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Modelling land surface temperature using gamma test coupled wavelet neural network

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Abstract. The climate change has made adverse effects on land surface temperature for many regions of the world. Several climatic studies focused on different downscaling techniques for climatological parameters of different regions. For statistical downscaling of any hydrological parameters, conventional Neural Network Models were used in common. However, it seems that in any modeling study, uncertainty is a vital aspect when making any predictions about the performance. In this paper, Gamma Test is performed to determine the data length selection for training to minimize the uncertainty in model development. Another measure to improve the data quality and model development are wavelet transforms. Hence, Gamma Test with Wavelet decomposed Feedforward Neural Network (GT-WNN) model is developed and tested for downscaled land surface temperature of Patna Urban, Bihar. The results of GT-WNN model are compared with GT-FFNN and conventional Feedforward Neural Network (FFNN) model. The effectiveness of the developed models is illustrated by Root Mean Square Error and Coefficient of Correlation. Results showed that GT-WNN outperformed the GT-FFNN and conventional FFNN in downscaling the land surface temperature. The land surface temperature is forecasted for a period of 2015-2044 with GT-WNN model for Patna Urban in Bihar. In addition, the significance of the probable changes in the land surface temperature is also found through Mann-Kendall (M-K) Test for Summer, Winter, Monsoon and Post Monsoon seasons. Results showed an increasing surface temperature trend for summer and winter seasons and no significant trend for monsoon and post monsoon season over the study area for the period between 2015 and 2044. Overall, the M-K test analysis for the annual data shows an increasing trend in the land surface temperature of Patna Urban.

Keywords: gamma test; downscaling; wavelet decomposition; neural network; temperature

1. Introduction

Possible variations in future climate are expected and it eventually changes all components of climate system. According to the report of Intergovernmental Panel on Climate Change (Pachauri

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et al. 2014), the global mean temperature increases for the period of 2016-2035 possibly be in the range of 0.3°C to 0.7°C. Knowledge of the changes in land surface temperature is essential in many biophysical processes, local rainfall, and hydrological regimes and henceforth it acts a significant parameter in environmental modeling (Hutengs and Vohland 2016). Globally available climate reanalysis data is often at a coarser scale of 20-200 km. Thus, there is a great need for downscaling the data to station scale to produce the inputs for different hydrological models.

Downscaling methods are broadly classified into dynamic and statistical downscaling. The latter is frequently used because it is easy to implement and is generally less expensive (Sachindra *et al.* 2014). Among the several methods of statistical downscaling like weather generator, weather typing and transfer function, downscaling with transfer function has minimum drawbacks (Wilby *et al.* 2004). Most of the recent literatures (Fu *et al.* 2013, Gaitan, Hsieh, and Cannon 2014) reported that artificial intelligence (AI) techniques outscored linear models and nonlinear models. However, despite of using these techniques on their own, there are still space for reducing the uncertainties and thereby improving the accuracy (Han, Kwong, and Li 2007). One such upcoming trend is to combine these AI techniques so that individual strengths of each approach can be utilized in an effective manner. With this, many new researchers have coupled neural networks with parameter optimization techniques to construct robust hybrid models in solving voluminous hydrological problems. For example,one day ahead seasonal basis forecasting of air quality for three major cities is carried by using Artificial Neural Networks (ANN) and Genetic Programming (Tikhe *et al.* 2015).

A hybrid model of discrete Wavelet transformed with neural nets (WNN) (Nayak *et al.* 2013) is used in this study. Despite the abundance of studies in WNN, there are still many uncertainties like neural network input data selection, sufficient length of data for training, over training etc are major concerns in mathematical modelling techniques. Hence a recently introduced statistical tool, gamma test (GT) (Stefánsson, Končar, and Jones 1997) is used to analyse the length of the data points and type of data. It is used to check the data, whether it is good enough for a reliable model or not and it also reveals the underlying dynamics of the system.

Only a very few work has been traced in GT and it shows that GT could be successfully used in studies of water level and flow modelling, solar radiation prediction (Remesan *et al.* 2009). On this background, the study specifically aims at improving the accuracy of statistically downscaling of land surface temperature on monthly scale by using a hybrid neural modeling: gamma test coupled wavelet neural network (GT-WNN). Its performance is being compared with GT-FFNN and conventional Feedforward neural network models (FFNN).

2. Study area and data collection

Patna Urban, the study area, is situated on the southern banks of the Holy River Ganga in India. It is an important commercial centre due to its central position and the junction of the three rivers: Son, Gandak and Punpun. Total coverage of this city is 99.45 km^2. Along the southern bank of Ganga is a thin belt of very fertile soil while other parts have fertile alluvial soil. Patna faces the subtropical region of temperate zone and its climate type is humid.

Thirty years (1985-2014) of monthly temperature data is collected from Indian Meteorological Department (IMD) Patna is used in this study. Another set of mean monthly temperature data of thirty years (from 1985 to 2014) is obtained from NCEP/NCAR REANALYSIS project for the area under consideration at different pressure level (1000 mb to 100 mb). These global variables act as predictors for neural networks. Future predictor variables can be downloaded from General Circulation Models (GCM). The GCM data are extracted for Coupled model International Project 5 (CMIP5) project. Model details are as follows: MPI- ESM-LR, T/63/L47, scenario-B1-5, experiment – RCP 85 for next thirty years (2015 to 2044).

3. Methodology and data processing

3.1 Selection of potential predictor

Impact of climate change estimation by using GCM, CMIP5 project data needed prior information regarding relationship between NCEP/NCAR Reanalysis data (predictors), GCM data (potential predictors) and the observed data (predictant). Since NCEP/NCAR Reanalysis data and GCM data are global atmospheric variables, these variables are influenced by global air circulation pattern whereas local climate variable like the predictant are available on lower topography, it becomes mandatory to establish a relationship between these set of data for proper training and validation of ANN. In this study a correlation is established between NCEP/NCAR Reanalysis data (predictors) and observed data (predictant) to find the potential predictors. The predictor variables of NCEP/NCAR Reanalysis data selected are geo-potential heights, air temperature, relative humidity, specific humidity, U wind and V wind at 11 pressure levels 1000, 925, 850, 700, 600, 500, 400, 300, 250, 200, 100 (in mb) available in NCEP/NCAR REANALYSIS site. Only those NCEP variables at the specific pressure level are selected as potential predictors which are perfectly correlated with the observed data. Correlation coefficient between predictor variables and predictant are calculated based on product moment correlation coefficient formula.

Prior to statistical downscaling, standardization is performed to reduce systematic biases in the mean and variance of the GCM predictors relative to observations (Wilby *et al.* 2004). The possible bias in GCM output could be due to partial ignorance about the geophysical processes, assumptions made for numerical modelling, parameterization and the use of empirical relationships (Subimal and Pradeep 2008). In this study, standardization was done by subtracting the mean and dividing this quantity by the standard deviation of the predictor for a baseline period.

3.2 Gamma test (GT)

Gamma test is a fast, non-linear modelling and analysis tool which defines the input/output relationship in a dataset. During model development (training period), gamma test is applied to make the model smooth and to overcome the problems like over fitting. If a dataset consists of m possible inputs for a corresponding output y, Gamma test gives that input configuration which renders the optimum model for y given available data. It works on the assumption that if two points in input space is close together then their corresponding outputs should be close in the output space and if this does not happen then there is noise in the dataset. In equation, $y=f(x_1 \ldots . x_m)+r$, where f is a smooth function and r is random variable that represent noise. Here it is assumed that mean of the distribution of the constant (r) as zero and the variance of the noise V(r) is bounded. Gamma statistic (Γ) is the estimation of that part of the variance of output that cannot be accounted by a smooth model.

The main equation required to compute Γ is derived after calculating Delta and Gamma.

$$\text{Delta, } \delta M(k) = \frac{1}{M}\sum_{i=1}^{M} |x_{N[i,k]} - x_i|^2 \quad (1 < i < M), (1 < k < p) \tag{1}$$

$$\text{Gamma, } \Upsilon M[k] = \frac{1}{2M}\sum_{i=1}^{M} |y_{N[i,k]} - y_i|^2 \tag{2}$$

where XN [I, k] is kth nearest neighbor in terms of Euclidean distance to Xi. and {(1<i<M); (1<k<p)}.

A least square fit regression line is constructed for the p points. The intercept on the vertical axis (ϒM[k] tends Var(Γ) and in probability as ξ M(k) tends to zero) is the Γ value. To obtain the value of delta and gamma, firstly Euclidean distance table is sorted in ascending order and the zeroth column is eliminated. The index table and Euclidean distance tables are used to obtain the value of delta and gamma. Zero(th) column occur in Euclidean distance table when two identical points occur in the dataset under examination which may be accounted due to repetition of data point or two or more separate independent observations therefore it has to be eliminated. M- test is conducted with a sequence of gamma statistic for increasing number of data points *M*. The sequence at which Γ stabilizes gives the variance of the noise and that much of data point is the least number of data point to construct a smooth model and that is capable of predicting the output y within a mean squared error of Γ. More details are found in (Stefánsson, Končar and Jones 1997).

3.3 Wavelet transformation (WT)

Wavelet is a class of functions used to centralize a given function in position and frequency. These functions are used in signal processing, and time series analysis. It is a small wave function denoted as Ψ(.) which grows and decays in a finite period. A function Ψ(.) is defined over the real axis (−∞, ∞) known as wavelet satisfying the following equation

$$\int_{-\infty}^{\infty} \Psi(u)\,du = 0 \tag{3}$$

$$\int_{-\infty}^{\infty} \Psi^2(u)\,du = 1 \tag{4}$$

Admissibility condition, $C_\Psi \frac{\int_0^\Psi |\Psi(f)|^2}{f} df$ where $0<C_\Psi<\infty$ <

Wavelet Transformation breaks the data into different components of frequency by a fully scalable modulated window and then each component resolution is compared with the equation

$$\Psi_{\lambda,t(u)} = \frac{\Psi}{\lambda}\left(\frac{u-t}{\lambda}\right) \tag{5}$$

where Ψ(.) denotes a mother wavelet and the dilation λ>0 and t is finite. Right hand side is normalized so that $||\Psi_{\lambda,t}|| = ||\Psi||$ for all λ, t (Daubechies 1992).

In the end, the result will be a collection of time-frequency representations of the signal, all with different resolutions. Choice of mother wavelet relies upon the signal to be examined. Predominantly the Daubechies and Morlet wavelet are utilized as "Mother" wavelets (Shoaib *et al.* 2014). Daubechies wavelets shows strong connection between parsimony and data abundance, it gives approximately similar events over the observed time sequence and show up in such a large number of various pattern that most forecast models can't distinguish them well. Wavelets transform are mainly of two types: continuous and discrete.

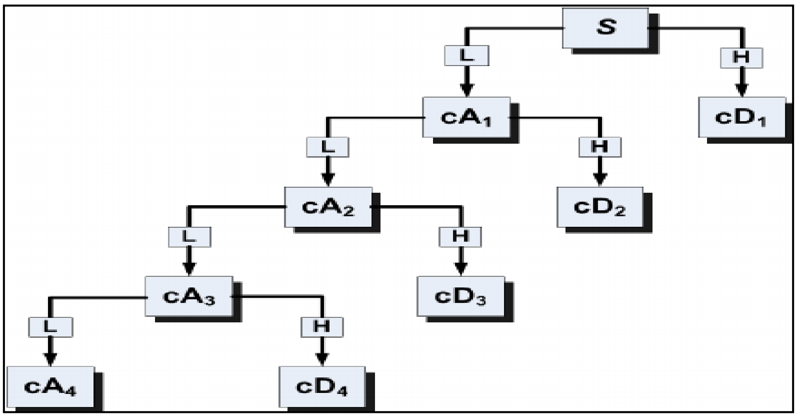


Fig 1 Wavelet Decomposition Tree upto 4^{th} level

In this study discrete wavelet transform (DWT) has been used to analyse a subset of a time series signal and works on discrete subset of function or time series $x(.)$ in the time range of t=0,1,2,3,.....N-1 to finite term by analyzing the data for discrete dilations and translations of the mother wavelet $\Psi(.)$. For example, if a signal is transformed for a dilation j of up to two, higher frequency noise is first removed and then the next lower one. Finally, approximation of the signal at the last level selected, which is much smoother than the original signal and it has all the property of showing any trend and original shape of the signal. This smooth version of the original signal is known as scaling coefficients. The first two level contained the wavelet coefficients at level one and two respectively.

The scale of the wavelet used for analysis at each stage is 2^{j-1}. So there are total, $N_j = \frac{N}{2j}$, wavelet coefficients at each level with their associated times, $t = (2n+1)2j - 1 - \frac{1}{2}$,n = 0,1,.....N_j-1.

DWT operates on two sets of functions seen as high pass and low filter. The original signal passes through high pass filters and low pass filters and the signals are separated at different frequency, shown in Fig. 1.

This signal is decomposed into low frequency and high scale by low pass filter (Approximate-cA) and high frequency with low scale by high pass filter (Detail-cD). Low frequency signal or the approximates (cA) carry valuable information about the signal and is therefore carry important feature of the data whereas high frequency signal or the detail (cD) carries very small characteristic of the interpreted data. The decomposition process is repeated, with successive approximations being decomposed so that one signal can be rundown into many lower resolution components. In the Fig. 1, the wavelet decomposition is done upto 4^{th} level. In each level, cA is again passed through low pass and high pass filters until it reaches the desired level of decomposition.

3.4 Feed forward neural network

An ANN is a data processing system made up of huge set of extremely unified processing elements (neurons). It comprises of millions of neurons interrelated with each other. Feedforward Neural Network (FFNN) with Back propagation algorithm is a supervised training algorithm in the MLP networks. This is based on transfer functions that have been used for downscaling large scale climatic variables structured between the predictors and the predictant. Its input layer consists of potential predictors, the second layer is a hidden layer to transform the inputs nonlinearly to output, and the output layer consists of the predictand. The basic idea involved in FFNN is the adjustment of weight and reduction of error between the target and the output given by the network. If the error computed is higher than the estimated value, the network back propagates from output layer to the input layer and accordingly adjusts its weight. This process continues till the error generated between the output and the target is reduced to a desirable limit. Once this condition is reached training is stopped. The Levenberg-Marquardt back propagation (LMBP) algorithm is used for this purpose with RMSE as the checking parameter (Govindaraju 2000a, 2000b).

3.5 Wavelet decomposed ANN (WNN)

The potential predictors obtained from product moment correlation formula for temperature is continuously broken down (mainly the approximation) into next approximate and detailed value for a particular time series using Daubechies wavelet of order 2 up to a dilation factor of three. The input variable to ANN contains three detail and one approximate value of each input signal and original signal (observed surface temperature) as output. To obtain the optimal weights (parameters) of the neural network structure, LMBP algorithm has been used to train the network with sigmoidal as transfer function between input and hidden layer in the analysis. The number of hidden nodes are decided by hit and trial method.

3.6 Gamma test induced WNN (GT-WNN)

The detailed flowchart of gamma test induced wavelet neural network is shown in Fig. 2.

The selected potential predictors are fed for gamma test analysis and then to M-Test. From this, the minimum length of the data for training set is selected and then fed for wavelet decomposition and then in to FFNN. If the difference in the output obtained and the targets are acceptable, then the model developed is acceptable, or else the weights are adjusted and again training is repeated till it reaches an acceptable error. All analysis is carried out in MATLAB 2015.

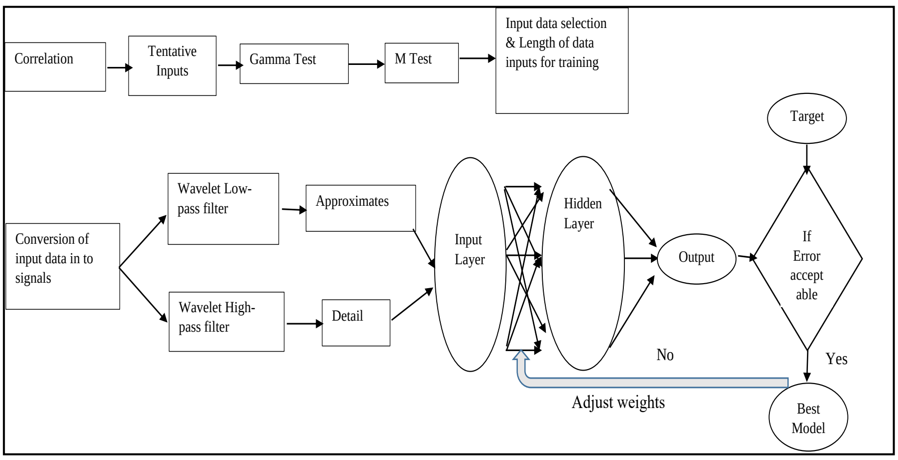


Fig. 2 Flowchart showing process involved in GT-WNN

3.7 Mann kendall test

After selecting the best model for downscaling, trend analysis is performed on the downscaled temperature from 2015-2044 by a non-parametric test. Mann- Kendell test is one of the non-parametric test that assumes no trend as null hypothesis *Ho* in comparison to increasing and decreasing trend H_1. The method considers two subsets of data and each data is compared to all subsequent data in pair. Mann Kendell statistic "*S*" is assumed to be zero initially and if the next data is greater than previous data, *S* is incremented by 1, or else decreased by 1. The net result of all such increment and decrement yield *S* value. If this *S* value comes to be positive, trend is increasing otherwise trend is decreasing. In this study, a two-tailed test is used since n>10.The theoretical distribution of *S* is compared to the value obtained from Mann –Kendell test. If *S* is greater than or equal to the $S\alpha/_2$ Null Hypothesis *Ho* is rejected against the hypothesis H_1 where $S\alpha/_2$ is the probability at 5 % confidence level. Let x_1, x_2, x_3. …… x_n are n data points, where x_j is the data point at time j. Then Mann – Kendall (M-K) test statistic (S) is given by

$$S = \sum_{k=1}^{n-1} \sum_{j=i+1}^{n} sign\left(x_j - x_k\right) \tag{6}$$

$$Sign = \left(x_j - x_k\right) \begin{cases} +1............., x_j - x_k > 0 \\ 0.............., x_j - x_k = 0 \\ -1..............., x_j - x_k < 0 \end{cases} \tag{7}$$

Positive value of S shows increasing trend and negative value of S indicates decreasing trend. Steps involved for evaluating M-K test are evaluate variance of S (Var(S)).

$$VAR(S) = \sigma^2 = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{g} t_p\left(t_p - 1\right)\left(2t_p + 5\right)\right] \tag{8}$$

where n=number of data points, g=number of tied groups (tied group is a set of sample data having same value), t_p=number of data points in the p^{th} group. To analyse the trend in data series, the test statistic Z is used. A normalized test statistic Z is computed as follows

$$Z = \begin{cases} \frac{S-1}{\sigma}................S > 0 \\ 0......................S = 0 \\ \frac{S+1}{\sigma}..................S < 0 \end{cases} \tag{9}$$

For a S value, Z is computed as Z_S. If Z is more than or equal to $S_{\alpha/2}$ the hypothesis is rejected and the trend is significant. Z_{CR} is the is the critical value for Z, two-tailed, at P<.05. P-value is another Mann Kendell statistic denoting probability value. This value checks whether the hypothesis term is true or not. If the hypothesis is false, it is rejected and the trend is significant. This test can also be performed by R statistic software developed by "Pumpkin Helmet".

4. Results and analysis

4.1 Selection of potential predictor

Potential predictor for the mean monthly surface temperature of whole year are obtained from

Table 1 Potential predictors for surface temperature of Patna urban

Predictor variable	Pressure level, mb	ρ_{xy} correlation coefficient
Precipitation (kg/m^2)	Surface	0.5755
Geopotential height (m)	200	0.928
Relative humidity (%)	700	0.5997
U wind (m/s)	400	-0.625
V wind (m/s)	850	0.6006

Table 2 Correlation between NCEP/NCAR data and data from selected GCMs

NCEP and GCM data	Correlation coefficient
Relative humidity (%)	0.78
U wind (m/s)	0.79
V wind (m/s)	0.89
Geopotential heights (m)	0.72
Precipitation (kg/m2)	0.89

product moment correlation and those predictors whose correlation value $0.5 \leq \rho_{xy} \geq 1$ were potentially responsible for affecting the surface temperature for the selected site. The potential predictors for land surface temperature by product moment correlation are shown in the Table 1. Table 2 shows correlation between NCEP/NCAR data and data from selected GCMs.

4.2 Gamma test analysis

Gamma test was carried out for all potential predictors to obtain the optimum dataset length for model training. Gamma test and M-Test on 360 input and output data is performed to obtain the optimum number of input for training ANN model. The Gamma constant (Γ) has been obtained initially from ten set of data length and then increasing successively the data sets which provides the estimation of the disturbances in the input data. Firstly, Euclidean distance table is prepared for a minimum data length, say 10 and then it sorted and indexed. The delta and gamma values are calculated for each data length in month (for ten data set shown in Fig. 3) and a least square fit regression line is drawn to compute Var(Γ). Likewise, for different data sets, same procedure is followed and Γ is computed. This gives the plot M-test.

Finally, a plot is obtained from Gamma statistic value of each data length against the total length of data that provides the M-test. Fig. 4 depicts the point where noise in the dataset stabilizes or where the undulation in the disturbances becomes nearly constant. It is concluded from Fig. 4 that 290 data length is optimum for training period, the model obtained will be a smooth one and it may not be subjected to any over fitting problem which generally occurred while training. This also indicates that the input data selected are also appropriate.

4.3 GT-WNN model

The input data length selected from Gamma test is then decomposed using DWT. The standardized input data is decomposed using Doubechies-2 mother wavelet as explained above up to 3rd level which is then fed in ANN for training. Fig 5 shows the signal decomposition of Geopotential heights at 200m pressure level at db-3 level.

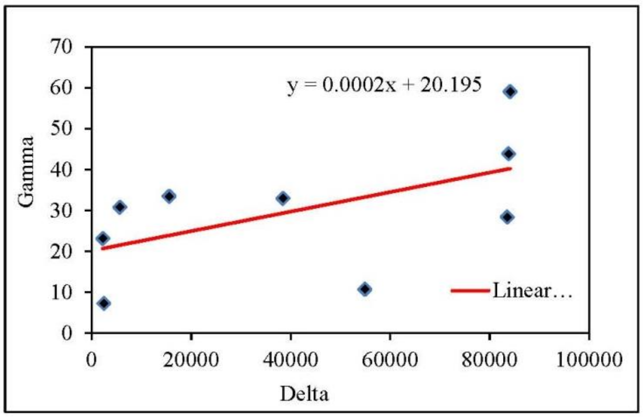


Fig. 3 Least square fit regression between gamma and delta

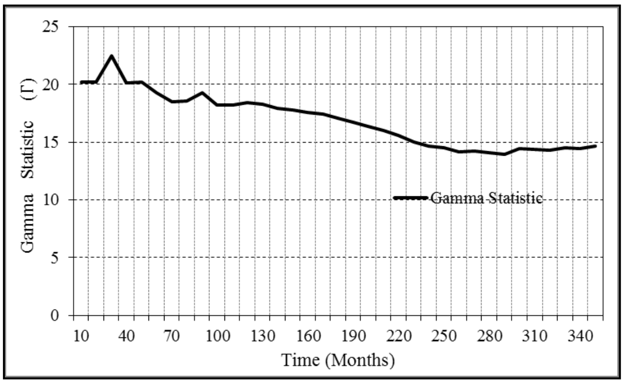


Fig. 4 M test results from 10 to 350 data length

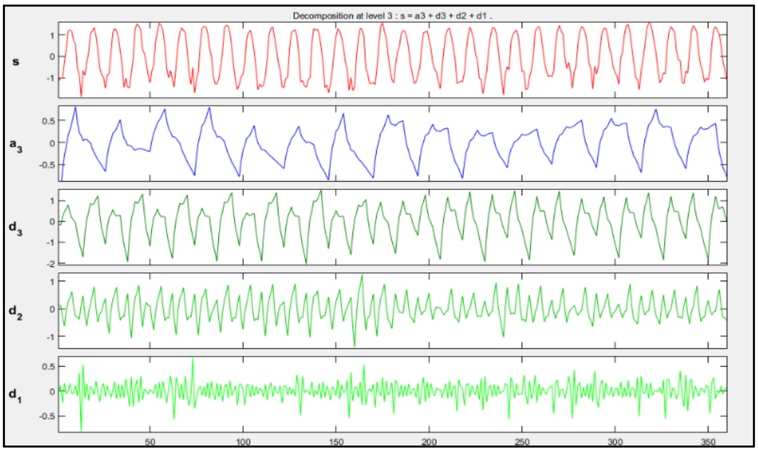


Fig. 5 Signal decomposition of Geopotential heights at 200m pressure level

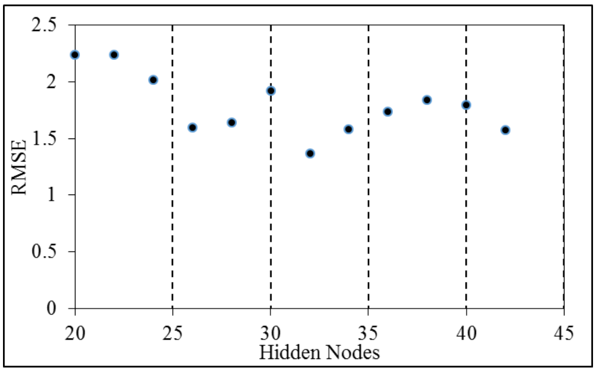


Fig. 6 Selection of optimum number of hidden nodes

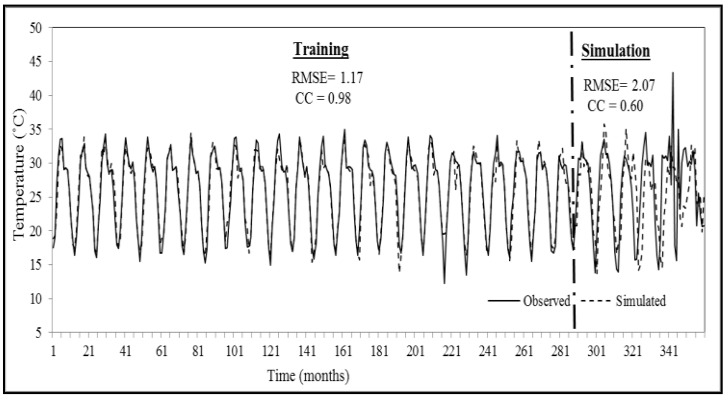


Fig. 7 Training and simulation results of temperature for GT-WNN

The idea of introducing wavelet in this study is to gather only the valuable information that lies in the input data as three approximate (carrying the valuable information) and one detail is selected from each input variable signal which in turn has been filtered in Gamma Test. Likewise each inputs are allowed to decompose and then they are fed for training using FFNN. A statistical relationship between potential predictors (NCEP variable) and the predictand (local surface temperature) is established using Feed Forward Back Propagation Neural Network. The decomposed variables act as input nodes in the two-layered feedforward back propagation using Levenberg-Marquardt algorithm with tansig as transfer function. Training of network is done at different hidden nodes by trial and error and the node at which minimum RMSE is selected as the optimum number of hidden nodes (Fig. 6). It shows 32 number of neurons has lowest RMSE value and hence it is selected for training the model architecture.

If the errors computed are acceptable, then training is stopped and thereafter the remaining set of values are given for simulation. Training and simulation result is shown in the Fig. 7, in which RMSE value obtained 2.07 and correlation value of 0.60 in the simulation result at the selected hidden node.

4.4 GT-FFNN model

To observe the difference between model with wavelet and without wavelet another model is

Table 3 Statistical performance of artificial neural network models

Models	GT-WNN		GT-FFNN		FFNN	
	RMSE (˚C)	Coefficient of correlation	RMSE(˚C)	Coefficient of correlation	RMSE(˚C)	Coefficient of correlation
Training	1.17	0.98	1.80	0.94	2.20	0.92
Testing	2.07	0.60	6.68	0.38	7.04	0.33

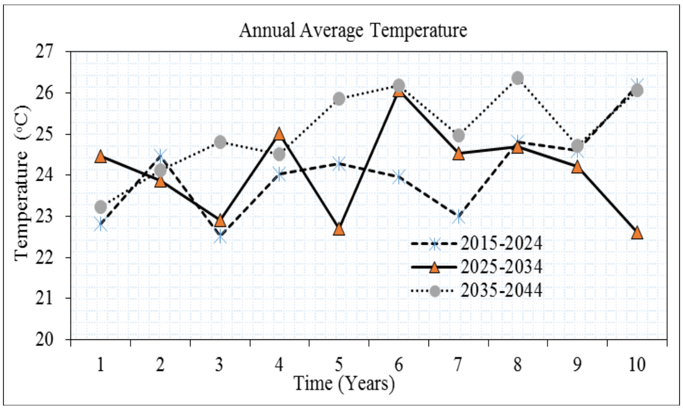


Fig. 8 Projected changes due to climate change in surface temperature from 2015-2044

built after selecting input data length from Gamma test and training and simulation of network is carried out using FFNN with Levenberg-Marquardt algorithm with tansig as transfer function at hidden node obtained from trial and error method. Performance indicators obtained after training and simulation for the network shows CC as 0.94 and 0.38. RMSE values for training and simulation are quantified as 1.80 ˚C and 6.68 ˚C.

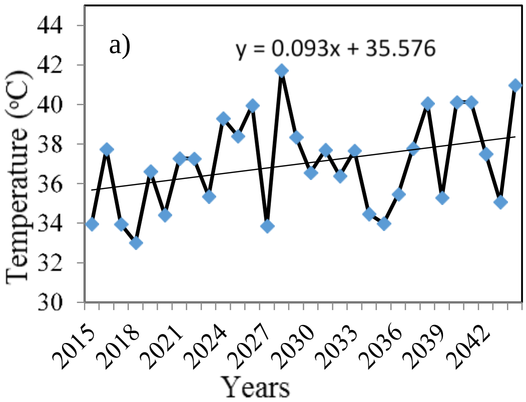
4.5 FFNN model

The next model created is conventional Feedforward Neural Network to observe the performances of Gamma test and Wavelet decomposition in the Neural Network Modeling. The training and simulation results reveal the performance indicator RMSE values as 2.2 ˚C and 7.04 ˚C and CC as 0.92 and 0.33 respectively. Though the model can be trained perfectly, however it is not capable of producing accurate output which generally happens due to noises incorporated in the dataset.

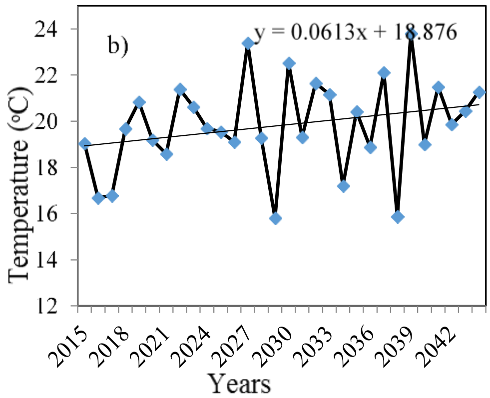
4.6 Model performances

The model performances of the three selected models are done by statistical parameters like RMSE and coefficient of correlation (CC) and are shown in Table 3. It shows the comparison of three models: GT-WNN, WNN and FFNN and it has been observed that though all three models are trained perfectly, but the GT-WNN outperformed the other models developed.

With the best model, the projected changes in the temperature are plotted in Fig. 8. It is proved in the model analysis that statistical model coupled with parameter selection can help highlighting the improved performance of the GT-WNN. This may be due to lessening the effect of uncertainty of internal parameters by GT in the model development and also due to noise removal of input data parameters by DWT.



(a)



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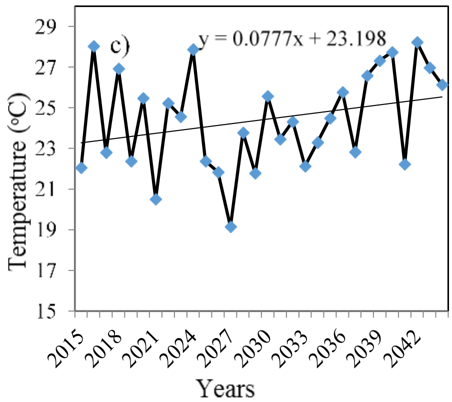
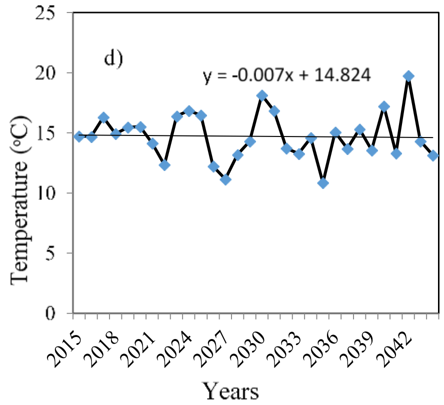


(c)

Fig. 9 Trend analysis of annual average temperature from 2015-2044 for (a) Summer, (b) Winter, (c) Monsoon and (d) Post monsoon seasons



(d)

Fig. 9 Continued

Table 4 Annual and seasonal trend analysis of surface temperature by Mann-Kendell test

Season	Trend observed from graph	M-K'S Test	Trend from M-K test	P- Value	Remarks
Annual	Increasing	ZS > ZCR	Increasing	0.0014	Significant trend
Summer	Increasing	ZS > ZCR	Increasing	0.0209	Significant trend
Winter	Increasing	ZS > ZCR	Increasing	0.0084	Significant trend
Monsoon	Increasing	ZS < ZCR	No significant trend	0.0541	No significant trend
Post Monsoon	Decreasing	ZS<(-ZCR)	No significant trend	0.1861	No significant trend

4.7 Trend analysis by Mann Kendell test

Trend analysis of the predicted temperature by the GT-WNN model is performed to observe the seasonal changes (Fig. 9(a), 9(b), 9(c) and 9(d)) and annual changes in the average monthly temperature from year 2015-2044 by Mann Kendell test. The results are summarized in Table 4.

A non-parametric statistical approach, Mann- Kendell was adopted for trend verification. Test showed that the trend in predicted temperature from 2015-2044 was increasing for the mean annual monthly temperature and in summer and winter season while no significant trend was observed in monsoon and post monsoon period. This may be accounted due to increase in the level of CO_2 emission with the increase in population and urbanization.

5. Conclusions

Like precipitation, temperature is also the most frequently used parameter for several hydrological models. Hence for climate change study, there is a need of downscaling these variables to regional scale. In this study, different hybrid neural network models were developed for downscaling land surface temperature statistically in Patna Urban of Bihar, India on a monthly basis.

Three hybrid models (GT-WNN, GT-FFNN and FFNN) were used for downscaling land surface temperature and the models performance evaluation were carried out by root mean square error and coefficient of correlation. The potential predictors selected based on correlation analyses are precipitation, geopotential height, relative humidity, U wind and V wind. Multiple trial and error procedures for determining optimum input data length in ANN training is reduced by Gamma Test (GT). Hence ANN model is created with 290 data length as training data set obtained from Gamma tests. Wavelet neural network model is then developed and coupled with GT to form GT-WNN model. Conventional feedforward neural network (FFNN) model is further used for comparison. Results showed that GT-WNN outperformed the GT-FFNN and FFNN in downscaling the land surface temperature.

From the results, for the projected land surface temperature (2015-2044), it is observed that there is an increase in the temperature in the coming decades which is also verified by the Mann Kendall trend analysis test. Seasonal trend analysis for the predicted monthly average temperature shows that there has been increase in the temperature for summer and winter seasons while no significant trend is observed in monsoon and post monsoon period. Overall this study compared the performances of the three developed models and the performance evaluation shows the effectiveness of Gamma Test coupled with WNN over GT-FFNN and FFNN. Moreover, it is proved that GT is an effective tool in data selection and for data length optimization.

This study helps to provide a technical guide for water resources planning professionals as these downscaled data can be used for several water balance models that can be used for future planning.

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