015.*
3. Barman, S. and Bhattacharjya, R.K. (2015), “Subansiri River and its Catchment Area Delineation from Satellite Image” *Assam Water Conference, held at Assam Water Research and Management Institute, Guwahati, Assam from 5-7 February, 2015.*
4. Barman, S. and Bhattacharjya, R.K. (2015), “Sensitivity of Snow Covered Area of Brahmaputra River Basin to Temperature”, *THA 2015 International Conference on "Climate Change and Water & Environment Management in Monsoon Asia", held at Swissotel Le Concorde, Bangkok, Thailand from 28-30 January, 2015.*
5. Barman, S. and Bhattacharjya, R.K. (2014), “Impact of change in Snow Covered Area on Discharge of River Brahmaputra”, *5th International Conference on Environmental Aspects of Bangladesh (ICEAB 2014), held at University of Dhaka, Bangladesh from 5-6 of September, 2014.*