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Role of Predictors in Statistical Downscaling of Surface Temperature for Malaprabha Basin

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Abstract

The earth's surface temperature is an important parameter for several atmospheric phenomena and process. It is also considered as an indicator of environmental degradation and climate change. This study aims to first evaluate different methods of sensitivity analysis for selecting potential climate predictors influencing the predictand (surface temperature) to establish predictor-predictand relationship. Another important objective of the study is to explore the Artificial Neural Network (ANN) method to downscale surface temperature to local scale using CanCM4-Global Circular Model to local scale on monthly time series.
The work focused on exploring various sensitivity analysis techniques, drawing comparisons between them and determining the evaluation criteria to assess the performance of a downscaling model, to understand the factor affecting the climate and causing climate variation of the Malaprabha basin for the future scenarios. Pearson`s correlation coefficient, Spearman`s rank correlation coefficient, Principal component analysis (PCA) and One-way analysis of variance (ANOVA) methods have been compared and contrasted for predictor selection. PCA screened the most potential predictors and these sensitive predictors are used as an input to ANN model trained for the time period of 1971-1995 and validated using the observed Indian Meteorological Department (IMD) data for the period of 1996-2005. Trained ANN model downscales the future projections of surface temperature for the period 2006-2035.

Keywords: *Artificial Neural Network, Climate change, Downscaling, Global Climate Model, Sensitivity analysis.*

Introduction

Climate change as defined by Environmental Protection Agency is, "change in weather pattern for a prolonged time". Factors such as temperature variation on earth, biotic process, plate tectonics and many to name are causing climate change on the earth surface. Certain human activities often cause global warming. The greenhouse gases (GHGs), considered as "a dangerous atmospheric gases" are

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the principle reason which permits solar radiation from the sun to go through the air yet keep the reflected warmth from getting away once more into space. This causes the world's temperature to rise.

Many research in the past has testified, the rise in surface temperature is a key indicator for variation in climate and thus, to focus on assessing the impact of surface temperature and its spatial variability in the study of climate change is indeed a trust area of research. To assess the impact of this climate variable, General circulation model (GCM) a robust and advanced mathematical model with coarse resolution data is accessed as the climate data. And later, downscaling technique is adopted for analysing the climate data at regional scale (Busuioc et al., 2006) [1]. Statistical downscaling is the most convenient method in terms of computational expense and feasibility in comparison with dynamic downscaling technique (Lenart et al., 2008) [2]

For the present work surface temperature considered as predictand is downscaled to basin scale using statistical downscaling method. The selection of suitable variables or predictors is an important step in a downscaling (Salvi et al., 2013) [3]. The choice of predictors could vary from region to region depending on the characteristics of the large-scale atmospheric circulation. Any type of variable can be used as predictor as long as it is reasonable to expect that there exists a relationship between the predictor and the predictand (Hewitson et al.,1996) [4]. This exercise of selection however include the previous study carried out in the river basin with similar climatic conditions (Anadhi et al, 2008) [5]

Different techniques for sensitivity analysis namely, Pearson`s correlation coefficient, Spearman`s rank coefficient, Principal component analysis and One-way analyse of variance (ANOVA) are used for screening most probable predictors. Another important objective of the study is to explore the Artificial Neural Network (ANN) method to downscale surface temperature to local scale using CanCM4-Global Circular Model to local scale on monthly time series.

Study Region

The Malaprabha 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 elevation 792 m and joins Kudala Sangama, Bagalkot district, Karnataka at a elevation of 488 m. The total area of catchment of Malaprabha basin is 11,549 km^2. Malaprabha basin shown in the figure 1 is delineated using Soil Water Analysis Tool (SWAT) hydrological model.

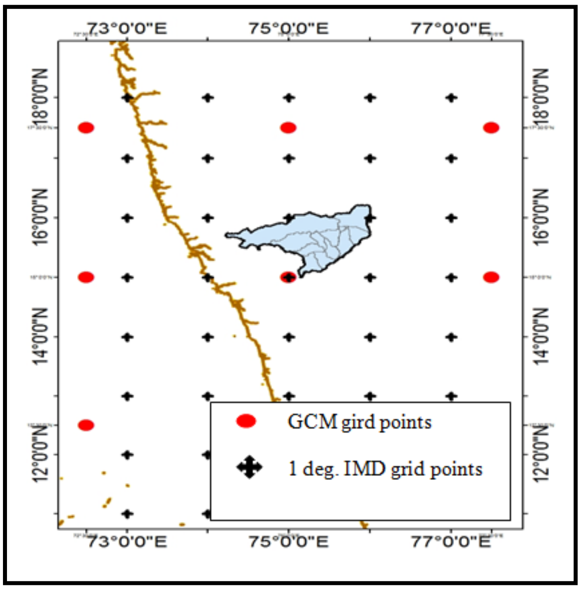

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Fig.1: Malaprabha Basin with GCM gird points

Data Utilized

In the present study, data of monthly mean maximum temperature prepared by Indian Meteorological Department (IMD) is used, for the period from January 1971 to 2005 for grid points which lies between 15° 45' N 74° 00'E and 16° 25' N and 75° 55'E at a spatial resolution of 1°. The maximum temperature are analysed using data available from two temperature gauging stations located in Santhibastwad, Karnataka at 16° 50`N latitude and longitude 75° 50'E and Gadag station at 16° 50`N latitude and 76° 50'E longitude. GCM was utilized from Canadian Centre for Climate Modelling and Analysis (CCCMA). The climate data was extracted for the time period from 1971-2005 for nine grid points at a spatial resolution of 2.5° which lies between 15° 45' N 74° 00'E and 16° 25' N 75° 55'E and the future datasets were extracted for the time period from 2006-2035 for monthly time series. The GCM data are available in Net CDF format and these data are processed using MATLAB programming.

Sensitivity Analysis:

Analysing the vulnerability associated with GCM to preliminary reduce the redundancy of input elements and making the qualified input elements (predictors) to be explored in details (patil et al., 2015) [6]. These techniques incorporate the numerical strategies, statistical techniques and graphical strategies for the examination, Few among the classic techniques available are, scatter plots, mathematical techniques such as, Spearman`s rank coefficient, analysis of variance (ANOVA), partial rank correlation, Kendall`s tau coefficient. In the present study, Pearson`s correlation coefficient, Spearman`s rank coefficient, Principal component analysis (PCA) and One-way Analyse of Variance (ANOVA) are used for the screening of most probable predictor variables. Hence, the screened potential predictors are used for the downscaling technique by ANN model. The list of possible predictors used in the present study is listed in **Table 1**.

Table 1: Lists of predictors used for the Sensitivity Analysis

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	Zg	M

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height		

Artificial Neural Network (ANN)

Artificial Neural Networks, a simplified biological neuron system and also a multi-linear regression method, is most popular approaches and works on the basis of transfer function statistically relating predictors and predictand (Laddimath et al., 2019) [7]. Figure 2 presents the ANN model developed based on central neural system of brain. Soft computing tools such as, MatLab/Simulink neural network tool box is engaged in this multi-linear regression analysis. Coarse scale GCM data is an input for this neural network tool and follows the learning algorithm and trained and validated through multiplying the weights to input data producing the activation function as depicted in figure 3.

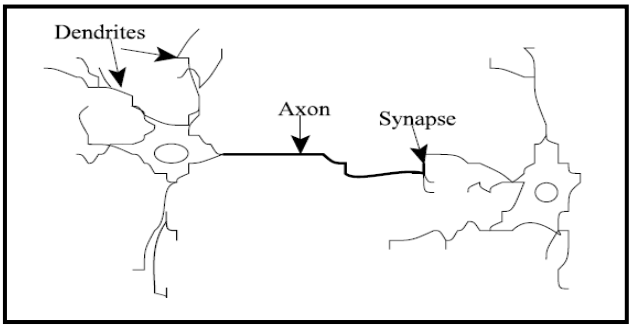

Fig. 2: Biological Representation of Neuron
(Source: Carlos Gershenson, 1997 [8])

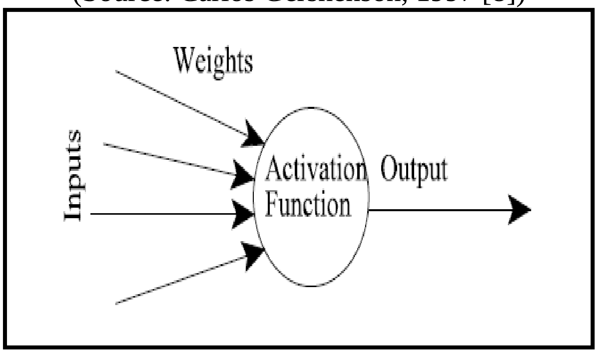

Fig. 3: Artificial Neural Network Architecture
(Source: Carlos Gershenson, 1997 [8])

This being the trial and error process and the weights used keep changing as the training process continues. Upon changing the weights on the input, the training of model keeps to improve and this strategy is well known as machine learning. The calculation involved in the aforementioned process is mentioned in the form of equations:

$$\mathbf{I = W_1X_1 + W_2X_2 + W_3X_3 + \ldots\ldots W_nX_n} \quad \mathbf{(1)}$$

where, I is the input data, $w_1, w_2, w_3 \ldots\ldots w_n$ is the number of weights and $x_1, x_2, x_3 \ldots\ldots x_n$ is the number of layers.

The overview of the methodology carried out for the current study is represented in the flowchart below shown in figure 4.

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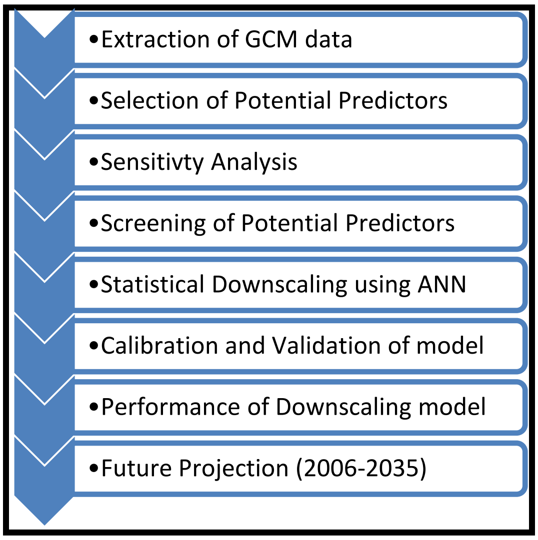

Fig.4. Flowchart of the Methodology

Methodology

Correction of inclination (Bias)

According to Wilby et al., (2004) [9], the standardisation of data is termed as bias adjustment. Normalization is fundamentally done for the reduction of unnecessary data. . This procedure reduces the data and lessen the dimension in every variable. The maxima and minima functions are used to standardize the extracted GCM data for the stations S1 and S2 considered for the present work. The 30 year data is taken as typical time to analyse strong climatologically changes.

Model training and validation

The model has been trained and validated for each station selected. Historical GCM information extracted is considered as an input variable for training the model utilizing MATLAB and the IMD stations data are used as target variable using ANN toolbox for the time period from 1971-1995. The validation of model is carried out for the time period from 1996-2005 by utilizing the potential predictors as an input variables and IMD data as target variables.

Performance of downscaling model

Assessment of the downscaled model is an essential part of the study to determine the efficiency of the model used. Therefore, the following methods listed below are analysed.

Nash Sutcliffe Coefficient:

The NS Coefficient (Nash and Sutcliffe, 1970) [10] is usually performed to assess the efficiency in a hydrological model. It is dimensionless with accuracy ranging from infinite to one. The efficiency of model nearer to 1 has greater precision. This method describes the accuracy of models as long as there is observed data to compare the model results. The equation below shows the mathematical representation of the coefficient.

$$E = \frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model})^2}{\sum_{i=1}^{n}(X_{obs,i} - \bar{X}_{model})^2} \qquad \textbf{(2)}$$

Root Mean Square Error (RMSE)

RMSE is usually used to evaluate the difference among the downscaled values stimulated by model and the observed downscaled values. It is dimensionless and ranges from 0.6 to 1. It gives good precision in the evaluation of the model performance without significantly harming the model`s predictive ability.

$$RMSE = \sqrt{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2/n} \qquad \textbf{(3)}$$

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where, Xobs is observed value and Xmodel is stimulated value.

Results and discussions

Screened Potential Predictor Variables

The sensitivity analysis of potential predictor's viz. Northward wind, Eastward wind, Air temperature, Geo-potential height, Precipitation, Sea level pressure and Surface upward sensible heat flux were analysed through the methods mentioned earlier. The consolidated list of potential predictors examined using the R value for stations S1 and S2 are outlined in **table 2**.

Performance of Downscaling Model

The performance of downscaling model ANN is carried out using N-S coefficient and RMSE. The assessment is carried out for each sensitivity analysis technique for stations S1 and S2 individually and the obtained result shows the most efficient sensitivity analysis method for the efficient/effective performance of the statistical downscaling model ANN. Thus, the **table 3** shows the results of the performance of downscaling model ANN.

Fig. 5 (a, b, c, and d) represents the graphs of training and validation of most potential predictors screened by Principal Component analysis (PCA) for station S1 and S2. The similar process of model calibration and validation is carried out for the other sensitivity analysis methods mentioned

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Predictors	**ID**	**Pressure level (millibar)**	**Units**	**R value**	**Method**
Northward wind	Va	_925_850_200_150_70_50_30_20_10_7_3_2	m/s	0.052,0.068,0.056,0.085,0.0715,0.0594,0.0616,0.0811,0.0652,0.0741,0.063,0.0571	**Pearson`s correlation Coefficient**
Eastward wind	Ua	_300_250_200_150_100_70_50_30_20_10_7_5_3_2_1	m/s	0.045,0.051,0.075,0.063,0.0423,0.0789,0.0814,0.0473,0.052,0.069,0.057,0.072,0.054,0.053,0.061	
Air temperature	Ta	_1000_925_700_600_20_7_5_3	°C	0.082,0.061,0.076,0.054,0.058,0.064,0.058,0.074	
Geo-potential height	Zg	_1000_925_850_700_600_500_400	M	0.06,0.041,0.065,0.084,0.056,0.055	
Precipitation	Pr	-	Mm	0.67	
Sea level pressure	Psl	-	Pa	0.56	
Surface upward sensible heat flux	Hfss	-	W/m^2	0.71	
Northward wind	Va	_850_700_300_200_150_100_50_30_10_7_5_3_2_1	m/s	0.062,0.052,0.078,0.062,0.095,0.064,0.055,0.064,0.066,0.089,0.072,0.0605,0.050,0.06,0.084,0.054,0.077	**Spearman`s Rank Correlation Coefficient**
Eastward wind	Ua	_700_500_400_300_250_200_150_100_70_50_30_20_10_7_5_3_2_1	m/s	0.081,0.050,0.045,0.051,0.075,0.063,0.0423,0.0789,0.0814,0.0473,,0.0715,0.0594,0.0616,0.0811,0.0652,0.0741	
Air temperature	Ta	_1000_925_850_500_400-_100_20_10_5_3_2	°C	0.080,0.061,0.097,0.054,0.058,0.061.0.077,0.069,0.052,0.0621,0.085	
Geo-potential height	Zg	_925_850_700_600_500_400	M	0.066,0.091,0.053,0.07,0.067,0.058	
Precipitation	Pr	-	Mm	0.82	
Sea level	Psl	-	Pa	0.64	

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pressure					
Surface upward sensible heat flux	Hfss	-	W/m^2	0.73	
Surface upward latent heat flux	Hfls	-	W/m^2	0.69	
Northward wind	Va	_850_200_150	m/s	0.78,0.64,0.55	**Principal Component Analysis**
Eastward wind	Ua	_1000_925_850_700_300_250_200_150_100_70_50_30_20_10_7_5_3_2_1	m/s	0.81,0.80,0.83,0.82, 0.76,0.75,0.85,0.88, 0.74,0.71,0.84,0.77, 0.79,0.78,0.88,0.77, 0.85	
Air temperature	Ta	_1000_850_700_600_500_400_300-_100_20_10_5_3_2	°C	0.77,0.65,0.75,0.96, 0.73,0.82,0.52,0.66, 0.67,0.93,0.89,0.75, 0.69	
Geo-potential height	Zg	_1000_925_850_700_600_500_400_250_200_150_70_50_30_10_7_5_3_2_1	M	0.72,0.80,0.65,0.74, 0.63,0.84,0.60,0.67, 0.55,0.74,0.90,0.84, 0.72,0.88,0.71,0.68, 0.84,0.87,0.77	
Surface temperature	Ts	-	°C	0.84	
Sea level pressure	Psl	-	Pa	0.70	
Surface upward sensible heat flux	Hfss	-	W/m^2	0.82	
Surface upward latent heat flux	Hfls	-	W/m^2	0.89	
Precipitation	Pr	-	Mm	0.86	**One-way ANOVA**
Northward wind	Va	_300_200_150_100_50_30_10_1	m/s	0.87,0.88,0.85,0.86, 0.77,0.9,0.74,0.86	
Eastward wind	Ua	_1000_925_850	m/s	0.86,0.84,0.89	
Air temperature	Ta	_1000_925_850_700	°C	0.75,0.80,0.87,0.81	
Geo-potential height	Zg	_1000_925_850_700_600_500_400_300	M	0.77,0.65,0.75,0.96, 0.73,0.82,0.52,0.66, 0.67,0.93,0.89,0.75,	

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		_250_200_150_100_70_50_30_20_10_7_5_3_2_1		0.69,0.789,0.814,0.73,,0.715,0.94,0.616,0.811	
Precipitation	Pr	-	Mm	0.94	
Sea level pressure	Psl	-	Pa	0.96	

Table 2. List of Potential Predictors Screened by Sensitivity Analysis

Table 3. Performance of downscaling model for station S1 and S2

Parameter	**Station S1**	**Station S2**	**Method**
Nash Sutcliffe Coefficient	0.802	0.834	Pearson`s Correlation Coefficient
R^2-Coefficient of determination	0.815	0.825	
Nash Sutcliffe Coefficient	0.761	0.75	Spearman`s Rank Correlation Coefficient
R^2-Coefficient of determination	0.793	0.789	
Nash Sutcliffe Coefficient	0.892	0.876	Principal Component Analysis
R^2-Coefficient of determination	0.90	0.899	
Nash Sutcliffe Coefficient	0.844	0.836	One-way ANOVA
R^2 -Coeff. of determination	0.852	0.873	

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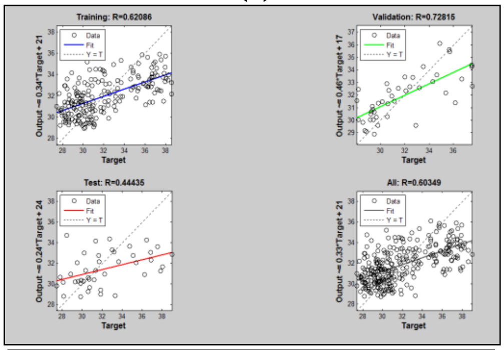
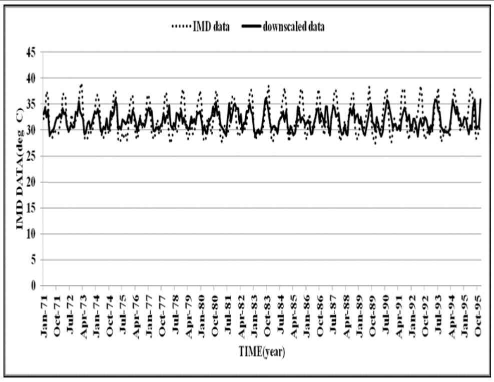
(a)





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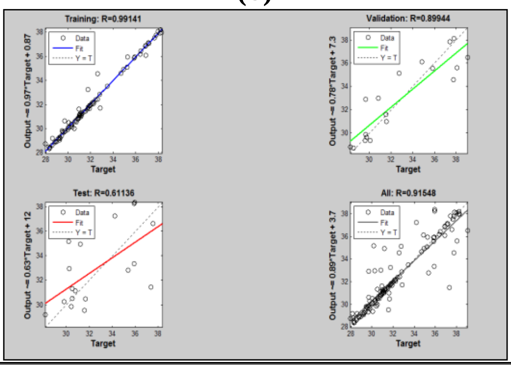

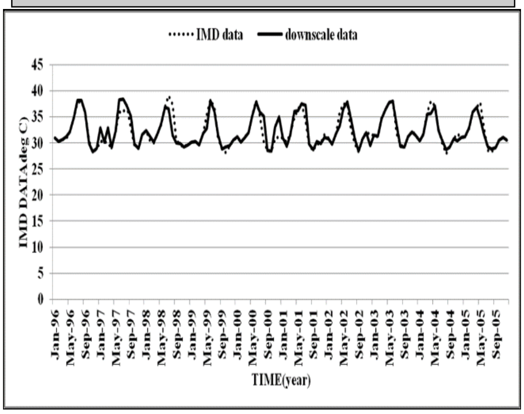

(c)

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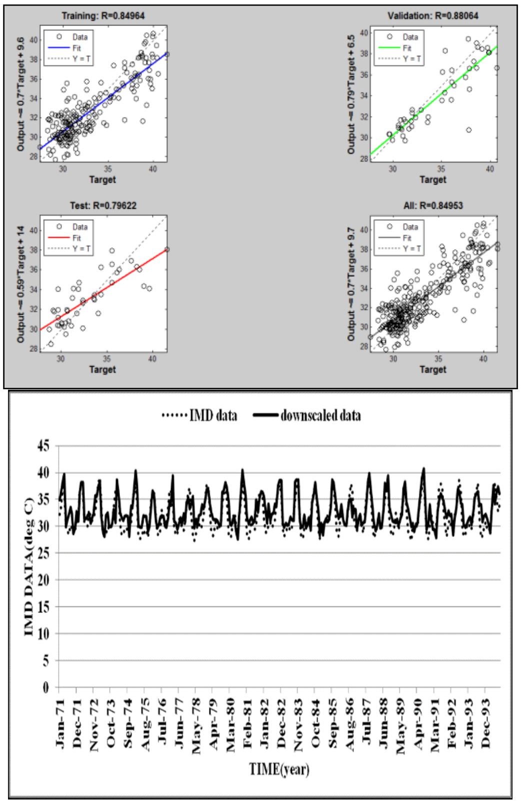
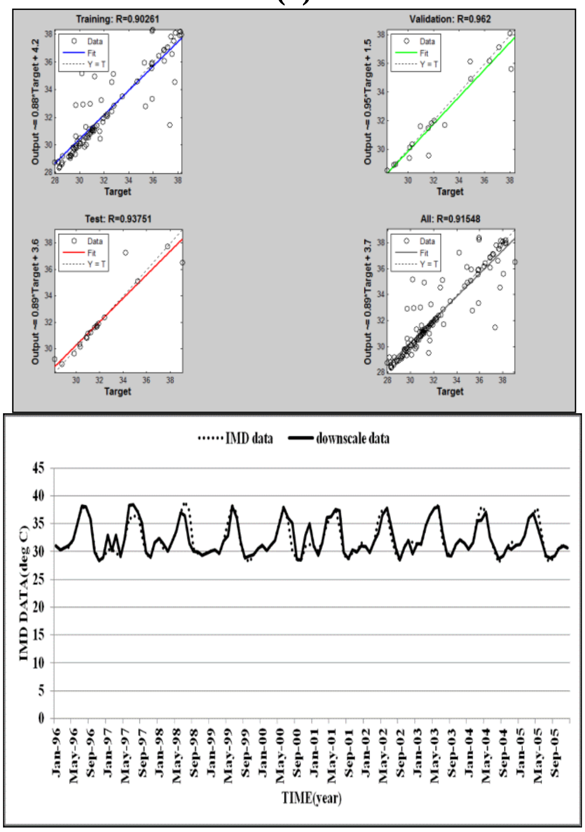


(d)



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Future projection of surface temperature

The annual maximum temperature projected for the period 2006-2035 using ANN is plotted in figure 6 for station S1 and figure 7 for station S1. It is inferred from the figure, the temperature for Malaprabha basin varies in the range of 300c to 40 0c and the trend shows increasing temperature for the future as projected from the CanCM4_RCP 4.5 scenario.

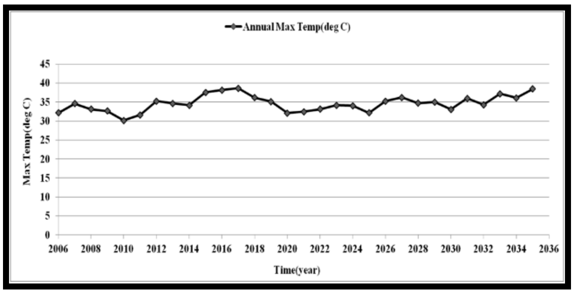

Fig. 6: Downscaled Annual Max. Temperature for the period (2006-2035) for Station S1

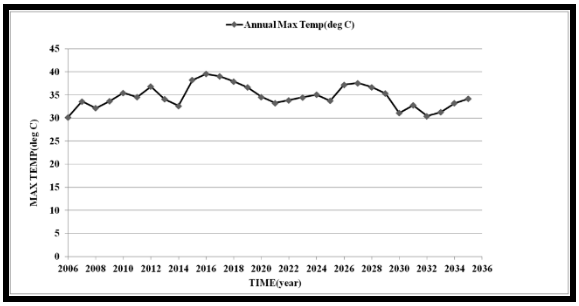

Fig 7: Downscaled Annual Max. Temperature for the period (2006-2035) for Station S2

CONCLUSIONS

The main objective of the research was to perform sensitivity analysis to choose the most likely predictors for the selected predictand i.e. surface temperature. The research focused on exploring various sensitivity analysis techniques, drawing comparisons between them and determining the evaluation criteria to assess the performance of a downscaling model, to understand the factor affecting the climate and causing climate variation of the Malaprabha basin for the future scenarios.

Principal component analysis (PCA) screened the most probable/potential predictors for the predictand compared to the predictors screened by other sensitivity analysis methods namely; Pearson`s correlation coefficient, Spearman`s rank coefficient and One-way ANOVA. The Artificial Neural Network (ANN) downscaling model is used to obtain projections for monthly mean maximum surface temperature (predictand) at monthly time scale for the time period from 1971-2005. The performance of downscaling model is evaluated using the statistical measures NSE and RMSE for each station considered for this study. The obtained results showed that the performance of the downscaling model ANN is efficient with the use of potential predictors screened by Principal component analysis (PCA). The results obtained provides the future projections of the surface temperature (predictand) for the time period from 2006-2035 for the two stations S1 and S2 in the Malaprabha basin at monthly time scale which shows the increasing trend.

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