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Statistical Downscaling of Temperature for Malaprabha Basin

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***Abstract*— A change in the statistical distribution of weather patterns which lasts for a prolonged time is called climate change. Researchers vigorously work to figure out past and future climate by using theoretical and observations models. Based on the physical sciences GCMs, are generally used in theoretical approaches to match past climate data, projection of future data, and to associate with the causes and consequences in climate change. As Global Climate Models are only accessible at coarse resolution the downscaling technique has been acknowledged as an essential component for the assessment of climate change impacts. The study aims at the statistical downscaling of temperature for Malaprabha basin using Artificial Neural Network (ANN) methodology. The data from CanCM4 GCM temperature is downscaled to local scale on monthly time series. The model is trained for the time period of 1971-1995 and validated for the period of 1996-2005. The future projections of surface temperature is downscaled for the time period of 2006-2035 where the predictand temperature shows an increasing trend for the stations considered for the study area.**

Index Terms*— *Artificial Neutral Network (ANN), Climate change, Downscaling, Global Climate Model (GCM).

I. INTRODUCTION

Climate change may refer to a change in average weather conditions, or in the time variation of weather around longer-term average conditions (i.e., more or fewer extreme weather events). Climate change is caused by factors such as biotic processes, variations in solar radiation received by Earth, plate tectonics, and volcanic eruptions. Certain human activities have also been identified as significant causes of recent climate change, often referred to as global warming. The rise in temperature has played an vital role in the variations of climate therefore, it is very essential to analyze and access the past and future temperature and its variability at various time series both at global and regional/local scales to study the impacts of climate change. General circulation model (GCM) is a computational tool which is available at coarser resolution to access the climate change impacts, but to analyze the impacts at regional/local scales the technique termed as downscaling is introduced *(Villa et al., 2010)*. The main objective of this study was to statistically downscale the temperature for Malaprabha basin and the most probable predictors are selected by using Pearson`s correlation coefficient. Artificial Neural Network (ANN) methodology is utilized to downscale CanCM4 GCM temperature to local scale on monthly time series and provide future projection for the time period 2006-2035 for the considered stations.

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II. STUDY AREA AND DATA EXTRACTION

A. Study Area

Malprabha basin lies between 15° 45' N and 16° 25' N and 74° 00'E and 75° 55'E at the right bank tributary of river Krishna. The flow of stream begins from the Chorla Ghats, part of the Western Ghats, Belagavi Region, Karnataka at 792 m and joins Kapila Sangam, Bijapur around 488 m. The total area of catchment of Malaprabha basin is 11,549 km2. SWAT is used to delineate the basin for the study. (Fig.1).

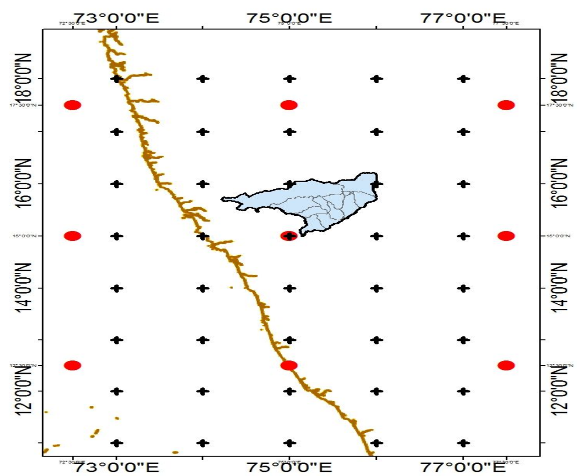

Fig.1: Delineation of Malaprabha Basin with GCM gird points

B. Data Extraction

GCM data is extracted from Canadian Centre for Climate Modelling and Analysis Canada (CCCM). CanCM4 the Historical data (1961-2005) and the Future data (2006-2035). The set of data are available in NetCDF format which is examined in MATLAB. Station data was used for the calibration and validation of the downscaling model with the GCM data. To carry out the statistical downscaling technique maximum temperature for the considered stations was taken from the Indian Meteorological Department (IMD) , at a period of 37 years from 1969 to 2005 . Thus, 2 years (1969-70) is taken as a buffer and subsequently IMD data of two station points were taken from 1971-2005 and was converted from daily data to monthly mean data.

III. Methodology

The flow of this task begins by deciding the most probable predictor variables for the statistical downscaling for every station for monthly time series. Further the future scenarios are downscaled utilizing these selected predictors. ANN method has been utilized for this study to downscale the predictand temperature for each station S1 and S2. Global Climate Model (GCM) is utilized for analyzing the impacts of variations around the globe and climate data at greater resolution which doesn't help in analyzing the impacts at finer resolution. Hence to resolve this difficulty, the technique called downscaling is introduced.

A. Selection Of Predictors

The choice of proper predictors are an essential part in this research. Selection of variables differ from area to area as the topography and the predictand varies. Several sort of parameters perhaps utilized as predictor for the study only if predictand and predictors are correlated. Generally, the following criteria is considered for the selection of predictors:

(1) reliably stimulated by the GCM,

(2) strong correlation with the predictand and

(3) taking into account of past studies

Arrangements of CanCM4 model climatic variables considered for the study is given in Table 1 below:

Table-1: CanCM4 model variables

Variable names	Short names	Units
Surface upward latent heat flux	Hfls	W/m^2
Surface upward sensible heat flux	Hfss	W/m^2
Precipitation	pr	$Kg/m^2/s$
Sea level pressure	Psl	Pa
Air temperature	Ta	K
Surface temperature	Ts	K
Eastward wind	Va	m/s
Northward wind	Ua	m/s
Geo-potential height	Zg	m

B. Pearson`s correlation coefficient

Pearson's coefficient of relationship was discovered by Bravais in 1846, however Karl Pearson was the first to depict, in 1896, the standard strategy for its figuring and show it to be the best one possible. A vital investigation in Pearson's 1896 commitment is the typicality of the variables examined, which could be genuine just for quantitative variables. This coefficient is degree of element that give consecutive link within two such variables. It is dimensionless and ranges from -1 to +1.

$$r = \sum_{i=1}^{n}(xi-x)(yi-y) / \sqrt{\sum_{i=1}^{n}(xi-x)2}.\sqrt{\sum_{i=1}^{n}(yi-y)2} \qquad \{1\}$$

where x= arithmetic mean of x(i)
y= arithmetic mean of y(i)
n= number of samples

C. Artificial Neural Network (ANN)

The development of the ANN model is inspired by the central neural system of humans/animals brain where the signals are transferred to the brain by dendrite. The toolbox of this model is used for the study to downscale the GCM data into regional scale where the inputs are transmitted to the main neural network and the output is generated. The working of the model is mainly based on the machine training and learning of algorithms. The number of input variables are trained and validated in model by multiplying the weights to the input data and the activation functions produces the output as shown in the Fig.2.

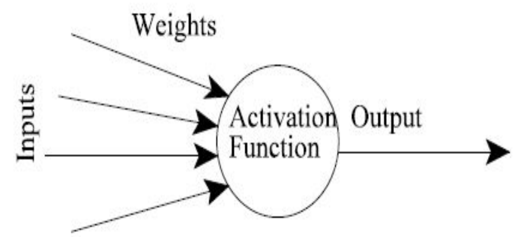

Fig.2: Artificial Neural Network Architecture (Source: Carlos Gershenson)

The weights used for the process of model training keeps on changing . Greater the weight of a neuron, more accurate the data will be produced. Weights can comparatively be negative, so we can say that the sign is controlled by the negative weight. By changing the weights on neurons or input will improve the training period of the model. Regardless, when we have an ANN of hundreds or a huge number of neurons, it would be uncommonly and uneasy to adjust the weights according to the requirement. Therefore, we use the calculations which can change the weights of the ANN to analyze the downscaling technique. This strategy for changing the weights is called machine learning or training.

D. Model Calibration and Validation

The model has been trained and validated for every point selected. Historical GCM information extracted is considered as a input variable for training the model utilizing MATLAB and, the IMD station data is used as target variable using ANN toolbox.

E. Evaluation Criteria for Downscaling Model

Assessment of the performance of the downscaled model by the use of potential predictors is an essential part of the study to determine the efficiency of the model used. Therefore, Nash Sutcliffe Coefficient (NSE) and Rot mean square error (RMSE) methods are used for the evaluation process.

IV. RESULTS AND DISCUSSION

The most probable predictors are screened using Pearson`s correlation coefficient where R> 0.087 for each station and the predictors are normalized using maxima and minima function. The normalized predictor variables are used for the statistical downscaling of temperature by using ANN toolbox. The evaluation of downscale model is determined by using NSE and RMSE. The values of NSE and RMSE ranges from -1 to +1, the most positive values provides the most efficient performance of the model ANN. The potential predictors screened by Pearson`s coefficient method is shown in Table 2 and the evaluation of model for station S1 and S2 is represented in Table 3. The future GCM data is downloaded from CanCM4_RCP45 and it is normalised by maxima and minima function to downscale future GCM into RCM for the period 2006-2035. The standardised input data from the extracted information is utilized in ANN toolbox to produce the output for future projection for each station individually. The annual maximum temperature for the time period 2006-2035 for the Malaprabha basin station is represented in the Fig.3 which shows the increasing trend in the temperature.

Table-2: Evaluation of downscale model for stations

Parameter	Value – S1	Value- S2
Nash Sutcliffe Coefficient	0.804	0.834
R^2- Coefficient of determination	0.809	0.825

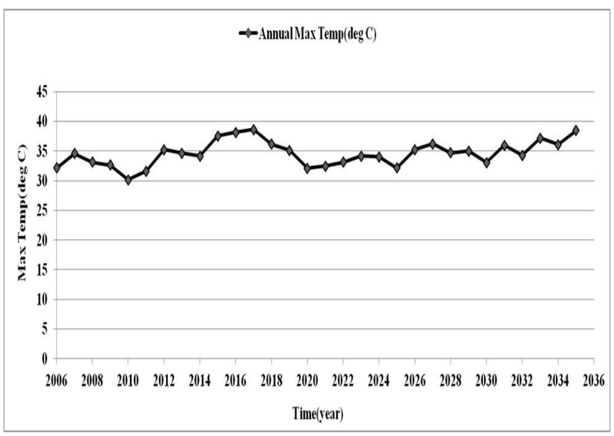

Fig. 3: Downscaled Annual Max. Temperature for the period (2006-2035) for Station S1

Abbreviations and Acronyms

GCM- General Circulation Model

ANN- Artificial Neural Network
IMD- Indian Meteorological Department
RMSE- Root Mean Square Error
NSE- Nash Sutcliffe Coefficient

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