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"Climate Change Projections in Jammu and Kashmir under A1B, A2 & B2 Scenarios"

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Abstract: The Global Climate Model (GCM) run at a coarse spatial resolution cannot be directly used for climate impact studies. Downscaling is required to extract the sub-grid and local scale information. The present study was undertaken to study the effect of climate change on weather parameters like maximum temperature, minimum temperature and precipitation for A1B, A2 and B2 scenarios. The study uses the Hadley centre coupled model (HadCM3) of the Intergovernmental Panel for Climate Change (IPCC) Forth Assessment Report. Thirty year weather data (1985-2015) obtained form Indian Metrological Department (IMD) Srinagar was used for the study. Statistical Downscaling Model (SDSM), R software and Artificial Neural Network (ANN) models were tested for the Srinagar area. This research investigates which among the three is better model for downscaling climate data for Srinagar area. The modelling results showed a first rate agreement between the experimental data and predicted values for temperature series with high coefficient of determination R2 values varying from (0.93-0.95) for different models. In case of precipitation R2 values varied from (0.08-0.249) for different models. The low values of coefficient of determination in precipitation time series are due to lot of uncertainty. occurrence of precipitation which could not be defined by the selected models. Based on Mean squared error (MSE), Root mean squared error (RMSE), Absolute average deviation (AAD), correlation coefficient and coefficient of determination, the R software performed better than the SDSM and ANN for maximum temperature, minimum temperature & precipitation. Thus R software was used for climate scenario generation. According to our simulated model, precipitation showed a decreasing trend whereas maximum and minimum temperatures showed an increasing trend. An overall increasing pattern of (9.81%) for A1B scenario, (15.24%) for A2 scenario & (10.32%) for B2 scenario for maximum temperature, (2.18%) for A1B scenario, (29.15%) for A2 scenario & (19.90%) for B2 scenario for minimum temperature and an overall decreasing pattern (22.60%) for A1B scenario, (17.23%) for A2 scenario & (7.11%) for B2 scenario for precipitation was noted.

Keywords: Global Climate Model (GCM), Hadley centre coupled model (HadCM3), Statistical Downscaling Model (SDSM), Artificial Neural Network (ANN), R software, Mean squared error (MSE), Root mean squared error (RMSE), Absolute average deviation (AAD).

I. INTRODUCTION

Climate change is a change in the long-term weather patterns that characterize the regions of the world. Climate involves the average weather condition over a long period of time (Arthur Newell Strahler, 1960). Climate change in Intergovernmental Panel on Climate Change (IPCC) usage refers to any change in climate over time, whether due to natural variability or as a result of human activity. This usage refers from that of United Nations Framework Convention on Climate Change (UNFCCC) which defines climate change as, "a change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere & which is in addition to natural climate variability observed over comparable time periods". Climate change is not only a major global environmental problem, but also an issue of great concern to a developing country like India. Climate in a narrow sense is defined as "average weather", or more rigorously, as the statistical description in terms of mean and variability of relevant quantities of weather parameters over a period of time ranging from months to thousands or millions of years. The classical period is 30 years, as defined by World Meteorological Organisation (WMO). The term "weather" refers to the short-term (daily) changes in temperature, wind, and/or precipitation of a region. Climate change is caused by factors that include oceanic processes (such as oceanic circulation), biotic processes, variations in solar radiation received by Earth, plate tectonics & volcanic eruptions, & human- induced alterations of the natural world; these latter effects are currently causing global warming, & "climate change" is often use According to the fifth Assessment Report (AR5) of the Intergovernmental panel on Climate Change (IPCC), global average temperature has shown a 0.85°C increase over the period of 1800-2012 (IPCC 2013), and a 0.18-0.74°C increase during the last 100 years (1906-2005) (IPCC 2007). This is probably due to the effects of industrialization that has increased greenhouse gas emissions.

However, the changes in extreme temperature events such as heat waves, severe winter and summer storms, hot and cold days, and hot and cold nights (Mastrandrea et al., 2011) can cause more severe impacts on human society and the natural environment.

The state of Jammu and Kashmir has also been presumed to suffer the consequences of global climate change. Jammu and Kashmir being one of the most sensitive ecological areas in Indian subcontinent has been at the vanguard of the discussions on climate change. It is clear that emissions of carbon dioxide and other gases and aerosols into the atmosphere from all sectors of human activities are central drivers of climate change. Their effects are now evident, and are becoming increasingly severe. A report prepared for the state's department of ecology, environment and remote sensing in 2013 claimed average temperatures in the Kashmir valley has risen 1.45 degrees Celsius over two decades. As a result of rising temperatures in Kashmir, "over the past 50 years, hundreds of natural springs and streams have dried up, prompting people to encroach floodplains. 1.2. Emission Scenarios IPCC (2000) defines emission scenario as "images of the future or alternative futures". They are neither forecasts nor predictions; rather all scenarios are one alternative image of how the future might reveal. A weather scenario must be representative, consistent and be a reasonable projection of possible future climates. It is not a forecast or prediction but it is an alternative image of how the future can be explained and its raw material is projected (IPCC, 2012). It should fulfil five criteria to be used for impact assessments and policy makers. According to IPCC (2012) report, these criteria are consistency with global projection, physical plausibility, applicability for impact assessments, representativeness and accessibility. Representative means that a scenario should be able to represent the

In this study the three scenarios A1B, A2 & B2 of HadCM3 model have been selected. Accordingly, the A1(low CO2 emission) scenario family describes a future world of very rapid economic growth, global population that peaks in mid-century and declines thereafter, and the rapid introduction of new and more efficient technologies. The A1 scenario family develops into three groups that describe alternative directions of technological change in the energy system (IPCC 2007). The three A1 groups are distinguished by their technological emphasis: fossil intensive (A1FI), non-fossil energy sources (A1T), or a balance across all sources (A1B) (where balanced is defined as not relying too heavily on one particular energy source, on the assumption that similar improvement rates apply to all energy supply and end-use technologies). Similarly, the A2 (medium high CO2 emission) scenario family describes a very heterogeneous world. The underlying theme is self-reliance and preservation of local identities. Fertility patterns across regions converge very slowly, which results in continuously increasing global population (IPCC 2007). The B2 (high CO2 emission) storyline and scenario family describes a world in which the emphasis is on local solutions to economic, social, and environmental sustainability. It is a world with continuously increasing global population at a rate lower than A2, intermediate levels of economic development. One of the most momentous potential concerns of weather prediction is hydrological components alteration and subsequent changes in lake/river water balance. Among the water balance components surface water inflow from ungauged and gauged catchments, precipitation and evaporation pattern alteration and their impact on water balance is not yet researched well. Therefore, this study investigates the pattern of climate change in the area

The present study is targeted to offer comprehensive simulations of extreme temperature events under three scenarios of HadCM3, A1B, A2 and B2, using Statistical Downscaling Model (SDSM), Artificial Neural Network (ANN) & R software in the area of Srinagar district with the following objectives: 1. To calibrate and validate the SDSM, ANN and R-software output for monthly parameters (i.e. precipitation, maximum temperature & minimum temperature) with observed patterns from meteorological station records. To analyse/compare each model to find out the best fit model amongst the three and to downscale the A1B, A2 and B2 scenarios from the HadCM3 using best fit model obtained above from the investigation. To evaluate the future change patterns of the best model for maximum, minimum temperature and precipitation

II. MATERIALS AND METHODS

The present investigation entitled "Climate change projections in Srinagar under A1B, A2 and B2 scenarios" was undertaken in Srinagar, Jammu and Kashmir, during 2016- 2017. The details of the software used, techniques followed and materials used during the course of investigation are presented below. Study Area Description The study area for the survey was district Srinagar of Kashmir province, Jammu & Kashmir state (Fig). Srinagar is the summer capital of the Indian state of Jammu and Kashmir. It is situated in the centre of the Kashmir Valley on the banks of the Jhelum river and is surrounded by five districts. In the north it is flanked by Kargil and Ganderbal in the South by Pulwama, in the north-west by Budgam. The capital city of Srinagar is located 1585 metres above sea level. Srinagar has a humid subtropical climate, much cooler than what is found in much of the rest of India, due to its moderately high elevation and northerly position. The valley is surrounded by the Himalayas on all sides. Winters are cool, with daytime with daytime temperature averaging to 2.5 °C, and drops below freezing at night.

Moderate to heavy snowfall occurs in winter and the only road that connects Srinagar with the rest of India may get blocked for a few days due to avalanches. Summers are warm with a July daytime average of 24.1 °C. 3.2

STUDY AREA

III. DATA REQUIREMENT

A. Meteorological Data (daily):

1) Precipitation (daily).

2) Temperature (Min and Max)

The daily weather parameters collected from Indian Meteorological Department (IMD) Srinagar are shown along with their units of measurement in Table . The parameters chosen for study in this setup are maximum temperature, minimum temperature, & precipitation. There is no particular reason behind this choice of weather parameters. The choice is made just to predict the temperature variable. 30 years (1985-2015) data have been used in this research.

The input parameters used for study are given in Table

S.No	Meteorological Variables	Units of Measuremen
1	Maximum Temperature	^{0}C
2	Minimum Temperature	^{0}C
3	Precipitation	mm

Climate Models General Circulation Models (GCMs), represent physical processes in the atmosphere, ocean, cryosphere and land surface. These are the most advanced tools currently available for simulating the response of the global climate system to increasing greenhouse gas concentrations. While simpler models have also been used to provide globally- or regionally-averaged estimates of the climate response, only GCMs, possibly in conjunction with nested regional models.

General Circulation Models (GCMs) are restricted in their usefulness for local impact studies by their coarse spatial resolution (typically of the order 50,000 km^2) and inability to resolve important sub-grid scale features such as clouds and topography. As a consequence, two sets of techniques have emerged as a means of deriving local-scale surface weather from regional-scale atmospheric predictor variables. Firstly, statistical downscaling is analogous to the “model output statistics” (MOS) and “perfect prog” approaches used for short-range numerical weather prediction. Secondly, Regional Climate Models (RCMs) simulate sub-GCM grid scale climate features dynamically using time-varying atmospheric conditions supplied by a GCM bounding a specified domain.

IV. MODELS USED

Statistical Downscaling Model (SDSM) SDSM was developed by Dr. Robert L. Wilby and Dr. Christian W. Dawson in UK for assessing local climate change impacts using a robust statistical downscaling technique. It is a Windows-based decision support tool for the rapid development of single-site, ensemble scenarios of daily weather variables under present and future regional climate forcing (Wilby et al., 2002).

It performs the tasks required to statistically downscale climate model output, namely: quality control of input data; screening of candidate predictor variables; model calibration; synthesis of present weather data; generation of future climate scenarios; basic statistical and time series analyses; and graphing results (Fig.)

It can be used for all locations in the world. Its key outputs are the site specific daily scenarios for maximum and minimum temperatures, precipitation, and humidity. It also produces a range of statistical parameters such as variances, frequencies of extremes, spell lengths. Its key inputs are the quality observed daily data for the statistical models. Daily GCM outputs for large-scale variables for future climate to drive the models. The SDSM software reduces the task of statistically downscaling daily weather series into seven discrete steps:

- Quality control and data transformation;
- Screening of predictor variables;
- Model calibration;
- Weather generation (using observed predictors);
- Statistical analyses;
- Graphing model output; and
- Scenario generation (using climate model predictors).

R (Programming Language)

R is an open source programming language and software environment for statistical computing and graphics that is supported by the R Foundation for Statistical Computing. The R language is widely used among statisticians and data miners for developing statistical software and data analysis (Saiz-Álvarez, 2016). R is an integrated suite of software facilities for data manipulation, calculation and graphical display. Among other things it has,

- an effective data handling and storage facility,
- a suite of operators for calculations on arrays, in particular matrices,
- a large, coherent, integrated collection of intermediate tools for data analysis,
- graphical facilities for data analysis and display either directly at the computer or on hardcopy,

The source code for the R software environment is written primarily in C.

The basic installation (for Linux, Windows or Mac) contains a powerful set of tools for most purposes. For regression analysis, R uses lm ( ) command function.

The basic syntax for a regression analysis in R is lm (Y ~ model) where Y is the object containing the dependent variable to be predicted and model is the formula for the chosen mathematical model.

```
> lm_1 < − l m (y ~ x) # Fit a linear regression model “y = B0 + (B1 * x)”
                        # store the results as lm_1
```

Where, the greater-than sign (>) is R prompt, left arrow (< −) is the assignment operator that assigns the value of the object on the right to the object on the left.

Estimation of Missing Rainfall Data

In this study missing rainfall data was estimated by using the rainfall data at neighbouring stations. The missed values of rainfall data estimated by arithmetic mean (equation) in a case the normal annual rainfall at any of the neighbouring stations is within 10% of the normal annual precipitation at target station. The normal rainfall is an average value of rainfall over a specified period (e.g. year, month or date). Target station is station with missing data and neighbouring stations are source stations used to estimate missing data. In case the normal annual rainfall at any of the neighbouring stations varies considerably (i.e. more than 10%) from the normal annual precipitation at target station, then the normal ratio method (equation) was used to calculate the missing value (PX).

$$P_x = \frac{P_1 + P_2 + \ldots + P_n}{n} \qquad P_x = \frac{N_x}{n}\left\{\frac{P_1}{N_1} + \frac{P_2}{N_2} + \frac{P_3}{N_3} + \ldots + \frac{P_n}{N_n}\right\}$$

Where, n is number of neighbouring stations;
Nx is normal annual precipitation of the target station;
P1, P2, P3, …, Pn are daily precipitations of respective neighbouring stations, and
N1, N2, N3,…, Nn are annual total precipitations of respective neighbouring stations.

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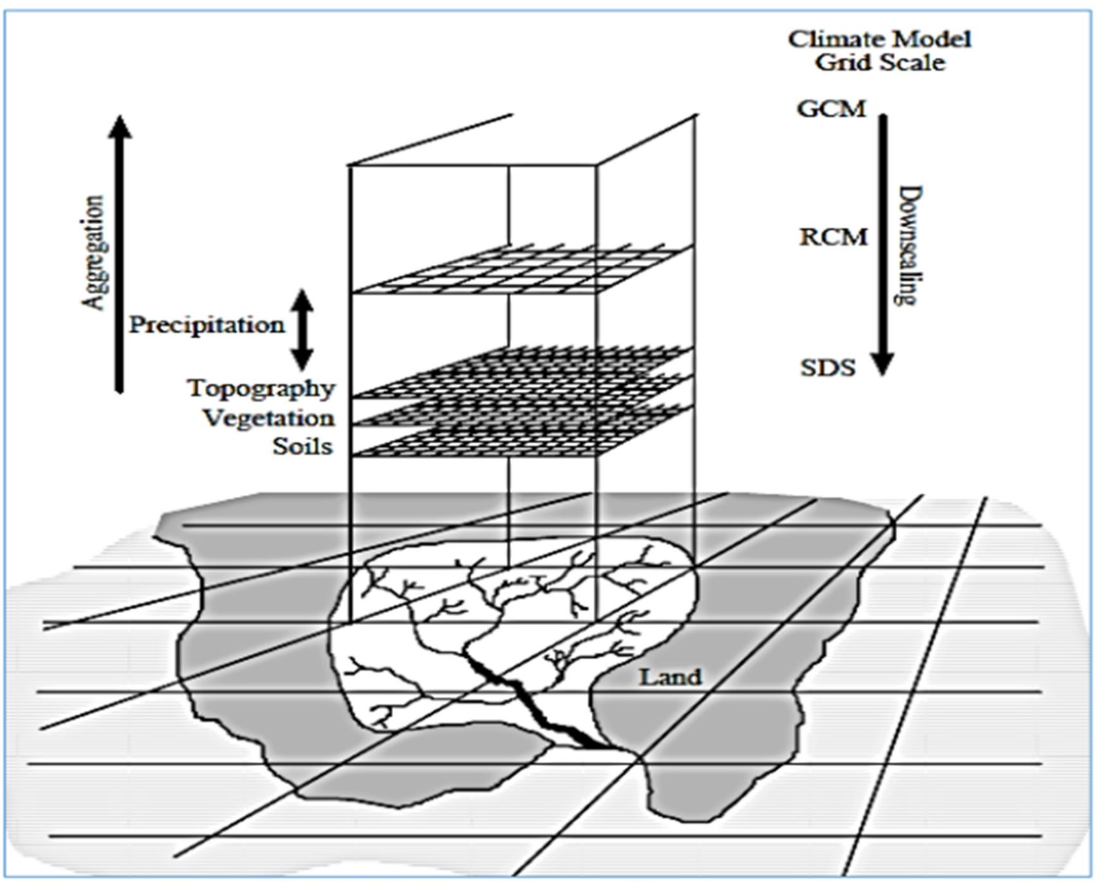
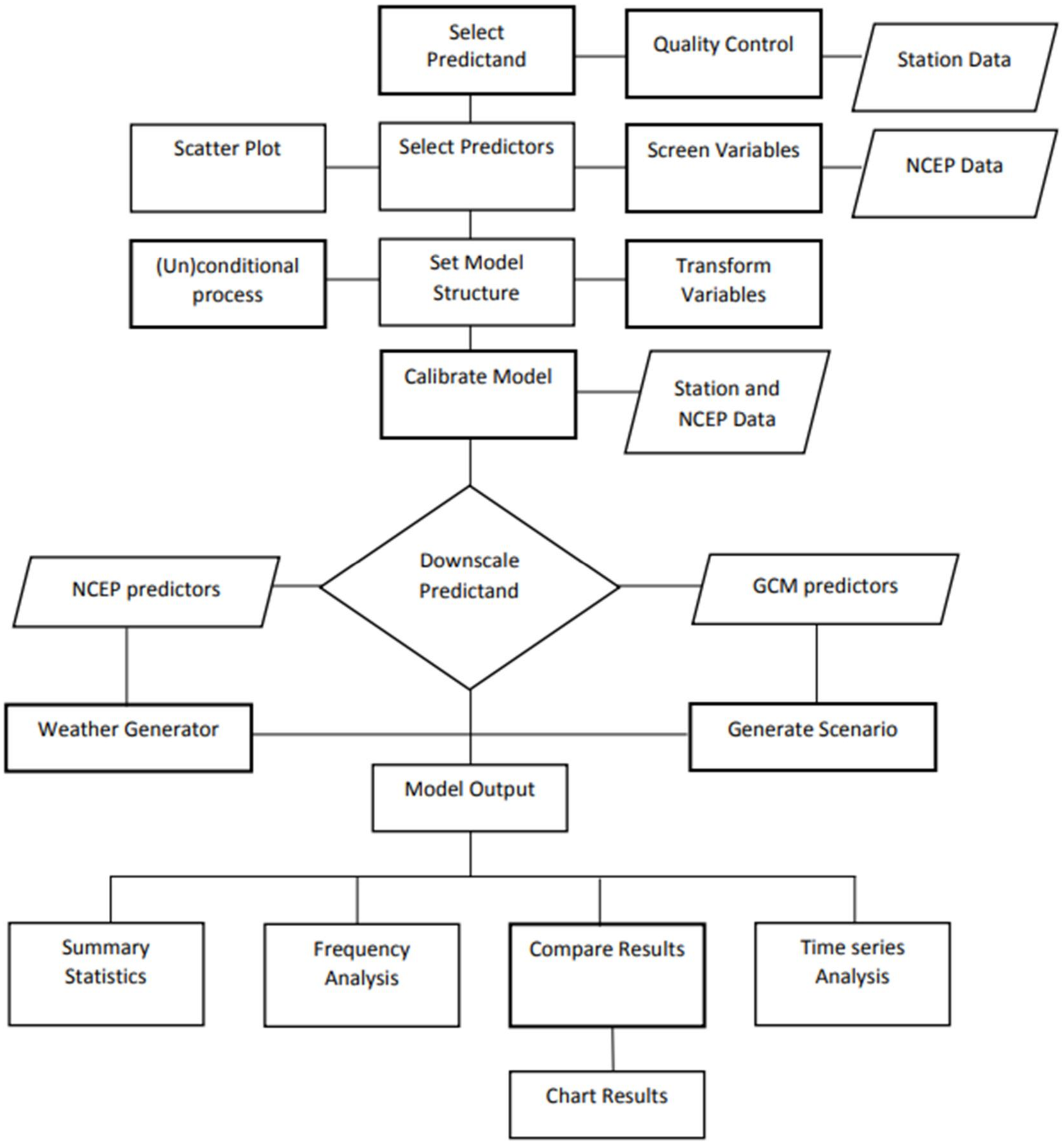
Large-scale atmospheric variables (Predictors) used as potential inputs in SDSM

No.	Predictors	Description	No.	Predictors	Description
1	Tempas	mean temperature at 2 m	14	p500as	500hpa geo-potential height
2	Shumas	surface specific humidity	15	p5_zas	500hpa velocity
3	Rhumas	near surface relative humidity	16	p5_vas	500hp meriodinal velocity
4	r850as	relative humidity at 850hpa	17	p5_zhas	500hpa divergence
5	r500as	relative humidity at 500 hpa	18	p5_uas	500pa zonal velocity
6	p8zhas	850 hpa divergence	19	p5_fas	500hpa air flow strength
7	p8thas	850hpa wind direction	20	p_zhas	surface divergence
8	p850as	850hpa geo-potential height	21	p_zas	surface velocity
9	p8_zas	850 hpa velocity	22	p_vas	surface meridian velocity
10	p8_vas	850 hpa meriodinal velocity	23	p_uas	surface zonal velocity
11	p8_uas	850hpa zonal velocity	24	p_thas	surface wind direction
12	p8_fas	850hpa airflow strength	25	p_fas	surface air flow strength
13	p5_thas	500hpa wind direction	26	Mslpas	men sea level pressure

General Downscaling Approach





V. SDSM CLIMATE SCENARIO GENERATION

The statistical test (i.e. t-test) was used to calculate a p-value, which is used to accept or reject the hypotheses that the two sets of data (i.e. observed and simulated) could have similar or the same statistical properties. Significant differences between the simulated and observed climate data may arise from the errors in the observed data, model smoothing of the observed data or random error.

A. Artificial Neural Network Processing

Experimentally developed 25915 observations for each input and output variables were used for developing the models. The dataset was randomly divided into two disjoint subsets, namely, training set having 21900 observations (80%) and validation set (20%) consisting of 4015 observations.

In this study, back-propagation training function in the toolbox was used to train feed-forward neural network. There are generally four steps in the training process.

1) Data preprocessing i. Assemble the training data ii. Normalization
2) Training the Neural Network
a) Defining the input and output

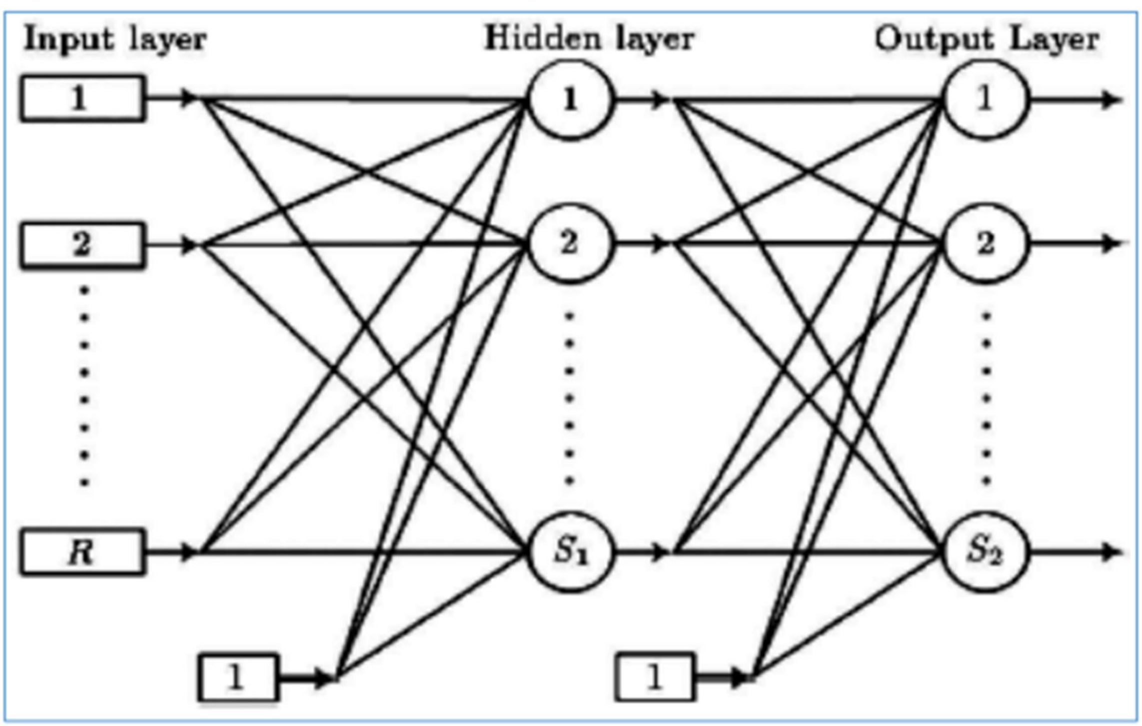
b) Choosing the architecture of the neural network
c) Create the network object.
d) Training the network
3) Post training analysis.
4) . Future data synthesis.

Data preprocessing

Statistics of SDSM

	MAX T (°C)				MIN T (°C)				PRECIPITATION (mm)		
	A1	A2	B2		A1	A2	B2		A1	A2	B2
MSE	6.9656	5.6368	5.7865	MSE	3.6958	3.0067	3.5115	MSE	5842.160	6285.715	6525.474
RMSE	2.6392	2.3742	2.4055	RMSE	1.9224	1.7340	1.8739	RMSE	76.4340	79.2825	80.7804
R	0.9565	0.9584	0.9573	R	0.9634	0.9681	0.9626	R	0.4728	0.2469	0.1105
R^2	0.9149	0.9186	0.9164	R^2	0.9281	0.9373	0.9265	R^2	0.2236	0.061	0.0122
AAD	17.348	13.492	13.650	AAD	32.388	-13.571	-10.514	AAD	103.366	77.8940	97.7343

Artificial Neural Network: A Multilayer Perceptron



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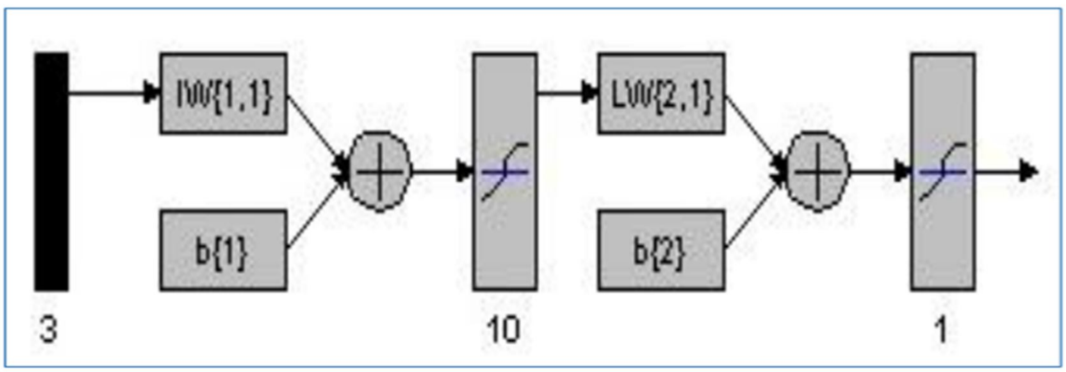
B. Artificial Neural Network (ANN)

The network developed was used for simulation modelling separately. The performance of a trained network was measured by performing a regression analysis between the network response and the corresponding targets. Both the networks showed variation in the outputs as regards to the maximum temperature, minimum temperature and precipitation. MSE, RMSE, and AAD were used to determine the accuracy of the model as well as its ability to predict the target values as shown in Table

It was observed that for Maximum temperature the overall best results were shown by the A1B scenario with lower values of MSE, RMSE and AAD as shown in Table. The similar kind of results were obtained for A1B scenario in case of precipitation. For Minimum temperature B2 scenario showed the good results among the three scenarios with lower values of statistical indicators. The relation between the actual values and predicted values obtained by ANN for maximum temperature, minimum temperature and precipitation for each of the scenarios A1B, A2 & B2 are represented by means of graphs shown in Fig The high value of R2 for Max T, Min T was obtained for each of the scenarios while the R2 for precipitation was not much because of erratic nature of the precipitation. For Maximum temperature the good results were shown by A1B scenario with a R 2 of 0.9534. For Minimum temperature B2 scenario showed the good results with a R 2 of 0.9450. While for precipitation the R 2 of 0.2163 was obtained for A1B scenario. Thus, the model got simulated very well with a high value of R 2 in each of the scenarios showing that the model is quite efficient in predicting the maximum temperature, minimum temperature and precipitation

View of network with transig transfer function



Statistics of ANN (MATLAB)

	MAX T (°C)				MIN T (°C)				PRECIPITATION (mm)		
	A1	A2	B2		A1	A2	B2		A1	A2	B2
MSE	4.0604	4.7397	4.4507	**MSE**	2.749	2.7052	2.6800	**MSE**	5886.815	6245.005	6664.337
RMSE	2.015	2.1771	2.1097	**RMSE**	1.658	1.6447	1.6371	**RMSE**	76.7256	79.0257	81.6354
R	0.9764	0.9656	0.9679	**R**	0.9705	0.9719	0.9721	**R**	0.4650	0.2705	0.1042
R^2	0.9534	0.9324	0.9369	**R^2**	0.9419	0.9445	0.9450	**R^2**	0.2163	0.073	0.0109
AAD	12.121	12.995	12.062	**AAD**	5.1046	-11.3851	-11.3525	**AAD**	100.1949	74.6794	92.3993

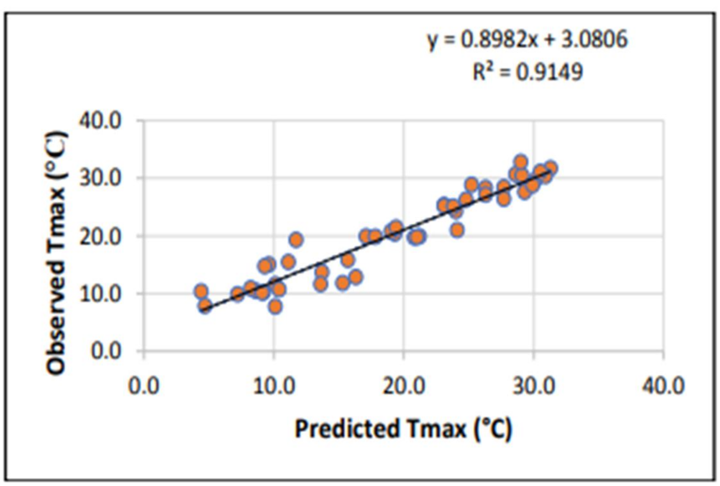
R (programming language)

The experimental values of maximum temperature, minimum temperature and precipitation were fitted in R software, which yield a good fit with a higher value of R2. The corresponding error values were found to be in the acceptable limit. The accuracy of the R software model as well as its ability to predict the target values was determined with help of statistical indices like MSE, RMSE, AAD, R 2 and R as shown in Table. It was observed that for Maximum temperature the overall best results were shown by the A1B scenario with lower values of MSE, RMSE and AAD as shown in Table. The similar kind of results were obtained for A1B scenario in case of precipitation. For Minimum temperature A2 scenario showed the good results among the three scenarios with lower values of statistical indicators. The actual values and the predicted values obtained by R software are plotted against each other in order to determine the goodness of fit criterion, i.e., coefficient of determination (R 2) for maximum temperature, minimum temperature and precipitation for each of the scenarios A1B, A2 & B2, which are graphically presented in Fig. For Max T the good results were deciphered by A1B scenario with a R 2 of 0.9553. For Min T, A2 scenarios revealed the satisfactory results with a R 2 of 0.9538. The R 2 of 0.2492 was observed for precipitation for A1B scenario. Based on these results it was clear that the model is quite efficient in predicting maximum temperature, minimum temperature and precipitation as the model got simulated very well with a high value of R2 in each of the scenarios

Statistics of SDSM

	MAX T (°C)				**MIN T (°C)**				**PRECIPITATION (mm)**		
	A1	**A2**	**B2**		**A1**	**A2**	**B2**		**A1**	**A2**	**B2**
MSE	4.0604	4.7397	4.4507	**MSE**	2.749	2.7052	2.6800	**MSE**	5886.815	6245.005	6664.337
RMSE	2.015	2.1771	2.1097	**RMSE**	1.658	1.6447	1.6371	**RMSE**	76.7256	79.0257	81.6354
R	0.9764	0.9656	0.9679	**R**	0.9705	0.9719	0.9721	**R**	0.4650	0.2705	0.1042
R^2	0.9534	0.9324	0.9369	**R^2**	0.9419	0.9445	0.9450	**R^2**	0.2163	0.073	0.0109
AAD	12.121	12.995	12.062	**AAD**	5.1046	-11.3851	-11.3525	**AAD**	100.1949	74.6794	92.3993

Relation between original & predicted values (Maximum) Temperature, A1B) by SDSM



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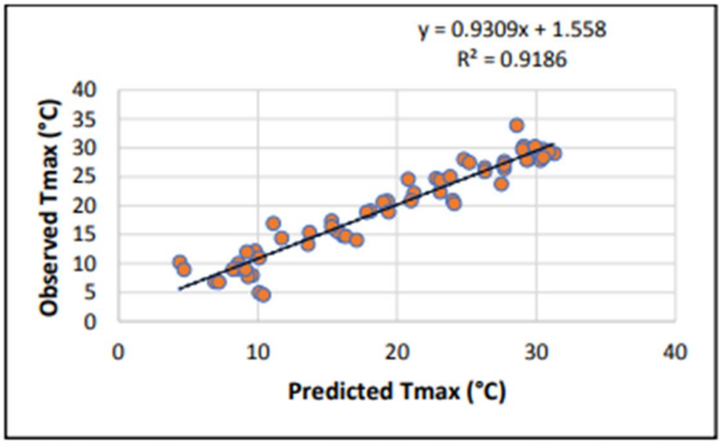
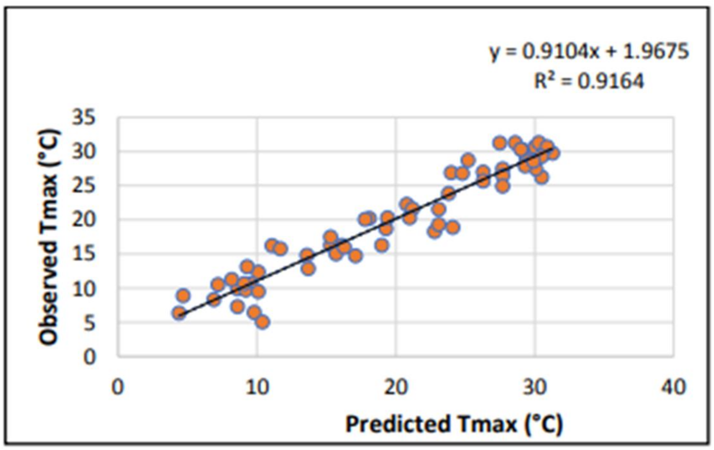
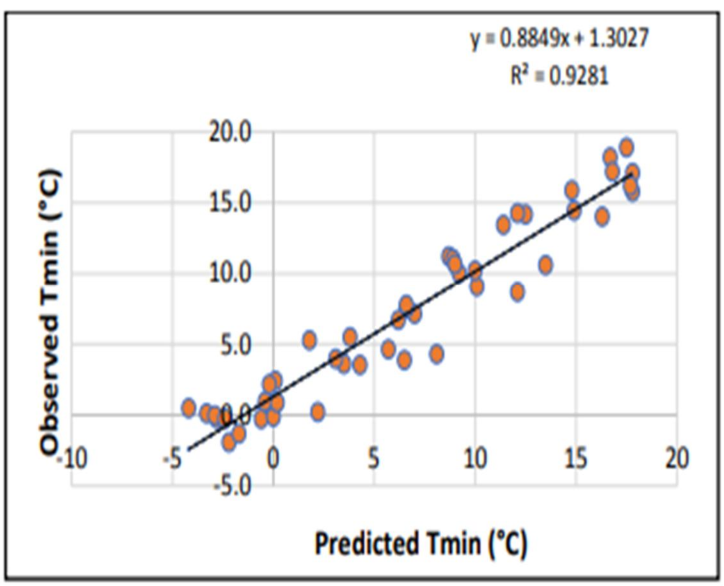
Relation between original & predicted values (Maximum Temperature, A2) by SDSM



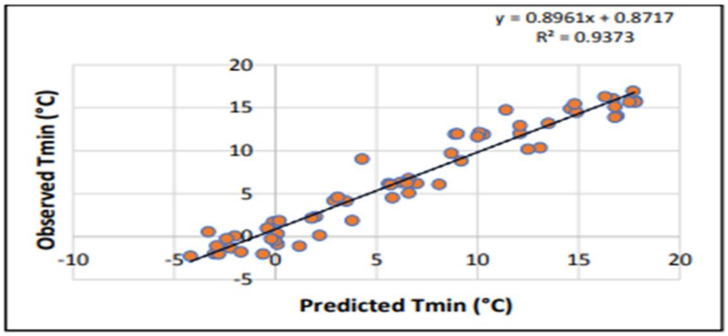
Relation between original & predicted values (Maximum Temperature, B2) by SDSM



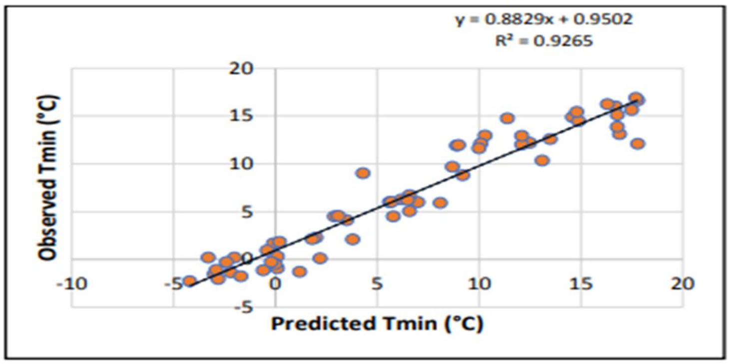
Relation between original & predicted values (Minimum Temperature, A1B) by SDSM



Relation between original & predicted values (Minimum Temperature, A2) by SDSM



Relation between original & predicted values (Minimum Temperature, B2) by SDSM



R (programming language)

The experimental values of maximum temperature, minimum temperature and precipitation were fitted in R software, which yield a good fit with a higher value of R2. The corresponding error values were found to be in the acceptable limit. The accuracy of the R software model as well as its ability to predict the target values was determined with help of statistical indices like MSE, RMSE, AAD, R 2 and R as shown in Table

It was observed that for Maximum temperature the overall best results were shown by the A1B scenario with lower values of MSE, RMSE and AAD as shown in Table. The similar kind of results were obtained for A1B scenario in case of precipitation. For Minimum temperature A2 scenario showed the good results among the three scenarios with lower values of statistical indicators.

Statistics of R Software

	MAX T (°C)				MIN T (°C)				PRECIPITATION (mm)		
	A1	A2	B2		A1	A2	B2		A1	A2	B2
MSE	3.6792	6.2352	5.3377	MSE	2.3456	2.3680	2.2882	MSE	5720.1829	6170.442	5921.584
RMSE	1.9181	2.4970	2.3103	RMSE	1.5315	1.5388	1.5127	RMSE	75.6319	78.5522	76.9518
R	0.9774	0.9547	0.9611	R	0.9746	0.9750	0.9766	R	0.4992	0.2898	0.3515
R^2	0.9553	0.9115	0.9237	R^2	0.9499	0.9507	0.9538	R^2	0.2492	0.0800	0.1235
AAD	12.5025	15.1770	12.9951	AAD	6.2827	7.6103	0.0995	AAD	93.7768	75.2598	75.4514

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VI. COMPARISON OF PREDICTABILITY OF MODELS

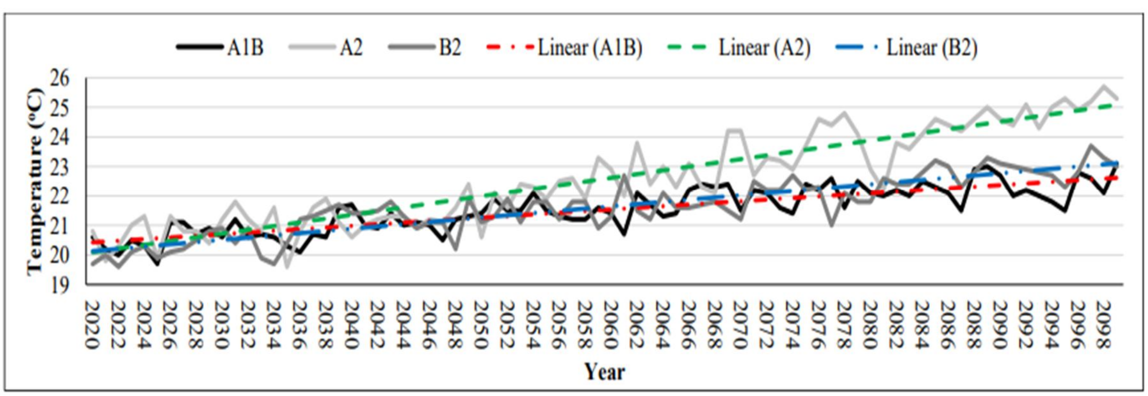
The results obtained by R software were compared with those obtained by ANN (MATLAB) and SDSM on the basis of values of the mean squared error (MSE), root mean squared error (RMSE), coefficient of determination (R2), correlation coefficient (R) and absolute average deviation (AAD) for maximum temperature, minimum temperature and precipitation for each of the scenarios A1, A2 and B2.

It was observed that for Max T the best results were given by the R software for A1B scenario with MSE of 3.6792, RMSE of 1.9181, R of 0.9774, AAD of 12.5025 and R2 of 0.9553. For A2 scenario ANN revealed good results with MSE of 4.7397, RMSE of 2.1771, R of 0.9656, AAD of 12.9956 and R2 of 0.9324. Similarly, for B2 scenario it was observed that the ANN revealed good results with MSE of 4.4507, RMSE of 2.1097, R of 0.9679, AAD of 12.0626 and R 2 of 0.9369 as shown in Table

Comparison of results obtained by SDSM, ANN(MATLAB) and R for Max T

		MSE	RMSE	R	R^2	AAD
A1	**SDSM**	6.9656	2.6392	0.9565	0.9149	17.3485
	ANN (MATLAB)	4.0604	2.015	0.9764	0.9534	12.1213
	R	**3.6792**	**1.9181**	**0.9774**	**0.9553**	**12.5025**
A2	**SDSM**	5.6368	2.3742	0.9584	0.9186	13.4924
	ANN (MATLAB)	**4.7397**	**2.1771**	**0.9656**	**0.9324**	**12.9956**
	R	6.2352	2.4970	0.9547	0.9115	15.1770
B2	**SDSM**	5.7865	2.4055	0.9573	0.9164	13.6507
	ANN (MATLAB)	**4.4507**	**2.1097**	**0.9679**	**0.9369**	**12.0626**
	R	5.3377	2.3103	0.9611	0.9237	12.9951

Change anomalies of Annual Maximum Temperature (2020-2098)



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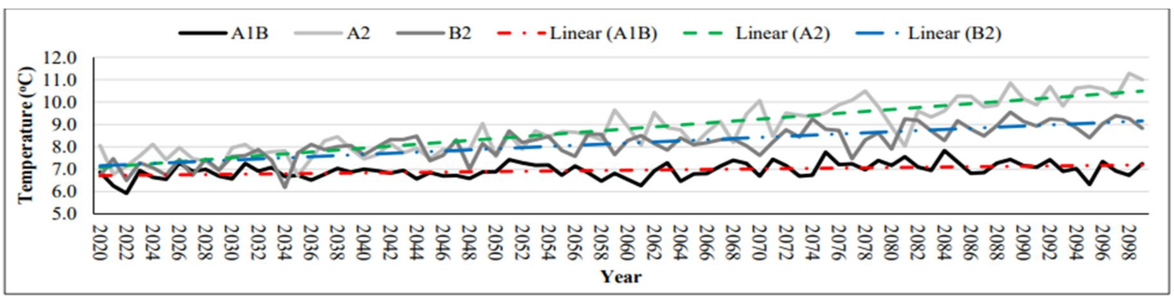
Comparison of results obtained by R, ANN(MATLAB) and SDSM for Min T

		MSE	RMSE	R	R^2	AAD
A1	**SDSM**	3.6958	1.9224	0.9634	0.9281	32.3884
	ANN (MATLAB)	2.7490	1.6580	0.9705	0.9419	5.1046
	R	**2.3456**	**1.5315**	**0.9746**	**0.9499**	**6.2827**
A2	**SDSM**	3.0067	1.7340	0.9681	0.9373	-13.5719
	ANN (MATLAB)	2.7052	1.6447	0.9719	0.9445	-11.3851
	R	**2.3680**	**1.5388**	**0.9750**	**0.9507**	**7.6103**
B2	**SDSM**	3.5115	1.8739	0.9626	0.9265	-10.5148
	ANN (MATLAB)	2.6800	1.6371	0.9721	0.9450	-11.3525
	R	**2.2882**	**1.5127**	**0.9766**	**0.9538**	**0.0995**

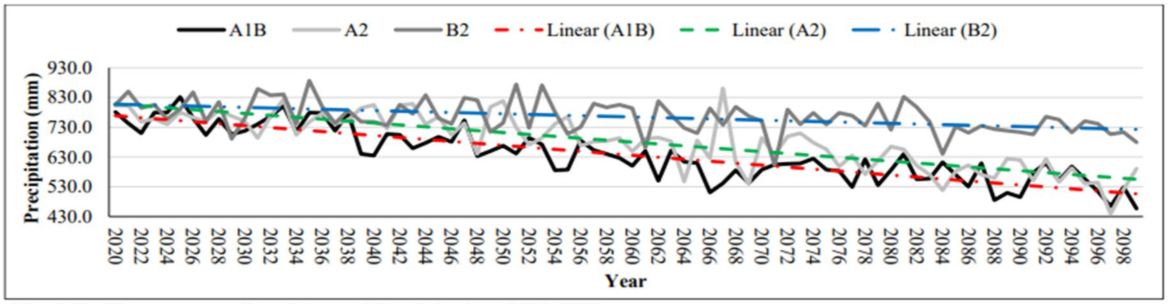
Change anomalies of Annual Minimum Temperature (2020-2098)



Comparison of results obtained by R, ANN(MATLAB) and SDSM for Precipitation

		MSE	RMSE	R	R^2	AAD
A1	**SDSM**	5842.160	76.4340	0.4728	0.2236	103.3660
	ANN (MATLAB)	5886.815	76.7256	0.4650	0.2163	100.1949
	R	**5720.182**	**75.6319**	**0.4992**	**0.2492**	**93.7768**
A2	**SDSM**	6285.715	79.2825	0.2469	0.061	77.8940
	ANN (MATLAB)	6245.055	79.0257	0.2705	0.073	74.6794
	R	**6170.442**	**78.5522**	**0.2898**	**0.0800**	**75.2598**
B2	**SDSM**	6525.474	80.7804	0.1105	0.0122	97.7343
	ANN (MATLAB)	6664.337	81.6354	0.1042	0.0109	92.3993
	R	**5921.584**	**76.9518**	**0.3515**	**0.1235**	**75.4514**

Change anomalies of Annual Precipitation (2020-2098)



The above tables revealed that R-software model gave least values of MSE, RMSE and AAD and highest value of R2 among the three models. SDSM and ANN models also gave good results. The values obtained by SDSM and ANN are in agreement of the actual values, but the values of fitness obtained from R software model are closer to observed values as compared to values obtained from SDSM and ANN models. Thus, while SDSM and ANN models are good enough for prediction, R software model is most efficient in predicting the maximum temperature, minimum temperature and precipitation giving values closer to the observed values than the other two models.

Thus, the R software model is used for future weather prediction

VII. FUTURE PROJECTED CHANGES

The term anomaly means a deviation of future climate condition from a baseline period (1985-2015) climate condition. In this study baseline period climatic condition is analysed based on meteorological station records of the study area. Positive anomaly indicates an increase from the baseline period value, while a negative anomaly indicates decrease from the baseline period value. The anomaly of monthly precipitation is calculated as the difference from future monthly average precipitation to the baseline period (1985-2015) monthly average precipitation values (Figs.), The temperature is also calculated in the same way precipitation is calculated.

VIII. CONCLUSIONS

In this study SDSM, ANN & R modelling was carried out to study the climate change over the Srinagar area for a period of (2020-2098). SDSM, ANN & R models were developed & tested for their performance on the basis of results obtained from these models. The simulated values were compared with the original values to establish the precision of these models.

The variation between the simulated and observed values of maximum, minimum and precipitation for A1B, A2 and B2 scenarios is represented by a set of graphs. The comparison between the models has been done on the basis of MSE, RMSE, AAD and R2 for their relative assessment

The following conclusions were made:

1) The results obtained from SDSM, ANN & R showed good agreement between the observed data and simulated values with a high coefficient of determination.
2) The results obtained by the three models are however close to each other as well as to original values. • R modelling gave better results than SDSM and ANN models, revealing that the model was superior over other two models.
3) The modelling results showed a first-rate agreement between the experimental data and predicted values for temperature series with high coefficient of determination R 2 values varying from (0.93-0.95) for different models. In case of precipitation R2 values varied from (0.08- 0.249) for different models. The low values of coefficient of determination in precipitation time series are due to lot of uncertainty in occurrence of precipitation which could not be defined by the selected models. The R modelling result showed best agreement between the observed data and simulated values with a high coefficient of determination.
4) The results established that the developed models were able to analyse the given data with very good performance, fewer parameters, and shorter calculation time. On comparing the simulated results with the observed data of the previous years (1985-2015) it is ascertained that:

5) An overall increasing pattern (9.81%) for A1B scenario, (15.24%) for A2 scenario & (10.32%) for B2 scenario in the monthly maximum temperature is noted particularly in January (98.50%) for A1B scenario, January (71.8%) for A2 scenario & January (63.5%) for B2 scenario, while a consistently minimum change is noted in the month of May (0.3%).
6) An overall increasing pattern (2.18%) for A1B scenario, (29.15%) for A2 scenario & (19.90%) for B2 scenario in the monthly minimum temperature is noted particularly in Feb (182.50%) for A1B scenario, Feb (888.75%) for A2 scenario & Feb (973.75%) for B2 scenario, while a consistently minimum change is noted in the month of July (1.0%) for A1B scenario, Sep (13.43%) for A2 scenario & Sep (4.45%) for B2 scenario.
7) An overall decreasing pattern (22.60%) for A1B scenario, (17.23%) for A2 scenario & (7.11%) for B2 scenario in the monthly precipitation is noted particularly in Oct (57.80%) for A1B scenario, Oct (45.8%) for A2 scenario & Nov (63.9%) for B2 scenario, while a consistently minimum change is noted in the month of Jan (5.4%) for A1B scenario, Jan (2.9%) for A2 scenario & Jan (1.6%) for B2 scenario

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