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Assessment of Climate Change Impact on Reservoir Inflow

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Abstract: Evaluating the effects of climate change is crucial in regions grappling with water scarcity. The Ujjani dam, a significant structure in Maharashtra, India, erected on the Bhima river in 1980, serves as a vital water source for the agricultural lands downstream in Solapur and Pune districts. Assessing climate change's impact involves analysing data from General Circulation Models (GCMs), which project climate parameters under various emission scenarios but often at a broader scale. Since hydrological models necessitate finer-scale climate data, a downscaling technique is employed to derive localized variables from GCM outputs. This study employs Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) techniques for downscaling. By utilizing projected temperature and rainfall data, three distinct models are developed to predict reservoir inflow: multiple linear regression, artificial neural network, and wavelet neural network. The findings indicate significant alterations in rainfall distribution patterns, with a decline during the monsoon season and an increase post-monsoon.

I. INTRODUCTION

During the period spanning from 1983 to 2012, it appears that the Northern Hemisphere experienced its warmest 30-year span in the past 1400 years. Data on combined land and ocean surface temperatures globally indicate a warming trend of 0.70°C from 1900 to 2000. The Intergovernmental Panel on Climate Change (IPCC) predicts future water scarcity due to alterations in precipitation patterns, seasonal distribution, and rising sea levels [1]. Numerous studies have observed changes in rainfall, streamflow quantity, and patterns attributed to rising temperatures [2].

General Circulation Models (GCMs) serve as mathematical representations of atmospheric circulation, simulating global climate variables over time considering factors such as greenhouse gas emissions. GCMs project future climate parameters under various emission scenarios, such as Representative Concentration Pathway (RCP) 6.0, which entails a radiative forcing of 6.0 W/m2 by 2100 relative to 1750 [3].

GCMs, however, simulate climate variables at a coarse scale, necessitating downscaling techniques to bridge the gap between large-scale GCM outputs and local-scale hydro-meteorological variables like rainfall and temperature [4]. Downscaling can be achieved through dynamic methods using high-resolution Regional Climate Models (RCMs) or statistical approaches, such as regression-based downscaling [5,6].

In this study, regression-based downscaling employing multiple linear regression and Artificial Neural Network soft computing techniques are utilized to simulate climate variables, specifically temperature and precipitation. These downscaled projections are then used to predict reservoir inflow using three models: multiple linear regression, Artificial Neural Network, and Wavelet Neural Network.

II. STUDY AREA

The Bhima River, a significant tributary of the Krishna River in India, originates from the sacred Jyotirlinga known as Bhima Shankar in Ambegaon Taluka of Pune district, Maharashtra. Spanning a length of 300 km, it flows southeast, covering a watershed area of 14,856 km^2 within the Maharashtra state [7]. The Ujjani dam, constructed across the Bhima River in 1980 in Solapur district, Maharashtra, stands as an earth cum gravity dam. With a height of approximately 56.40 m above the lowest foundation and a length of 2540 m, it boasts a gross storage capacity of 3320 km^3 and a reservoir surface area of 290 km^2, with an effective storage capacity of 1520 km^3. This multipurpose dam serves irrigation, water supply, and hydroelectric power generation purposes, featuring a designed spillway capacity of around 18010 m^3/s. The basin area upstream of the Ujjani dam, known as the Upper Bhima basin, occupies coordinates from 17.18 N to 19.24 N latitude and 73.20 E to 76.15 E longitude, experiencing rainfall variations ranging from 415 mm to 4240 mm. The Ujjani dam plays a pivotal role in providing a wide array of economic, environmental, and social benefits to the region.

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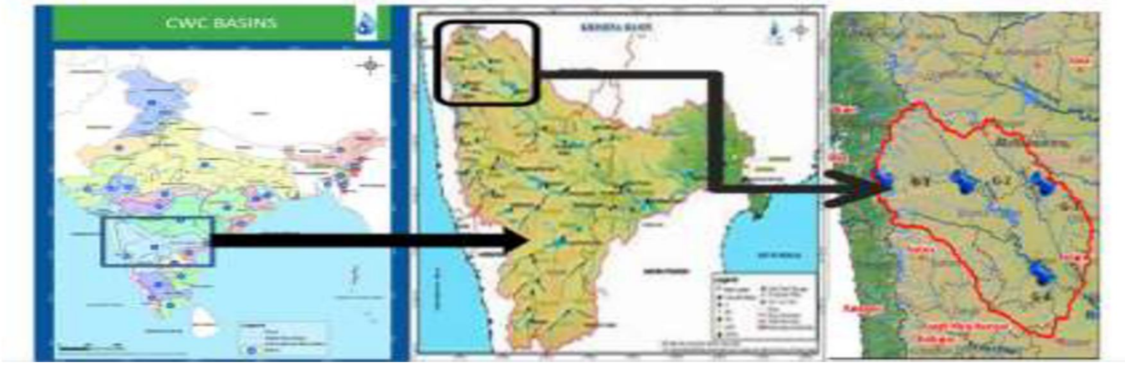

Figure 1. Basin map of India, Krishna Basin, and Upper Bhima basin
(Source: India WRIS, http:// www.indiawris.gov.in)

III. DATA COLLECTION

Three distinct types of data have been utilized to conduct the impact study.

A. Observed Temperature and Precipitation Data

The temperature and rainfall data, which are the variables being predicted (known as predictands), have been gathered from the Indian Meteorology Department in Pune. This data is provided on a 10 x 10 grid. Specifically, information from four grid stations, as detailed in Table 1, situated within the Upper Bhima basin, has been obtained. The collected data spans from January 1969 to December 2015.

Table1. Station Points for Upper Bhima basin

Station	Latitude-Longitude	Place	State
1	17.25N -75.25E	Tembhurni	Maharashtra
2	18.25N -73.25E	Mulshi	Maharashtra
3	18.25N -74.25E	Supa	Maharashtra
4	18.25N -75.25E	Kashti Ghod	Maharashtra

B. National Centre for Environmental Protection (NCEP) Data

The NCEP data, serving as predictors for training, consists of observed atmospheric variables. This data, obtained from the website https://sdsm.org.uk, has a spatial resolution of approximately 2.5^0 x 2.5^0. It is downloaded on a daily basis and then converted into average monthly values. From the predictors listed in Table 2, those that exhibit strong correlations with the predictand are selected and utilized. Given that NCEP data is available at a resolution of 2.5^0 x 2.5^0 and GCM data at 2^0 x 2.5^0, it becomes necessary to interpolate both datasets to match the 1^0 x 1^0 grid size of IMD data. This interpolation process can be carried out using software tools like Panoply or MATLAB.

Table 2. Predictor variables for downscaling Precipitation

Predictor Variables	Notation	Units
Eastward wind@500hpa	p5_u	metres/second
Eastward wind@850hpa	p8_u	metres/second
Northward wind@500hpa	p5_v	metres/second
Northward wind@850hpa	p8_v	metres/second
Geopotential height @500hpa	p500	metres
Geopotential height @850hpa	p850	metres
Air pressure at sea level	mslp	Pascal
Near surface relative humidity	hurr	%
Near surface specific humidity	Hurs	Kilogram of vapour /kilogram of air
		Kelvin
Surface air temperature @ 2m	Temp	Mm
Precipitation	prec	

C. Global Climate Model Data

The GCM (General Circulation Model) data, used as predictors for forecasting, is sourced from the GFDL-CM3 model and downloaded from the website https://esgf-node.llnl.gov on a monthly basis. This data corresponds to the RCP 6.0 scenario. It is provided in .netcdf format, which can be converted into a readable form using software tools like ArcGIS, MATLAB, or Panoply. These software programs facilitate the conversion process, enabling users to interpret and analyze the GCM data effectively.

D. Inflow Data

The monthly inflow data for the Ujjani reservoir at the Daund station has been gathered from the Water Resources Department, Government of Maharashtra, covering the period from 1981 to 2015.
To facilitate analysis and comparison across different datasets, standardization of the data has been performed. Standardization involves rescaling the data to ensure that it has a mean value of zero and a standard deviation of one. This process effectively converts disparate datasets into a common format, ensuring consistency and removing biases. Standardization is a conventional method employed to normalize GCM output datasets, thereby enabling accurate comparison and analysis [8].

IV. METHODOLOGY

The methodology for conducting downscaling and predicting inflow is depicted in Figure 2.

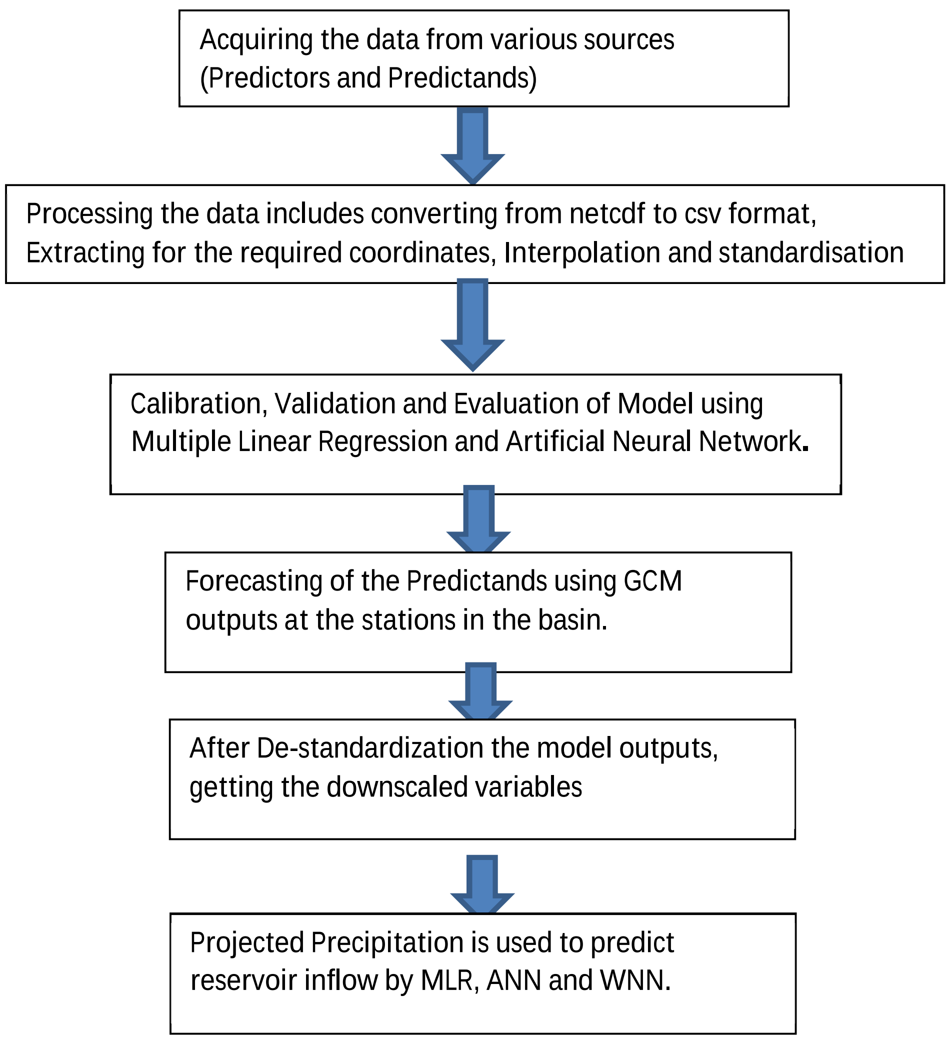

Fig 2. Flow Chart of the present methodology

A. Statistical Downscaling of Temperature and Rainfall

In the study, statistical downscaling has been conducted using two techniques: Multiple Linear Regression (MLR) and Artificial Neural Network (ANN). This downscaling is performed specifically for the Upper Bhima basin, considering data from four stations within the basin.

The analysis is carried out under the RCP 6.0 scenario, which represents the Representative Concentration Pathway. In this scenario, the radiative forcing is projected to be 6.0 W/m2 by the year 2100 relative to the reference year of 1750. This scenario serves as a framework for estimating future greenhouse gas concentrations and their impact on climate variables.

By employing MLR and ANN techniques and considering the RCP 6.0 scenario, the study aims to provide insights into the potential future climate patterns within the Upper Bhima basin.

B. Development of Rainfall-Runoff Model

A rainfall-runoff model has been developed utilizing three different techniques: Multiple Linear Regression (MLR), Artificial Neural Network (ANN), and Wavelet Neural Network (WNN). The inputs to the model consist of temperature and rainfall data within the Upper Bhima basin.

To train and test the model, historical data of temperature, rainfall, and runoff at gauging stations are utilized. The historical data are divided into training and testing datasets. The model is trained using the training dataset, which encompasses a certain time period, and then tested using the testing dataset, which covers a separate time period. This approach ensures that the model is robust and capable of generalizing beyond the training data.

The performance of the model is evaluated using the mean square error (MSE) criteria. MSE measures the average squared difference between the observed and predicted values. A lower MSE indicates better performance and accuracy of the model in predicting runoff based on the given inputs of temperature and rainfall.

By employing MLR, ANN, and WNN techniques and evaluating the model's performance using MSE, researchers can assess the effectiveness and suitability of each modeling approach for predicting runoff in the Upper Bhima basin.

C. Multiple Linear Regression (MLR)

In Multiple Linear Regression (MLR), the dependent variable (predictand) is singular, while there are multiple independent variables (predictors). The MLR model is constructed using the least squares method, where the basic premise is to establish a linear relationship between the dependent and independent variables.

The process involves fitting a linear equation to the observed data points in such a way that the sum of the squares of the vertical distances between the observed and predicted values is minimized. This equation represents the relationship between the dependent variable and the independent variables, allowing for the prediction of the dependent variable based on the values of the independent variables. Once the MLR model is developed using historical data, it can be utilized for forecasting the predictand value corresponding to the predictor values obtained from General Circulation Model (GCM) outputs. This forecasting enables researchers to estimate future values of the predictand based on the projected values of the predictors provided by the GCM outputs.

D. Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a computational model inspired by the functioning of the human brain and neural biology [9]. It consists of interconnected nodes organized in layers, where each node is linked to others in adjacent layers. The typical structure of an ANN, as illustrated in Figure 3, includes an input layer, one or more hidden layers, and an output layer [10].

In this architecture, the input layer receives the input data, while the output layer provides the final result or prediction. The hidden layers, located between the input and output layers, perform complex computations by processing the information received from the input layer and passing it to the output layer. Nodes within each layer are interconnected through links, and each link is associated with a weight that determines the strength of the connection between nodes. During training, the ANN learns to adjust these weights and bias values to minimize the error between predicted and actual outputs. The backpropagation algorithm, rediscovered by Rumelhart in 1986, is a key component of training ANNs. It involves propagating the error backward through the network, adjusting the connection weights and biases in a way that reduces the error iteratively. This process enables the ANN to learn from the data and improve its predictive capabilities over time. By leveraging the ANN's ability to capture complex relationships within data, researchers can develop models capable of making accurate predictions and generalizing from the training data to unseen data [11].

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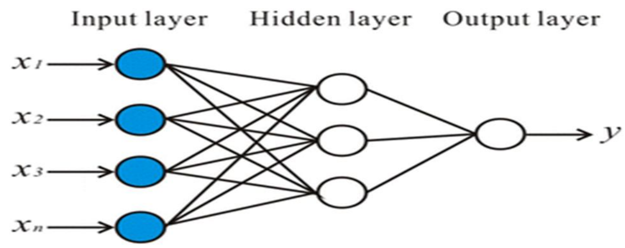

Fig 3. Feed forward back propagation neural network

E. Wavelet Neural Network (WNN)

The Wavelet Neural Network (WNN) represents a fusion of wavelet transformation and artificial neural network methodologies. Unlike Fourier transform, which utilizes sinusoidal functions, wavelet transformation utilizes wavelets, which are small, localized oscillations [12].

Wavelet transformation offers advantages over Fourier transform, particularly in its ability to analyze both stationary and non-stationary data, providing information about frequency and time domains with high resolution. This is in contrast to Fourier transform, which is primarily suited for stationary data decomposition.

A wavelet function, denoted as ψ(t), satisfies the integral equation:

$\int_{(-\infty)}^{\infty} \psi(t)dt = 0$ (Equation 1)

Several families of wavelets exist, including the Haar wavelet (the oldest and simplest), Daubechies wavelet, Coiflet wavelet, and others [13,14]. In the WNN model, the discrete wavelet transformation is applied to the input data (rainfall and temperature), decomposing it into a number of sub-signals in the form of approximations and details. These discretized data are then utilized as inputs to the artificial neural network, as depicted in Figure 4. The output data of the WNN model is the runoff.

To train the WNN model, historical data of monthly average discharge from inflow at the Daund station spanning the years 1981 to 2015 are utilized. The first 25 years of data are used for training, while the remaining 10 years are used for testing the model's performance. The performance of the WNN model is evaluated using the mean square error (MSE) criteria, which measures the average squared difference between the observed and predicted values of the discharge. By applying the WNN methodology and evaluating its results, researchers can assess its effectiveness in predicting runoff based on the input data of rainfall and temperature, ultimately contributing to improved understanding and forecasting of hydrological processes.

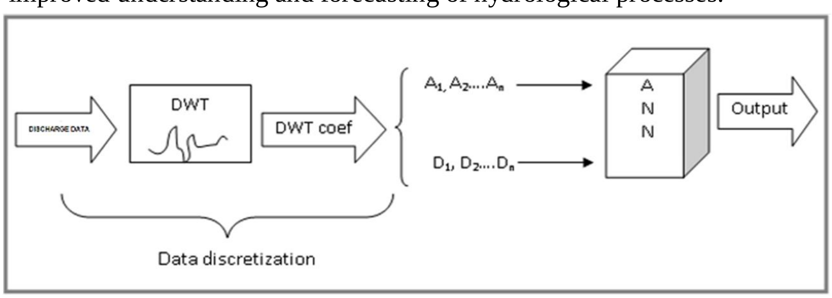

Fig.4 Wavelet Neural Network Structure

V. RESULTS AND DISCUSSION

The evaluation results indicate that the Artificial Neural Network (ANN) based downscaling technique outperforms Multiple Linear Regression (MLR), as evidenced by a higher coefficient of determination (R^2) value. This superior performance can be attributed to ANN's capability to capture nonlinear relationships between predictors and predictands. The coefficient of determination (R^2) values presented in Table 3 demonstrate a strong correlation between observed and simulated values. According to the interpretation guidelines, R^2 values exceeding 0.67 indicate a strong correlation, values between 0.36 to 0.67 suggest a moderate correlation, and values below 0.35 represent a weak correlation [15]. Due to its better performance, the ANN technique has been selected for predicting temperature and rainfall using the GFDL-CM3 (GCM) model in the Upper Bhima basin up to the year 2100. Forecasts are made for three different time frames: 2020-2029, 2050-2059, and 2080-2089, across all four grids.

Table 3. Comparison of R^2 Value

MLR	Climate Parameter	CALIBRATION				VALIDATION			
		Station 1	Station 2	Station 3	Station 4	Station 1	Station 2	Station 3	Station 4
	Tmax	0.932	0.948	0.947	0.956	0.938	0.929	0.947	0.938
	Tmin	0.953	0.973	0.946	0.958	0.941	0.962	0.969	0.937
	Rainfall	0.894	0.5	0.5	0.51	0.887	0.09	0.53	0.13
ANN		CALIBRATION				VALIDATION			
		Station 1	Station 2	Station 3	Station 4	Station 1	Station 2	Station 3	Station 4
	Tmax	0.977	0.982	0.977	0.982	0.957	0.946	0.938	0.946
	Tmin	0.981	0.989	0.979	0.985	0.938	0.967	0.966	0.936
	Rainfall	0.954	0.849	0.815	0.888	0.878	0.5	0.67	0.606

These forecasted temperature and precipitation values are visually represented in graphical form from Figure 5 to Figure 8, providing a clear depiction of the projected climate trends in the Upper Bhima basin over the specified time periods.

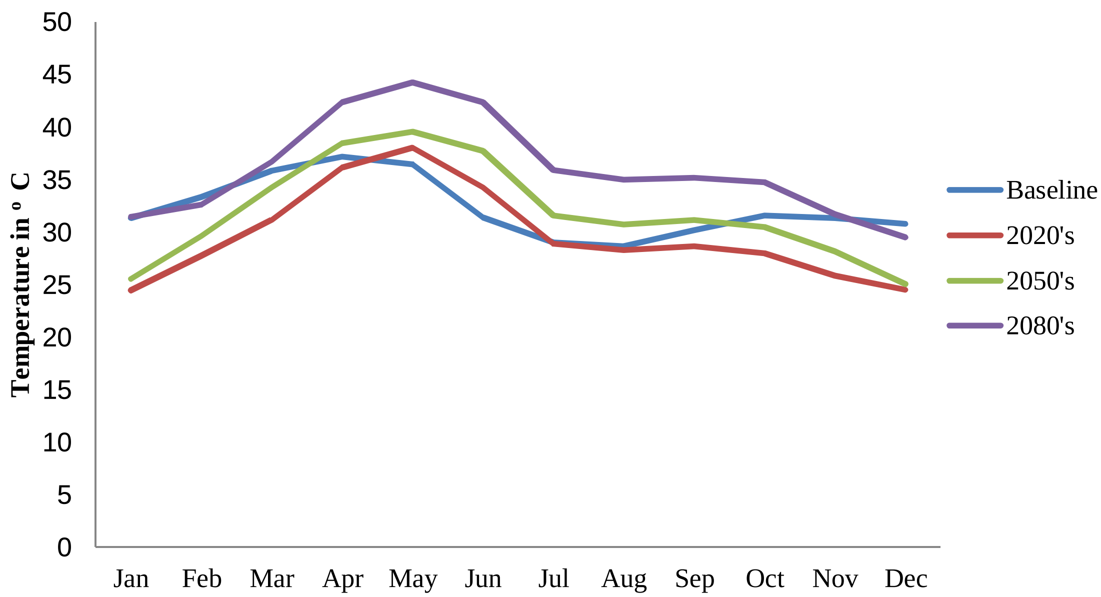

Fig 5. Max. Temperature at station 4 by MLR

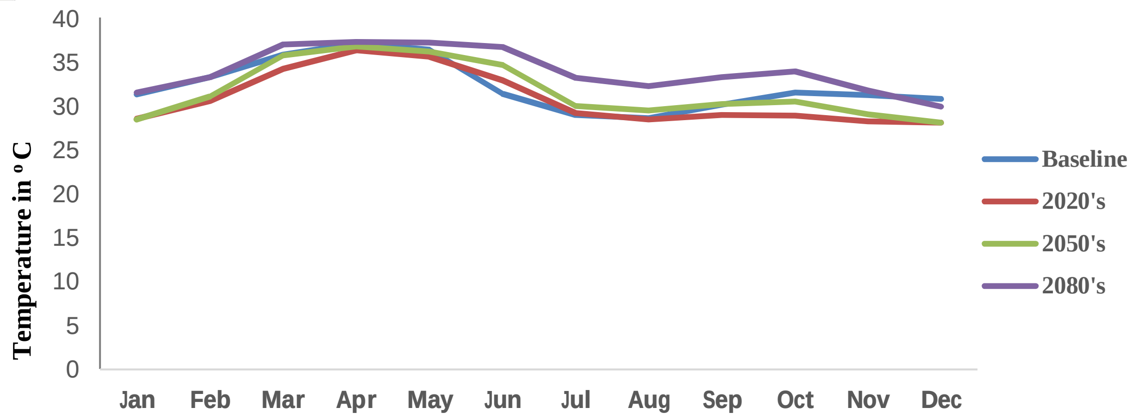

Fig 6. Max. Temperature at station 4 by ANN

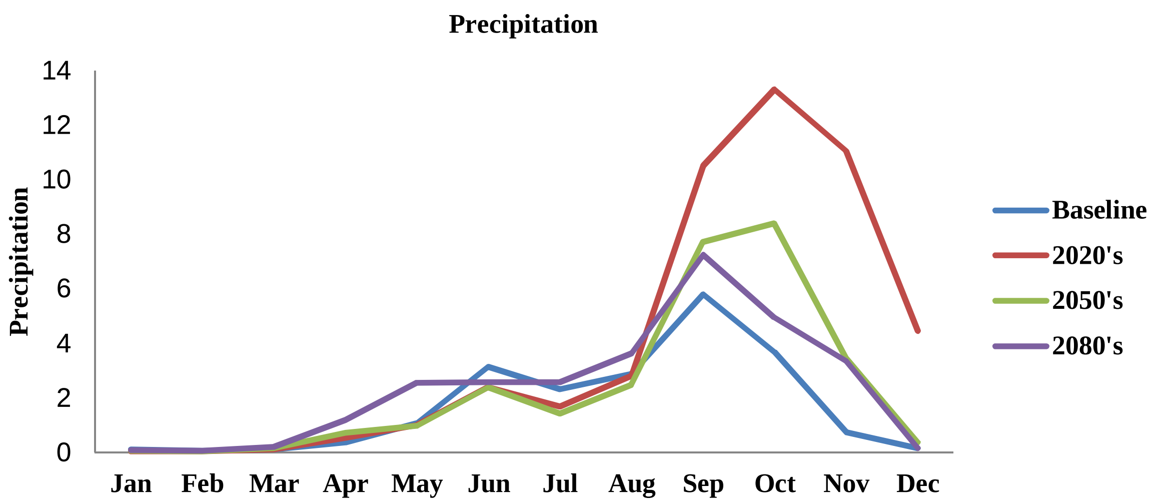

Fig 7. Precipitation at station 4 by MLR

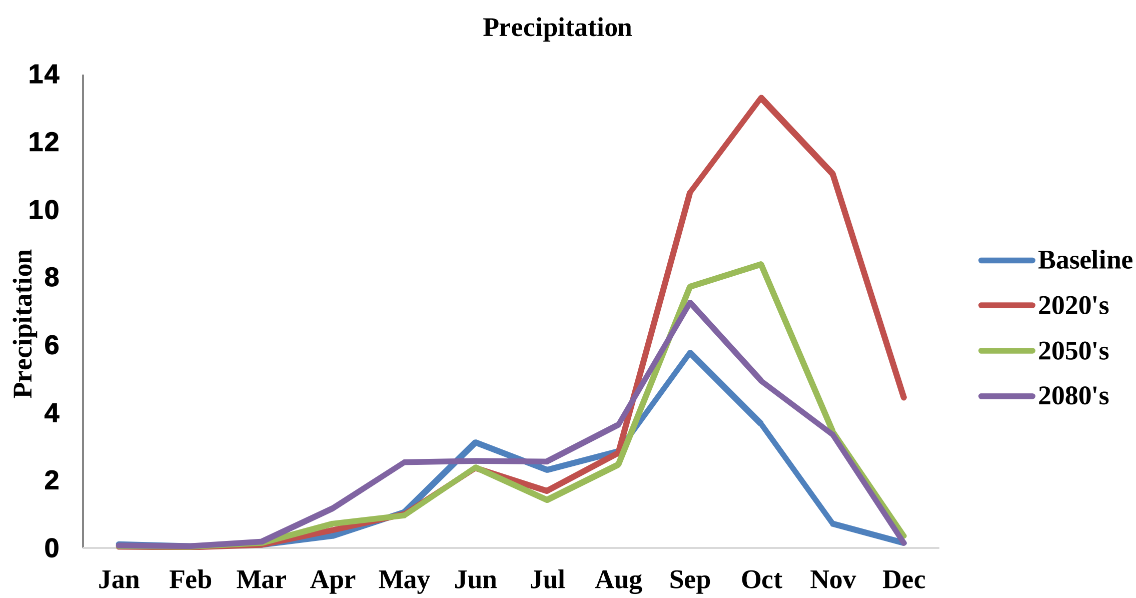

Fig 8. Precipitation at station 4 by ANN

The results reveal a notable increase in maximum temperature during the monsoon season. In Figures 5 and 6, it is evident that during the month of July, the average maximum temperature rises significantly, from 28°C to 33°C. This represents an increase of approximately 5°C compared to the baseline period. Moreover, by the 2080s time period, there is a substantial 5°C rise in temperature compared to the baseline period.
Figures 7 and 8 indicate a projected increase in precipitation during the months of September to December. However, during the July, August months, precipitation levels remain relatively similar to those of the baseline period.

A. Results of Rainfall -Runoff Model

Results are obtained from the calibration of the three models namely MLR, ANN and WNN. The projected rainfall and temperature are used as input to the calibrated and tested MLR model. The future probable values of inflow are predicted by simulation of the model. From the simulated results, the mean square value is obtained. Similarly, the inflows are also predicted by using optimal ANN model using the inputs as the projected temperature and rainfall from 2006-2100. In WNN model, discrete wavelet transformation is used with various types of wavelets such as Daubechies wavelet of order 4 (DB4), Coiflet-2 and Symhlet-4 wavelet selected as mother wavelet considering the similarity with the time series signals. The effects of various decomposition levels on model efficiency have in the form of approximations are also investigated to optimize the result. The optimum result from the discrete wavelet transformation and detailed sub signals at different levels are presented in figure 9.

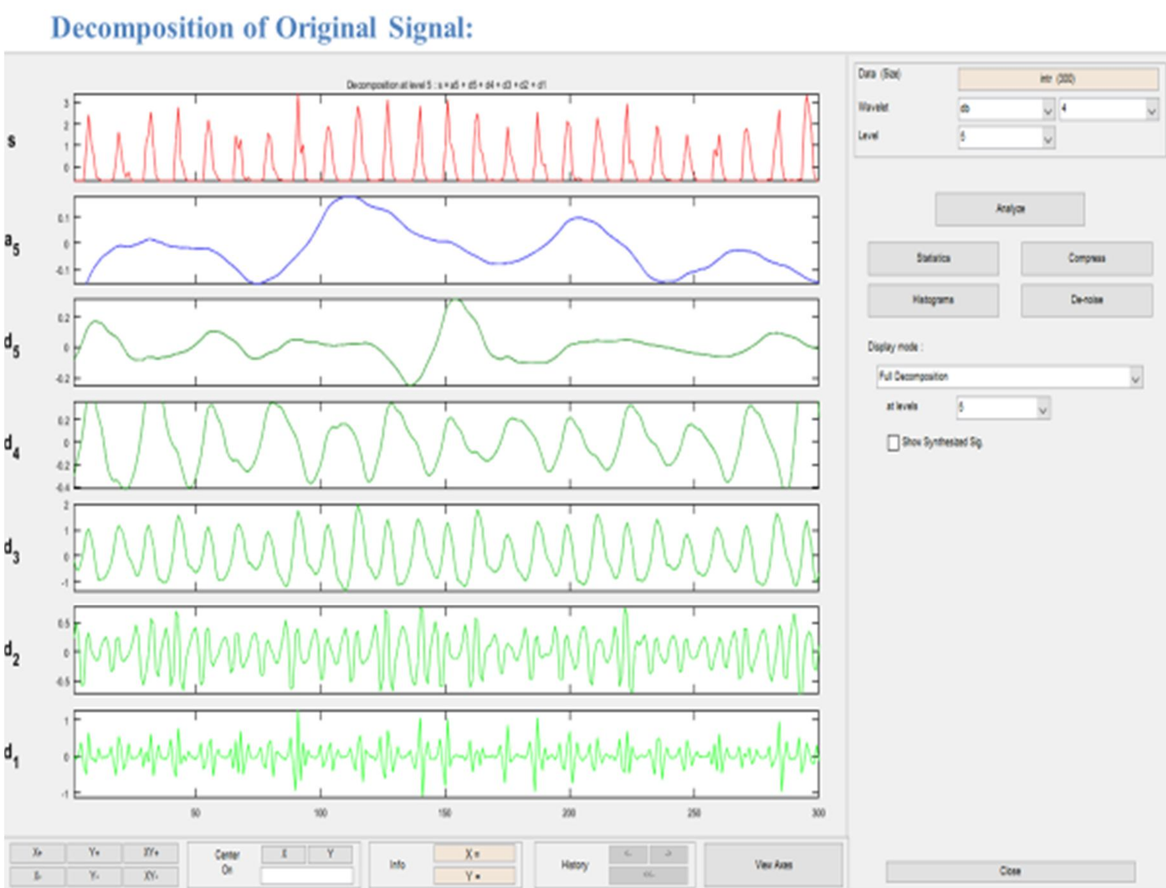

Fig.9. Decomposition of Original Signal using DB-4 Wavelet

The inflow to the reservoir using the three models is compared with the observed values for the period 2006-2015. It is seen from figure 10 that MLR model is giving comparatively closure results with the observed values and mean square error by the MLR model is shown in Table 4. lesser as compared to ANN and WNN model. Therefore, MLR model has been used for the prediction of inflow from 2006 to 2100.

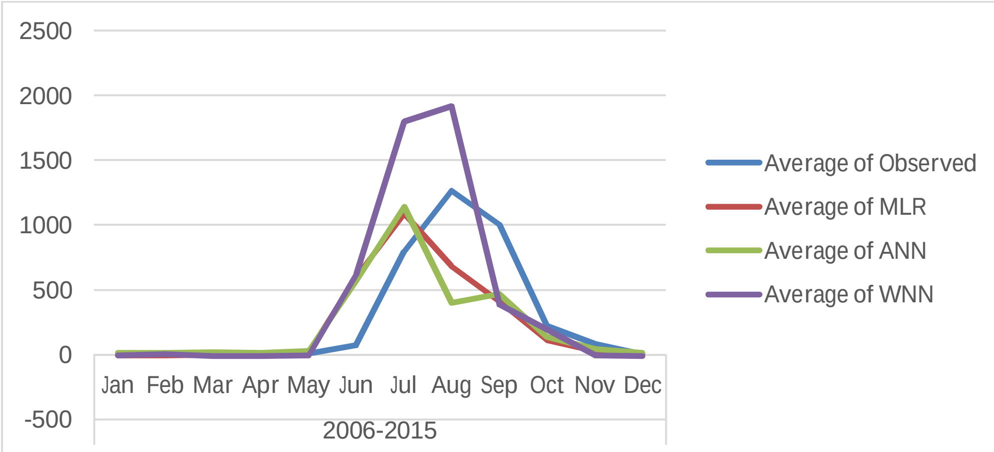

Fig. 10 Comparison of Observed Inflow by MLR, ANN and WNN

Table 4. Comparison of Mean Square Error

Mean Square Error (MSE) Value for Inflow		
MLR	ANN	WNN
0.34	0.419	0.482

The projected rainfall and temperature are used for the prediction of inflow to the reservoir. The results are presented in graphical form in figure 11 for the different periods of 2020-29, 2050-59 and 2080-89.

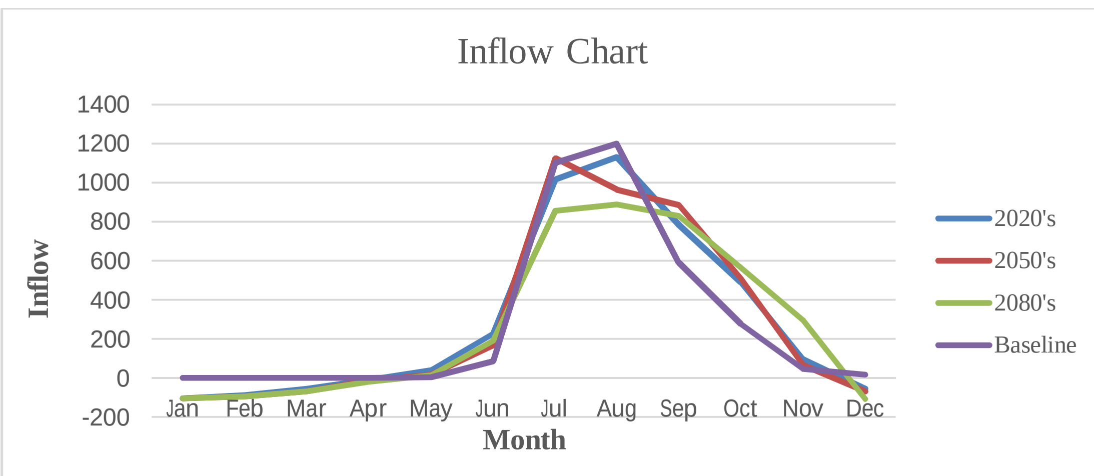

Fig. 11 Probable future Inflow

VI. CONCLUSION

The present paper investigated the applicability of Multiple Linear Regression and Artificial Neural Network. It is observed that there is a change in temperature, precipitation in the basin in future periods. Even though the uncertainties associated with GCM and ANN models are not considered in the modelling, the model results showed changes in rainfall distribution pattern. Accordingly, it has to consider in reservoir operation system. Overall amount of temperature and hence precipitation has been found increased in future periods. This projected climate parameters can be used to study its influence on runoff and inflow to the reservoir. Inflow to the reservoir has been simulated using MLR, ANN and WNN models for three different time periods. Increase in runoff has been observed in September to December, this is because of increase in rainfall have direct impact on runoff. MLR showed better performance according to MSE criteria. These observed changes in inflow pattern have to be considered in reservoir operation schedule.

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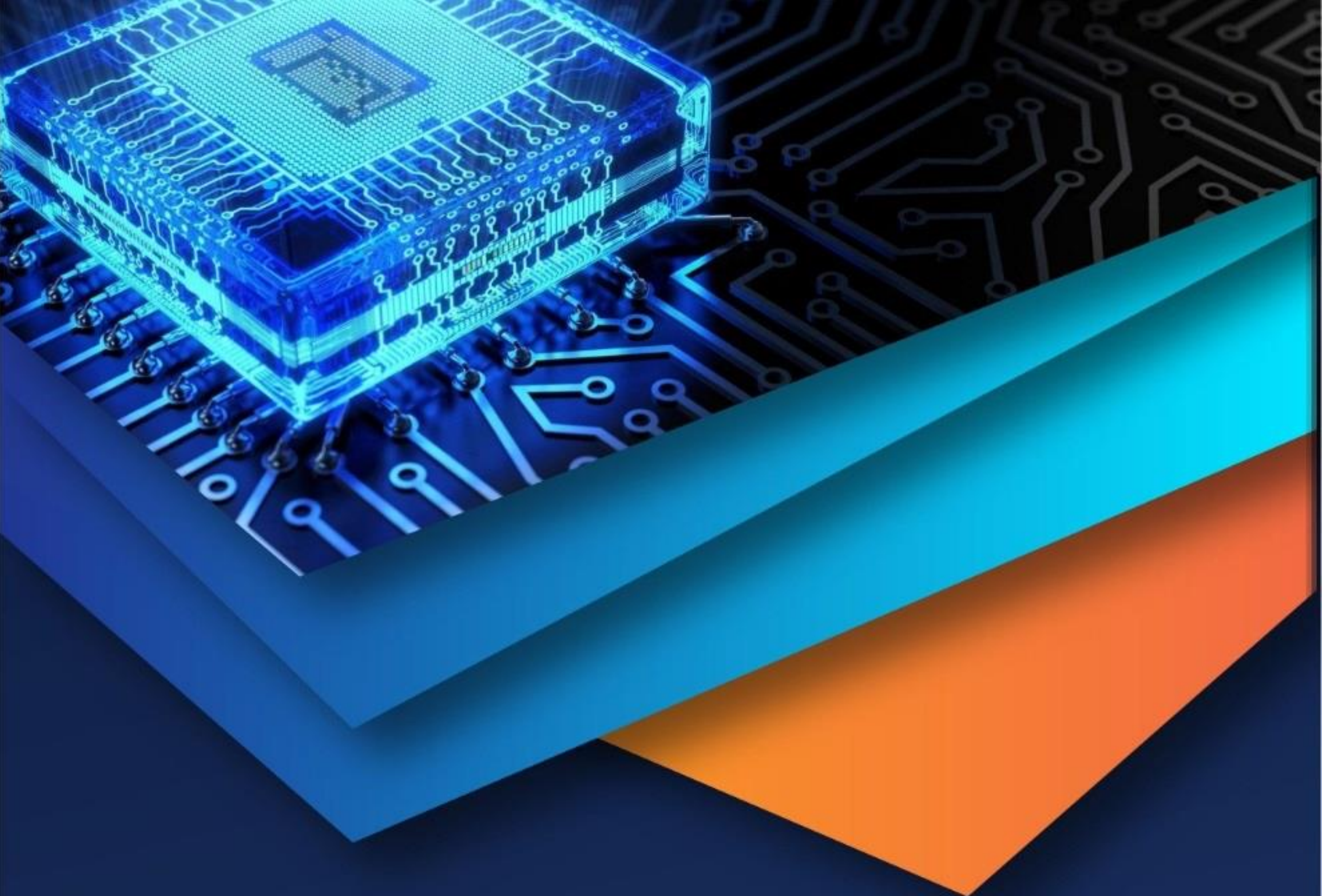

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