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Artificial neural network model for downscaling of temperature forecast over Western Himalaya

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सार - हिमालय के पश्चिमी भाग में सर्दी के महीनों के दौरान नवम्बर से अप्रैल तक वर्षा हिम के रूप में अच्छी मात्रा में वर्षण होता है इन क्षेत्रों में सर्दी के दौरान भारी हिमपात होने के कारण हिमस्खलन की घटनाएँ होती हैं। हिम पुंज के भीतर रूपांतरण (मेटमोरफिज्म) की प्रक्रिया में तापमान की महत्वपूर्ण भुमिका होती है जिसके कारण हिमस्खलन होता है। किसी स्थान विशेष के तापमान के सटीक पुर्वानुमान साए हिमस्खलन का सटीक पुर्वानुमान देने में मदद मिलती है। इस शोध पत्र में कृत्रिम तंत्रिका नेटवर्क (ANN) विधि का उपयोग तापमान के पूर्वानुमान की सांख्यिकीय डाउनस्केलिंग के लिए किया गया है। 10×10 कि. मी. ग्रिड पर मेसोस्केल मॉडल एम एम 5 तापमान पूर्वानुमान के लिए वर्ष 2003-2008 तक की सर्दियों के लिए तीन स्थानों- कानजलवान, स्टेज-II और गुलमर्ग को लिया गया है ताकि इन स्थानों पर तापमान का पूर्वानुमान देने के लिए ANN मॉडल की कार्यक्षमता के प्रदर्शन का अध्ययन किया जा सके। प्राप्त परिणाम बताते है कि इन तीनों स्थानों पर तापमान पूर्वानुमान के लिए ए एन एन मॉडल का प्रदर्शन 2 दिनों तक के लिए अच्छा है। औसत वर्गमूल त्रुटि (RMSE) सभी तीनों स्टेशनों के लिए महत्वपूर्ण रूप से कम है और यह मानक विचलन (एस. डी.) से भी कम है। जिससे ए एन एन मॉडल के अच्छे प्रदर्शन का पता चलता है। इस क्षेत्र में तापमान में अधिक परिवर्तशीलता के बावजूद ए एन एन मॉडल में औसत वर्गमूल त्रुटि (RMSE) 2° सेल्सियस के करीब है। कानजलवान के लिए एम एम 5 तथा ए एन एन मॉडल द्वारा प्रेक्षित तापमान और अनुमानित तापमान के बीच का निर्धारण गुणाकं सत्यापन सेट के अनुरूप क्रमशः 0.28 और 0.66 है जो डाउनस्केलिंग के बाद पूर्वानुमान देने के कौशल में सुधार को प्रदर्शित करता है। एम एम 5 मॉडल के डाउनस्केलिंग से प्राप्त परिणाम किसी स्थान विशेष के लिए दिए गए अनुमानित तापमान के प्रेक्षित मानों के करीब है।

ABSTRACT. The western Himalaya receives good amount of precipitation in the form of rain and snow during winter months from November to April. Heavy snow fall during winter over these regions causes avalanches. Temperature plays a vital role in the process of metamorphism within the snow pack which leads to avalanches. Accurate prediction of temperature over specific location helps to predict the avalanche accurately. In this paper artificial neural network (ANN) method has been used for statistical downscaling of the temperature forecast. Mesoscale model MM5 temperature forecast on 10×10 km grids has been taken over three locations Kanzalwan, Stage II and Gulmarg for winter from 2003-2008 to study the performance of the ANN model for its ability to forecast temperature over these locations. Results show that the performance of ANN model for temperature forecast over these three location is good up to day 2. Root mean square error (RMSE) decreases significantly for all the three stations and is also less than the standard deviation (SD) which shows good performance of the ANN model. RMSE is close to 2 °C in case of ANN model, in spite of large variability in temperature over the region. The coefficients of determination between observed and predicted temperature by MM5 and ANN model for Kanzalwan, corresponding to validation set are 0.28 and 0.66 which shows improvement in forecast skill after downscaling. Predicted temperatures at particular location, after downscaling of MM5 model output are closer to the observed values.

Key words – Downscaling, Artificial neural network, NWP, Temperature forecast.

1. Introduction

Western Himalaya is badly affected by snow avalanches during winter months due to heavy snowfall associated with the western disturbance (WD). A huge loss of property and human life is witnessed every year because of avalanches in the snow bound regions of western Himalaya. Many factors are responsible for the avalanche initiation. Snowpack at a particular place consists of different layers of snow and changes continuously due to metamorphic processes. Temperature is one of the most important parameters responsible for these processes. Thus temperature forecast plays an important role in the prediction of avalanches.

Due to the geomorphology, high altitude and different orientations of mountain ranges in western Himalaya, prediction of surface weather parameters becomes very complex. Therefore forecast generated by NWP model available on a coarse grid of 10 km resolution over western Himalaya needs to be statistically treated for downscaling to specific location. Downscaling is the method used to convert NWP output on a course resolution into local meteorological variables. Local weather is also affected by the past state besides the large scale atmospheric state. There are two approaches for downscaling, dynamical downscaling and statistical downscaling. Dynamical approach is based on high resolution climate models or limited area models. These methods require high computing power and their resolution is too coarse to use for station specific requirements. Statistical downscaling techniques are easier and require inexpensive and simpler computation (Khalili *et al*., 2013).Two widely used statistical methods for downscaling and forecasts are: the perfect prognostic method (PPM) (Klein *et al*., 1959) and the model output statistics (MOS) (Glahn and Lowry, 1972).

Several studies have been carried out to predict location specific weather parameters over the western Himalaya. Analogue method has been used for location specific surface weather parameters over the western Himalaya by Singh *et al*. (2008). A perfect prognostic approach has been employed for location specific prediction of maximum and minimum temperature by Dimri and Mohanty (2007) and probability of occurrence and quantity of precipitation by Mohanty and Dimri (2004) over the western Himalaya. Srinivasan *et al.* (2010) demonstrated that a statistical regression approach to statistical downscaling (SDM) of MM5 model output yields significant improvements in the prediction of surface weather parameters over the western Himalaya. In the present study an Artificial Neural Network (ANN) model is developed to downscale the MM5 temperature forecast over selected stations in Western Himalaya and it gives better results than simple linear techniques and persistent forecast. A number of studies have also been conducted using statistical downscaling techniques and ANN based methods. ANN promises to deal with the complex and highly non-linear problems associated with natural systems including atmosphere, ocean and climate systems.

Joshi and Ganju (2013) used ANN, a non-linear method for downscaling of MM5 model output to provide station specific precipitation forecast over western Himalaya. Gardner and Dorling (1998) presented a detailed review of application of ANN in the atmospheric science. Adya (1998) found that ANN had potential for forecasting and prediction. Hall (1998) developed a neural network model using input from Eta model and upper air soundings. The neural network produced a very good forecast of both the probability and amount of precipitation. Holger (2000) presented modeling issues of neural network models in the prediction of water resource variables. Neural network was used to improve temperature forecasts produced by the Advanced Regional Prediction System and the improvement varied between 5% and 90% in terms of mean-squared error (Marzban, 2003). Coppola (2006) applied ANN to combine satellite imageries and data from NWP model to estimate real time rainfall. Roebber (2006) developed ANN model for real time snow forecasting across the contiguous United States east of the Rocky Mountains. Forecast skills of maximum and minimum temperature over Delhi improved by applying ANN (Roy *et al*., 2009). Hoai *et al*. (2011) applied feed-forward multilayer perceptron (MLP) using error training back-propagation method to develop an empirical-statistical approach to downscale the precipitation from global NWP outputs to a basin-scale for flood runoff prediction. ANN model was developed for prediction of maximum and minimum temperature at different locations in western Himalaya (Joshi and Ganju, 2012). Coulibaly and Dibike (2005) proposed the time-lagged feed-forward neural network (TLFN) for downscaling daily total precipitation and daily maximum and minimum temperature series for the Serpent River watershed in northern Quebec (Canada). The downscaling models are developed and validated using large-scale predictor variables derived from the National Centers for Environmental Prediction - National Center for Atmospheric Research (NCEP - NCAR) reanalysis dataset. The study results show that the time-lagged feed forward network (TLFN) can be an effective method for downscaling daily precipitation and temperature data as compared to the commonly used statistical method. Schoof and Pryor (2001) applied regression techniques and ANNs to downscale maximum and minimum daily air temperature and daily and monthly precipitation totals at Indianapolis and quantified the relationships between the synoptic-scale circulation and local climate parameters in the Midwestern United States.

Kidson and Thompson (1998) compared Statistical and Model-Based Downscaling Techniques to estimate Local Climate Variations over New Zealand, using boundary conditions from European Centre for Medium-Range Weather Forecasts (ECMWF). Statistical downscaling (SD) models, the non-homogeneous hidden Markov model (NHMM) and the statistical down-scaling

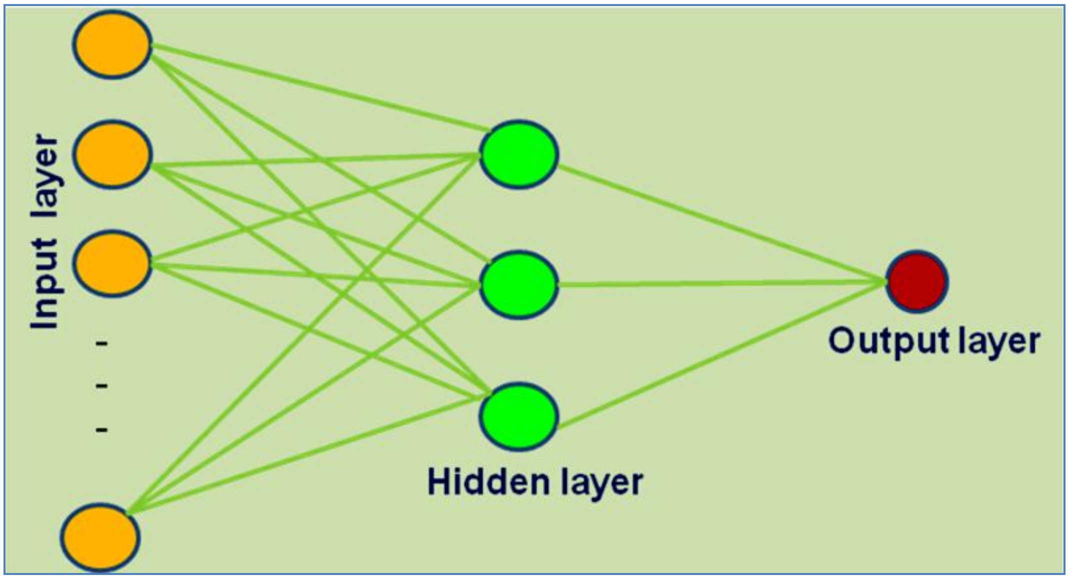


Fig. 1. Schematic diagram of multi layered ANN

model (SDSM) were used to downscale precipitation over the Tarim River basin, located in China (Liu *et al*., 2011). Ferrero *et al.* (2009) compared several statistical downscaling methods for operational short-term forecast of precipitation in the area of Bilbao (Spain). It was found that the coarse resolution models in combination with a statistical downscaling provide usable information to achieve a quantitative precipitation forecast. Wilks (1999) used a simple stochastic precipitation model to downscale precipitation for 6 groups of 5 U.S. stations. There was a large difference in climate statistics between local and area-averaged series. A computationally economical and flexible approach to produce local climate-change 'scenarios' is through the use of stochastic weather models, or 'weather generators' (Wilks, 1999).

Charles *et al.* (2004) investigated the ability of the extended non-homogeneous hidden Markov model (extended-NHMM) to reproduce observed inter-annual and interdecadal precipitation variability. He presented the relevance of statistical downscaling to hydrological research, potential applications of the extended-NHMM. Huth (2001) compared the performance of several linear downscaling methods and several sets of large-scale predictors and the performance of the two ways of reproduction of variance (inflation vs. randomization). He also estimated the dependence of the downscaling output on the size of the domains on which the predictors and predictands are defined. The downscaling is performed for daily mean temperature in winter at a network of stations in central Europe. Flexible nonlinear regression models like ANNs, which represents arbitrary forms of nonlinearity and complicated interactions between predictors may yield better predictions than classical linear models for a variable. A nonlinear, probabilistic synoptic downscaling algorithm for daily precipitation series at multiple sites is presented by Cannon (2008).

In the present study ANN method has been used to downscale temperature forecasts by MM5 model, to provide location specific temperature forecast for three stations under study over the western Himalaya (Fig. 4). A multilayer ANN model has been developed to downscale daily temperatures over three stations in the western Himalayan region. The model is validated with the observed data. The MM5 and ANN model description has been given in section 2 while Data and methodology have been described in section 3. Results are provided in section 4 and conclusions are given in the last section 5.

2. Model description

SASE used the fifth generation Pennsylvania State University (PSU)/National Centre for Atmospheric Research (NCAR) mesoscale model, MM5 to forecast different meteorological parameters such as precipitation, temperature, wind etc from 2002 to 2011. MM5 is a Limited Area Model (LAM) to simulate and predict mesoscale systems and regional atmospheric circulations (Anthes and Warner 1978). Its vertical coordinate system is terrain following sigma coordinates with options for non hydrostatics approximations. The complete MM5 modeling system consists of five modules: TERRAIN, REGRID, RAWINS/little_r, INTERPF and MM5. For the

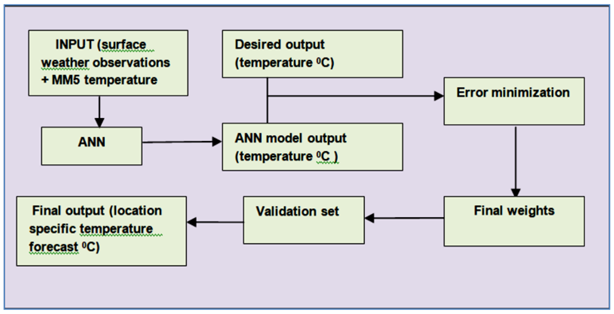


Fig. 2. Flow chart of ANN methodology

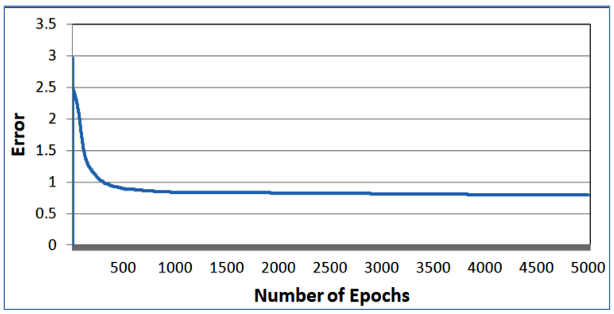


Fig. 3. Error minimization curve with numbers of epochs in x-axis and error (ºC) in y-axis

generation of terrain and land use, USGS 2’ and 30” topography and land use data are used in MM5. Initial and lateral boundary conditions for the model are taken from National Centre for Medium Range Weather Forecasting (NCMRWF) T254 analysis and its forecast.

ANN is a computational structure modeled loosely on biological processes. Development of an ANN for any system involves topology of the network, a proper training algorithm and activation function (Chattopadhyay and Bandyopadhyay, 2007). In any ANN, there is an input layer connected to output layer with different weights. In between there may be one or more hidden layers also connected by weights. This interconnected set of weights contains the knowledge generated by the ANN.

In the present work, a three layer ANN model with single hidden layer is developed using back propagation learning algorithm. Joshi and Dimri (2008) developed a three layer ANN model for precipitation forecast over western Himalaya using surface parameters. In present model there are 8 nodes (number of input parameters) in input layer, 7 nodes in hidden layer and one node (temperature) in output layer. Fig.1 shows the architecture of a three layer neural network. The number of hidden layers is variable according to the problem. Generally one hidden layer is considered sufficient to approximate any smooth measurable function between inputs and outputs (Hornik *et al*., 1989).

TABLE 1

Three layer artificial neural network architecture

Network parameters	Optimal numbers
No of inputs	8
No of hidden layers	1
No of hidden nodes	7
No of outputs	1
Learning rate	0.8
Momentum	0.5
Activation function	Sigmoid transfer function $f(x) = (1+e^{-x})^{-1}$

TABLE 2

Input parameters considered for the study

Parameter	Time of observation
Maximum temperature (T_x)	1730 (previous day)
Minimum temperature (T_n)	0830 (current day)
Dry bulb temperature (T)	0830
Av wind speed (ws_{avg})	Average of last 24
Pressure Change	24 hour
Cloud amount (cla)	0830
Precipitation amount (mm)	0830
MM5 predicted temperature	Day 1, day 2 and day 3

If the learning rate is high, training is fast but there is a problem of generalization as the network memorizes the patterns and large error is produced when validated with independent data set. This is the case of over fitting. With a large number of hidden nodes the complexity of network increases and it takes too much time to train the network. With very small learning rate and less number of hidden nodes, network is not able to capture the variability in data (under fitting) and the error even with training set is very large. To overcome the problems of over fitting and under fitting the parameters of the networks are to be optimized. To determine the optimal numbers of network parameters, network has been tested with various combinations of hidden layer, hidden nodes, learning rate and momentum and 8-7-1 network with learning rate 0.8 and momentum 0.5 was found to be the best and used for the present study (Table 1). Fig. 2 represents the flow chart of the methodology.

Initially random weights are assigned between input-hidden and hidden output layers. If number of

TABLE 3

Principal observatories considered for study

Station	Altitude (m)	No of data points (training set)	No of data points (validation set)
Kanzalwan	2440	400	135
Gulmarg	2800	400	135
Stage II	2650	400	139

inputs, patterns and hidden nodes are denoted by *n*, *m* and *p* respectively, the input at hidden layer is computed as:

$$Z_i = f\left(\sum W_{ij} \times X_{kj}\right) \quad (1)$$

Final output O is computed with this input and hidden-out weights as;

$$O_k = f\left(\sum V_i \times Z_i\right) \quad (2)$$

where, $i = 1, 2 \ldots p$, $j = 1, 2 \ldots n$, $k = 1, 2 \ldots$m.

and f is a function called activation function. In this study the activation function is a sigmoid transfer function for both input-hidden layer and hidden output layer, given as:

$$f(x) = \left(1 + e^{-x}\right)^{-1} \quad (3)$$

The weights are adjusted in such a way that the error, the difference between the network output and desired output is reduced. The error is given by:

Error = 1/2∑ (desired output-network output)^2

$$E = \frac{1}{2}\sum\left(Y_k - O_k\right)^2 \quad (4)$$

The error term at output layer is computed as:

$$E_T = \left(Y_k - O_k\right) \times O_k \times \left(1 - O_k\right) \quad (5)$$

This error is propagated backward to the hidden layer and error term at hidden layer is computed as:

$$E_H = V_i \times E_T \times Z_i \times \left(1 - Z_i\right) \quad (6)$$

These error terms are used for modification of the weights. The weights are adjusted so as to minimize the error functions. This technique is called gradient descent. Change in the weights is given as:

$$\Delta W_{ij} = \eta \times E_H \times X_{kj+\alpha} \times \Delta W_{ij} \quad (7)$$

and

$$\Delta V_i = \eta \times E_T \times Z_{i+\alpha} \times \Delta V_i \quad (8)$$

where, η is the learning rate and α is the momentum.

These modified weights are used for the next pattern and error at each pattern is summed up to get the net error. The network is trained till the net error is minimized to a desired accuracy. This has been presented in Fig. 3.

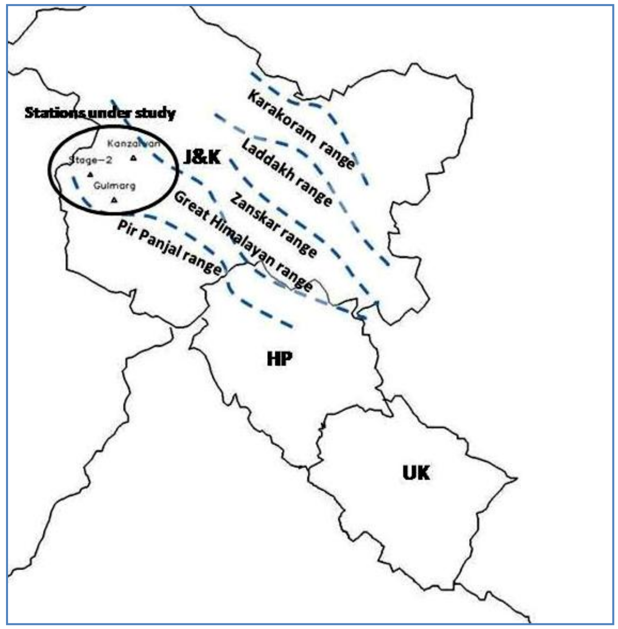
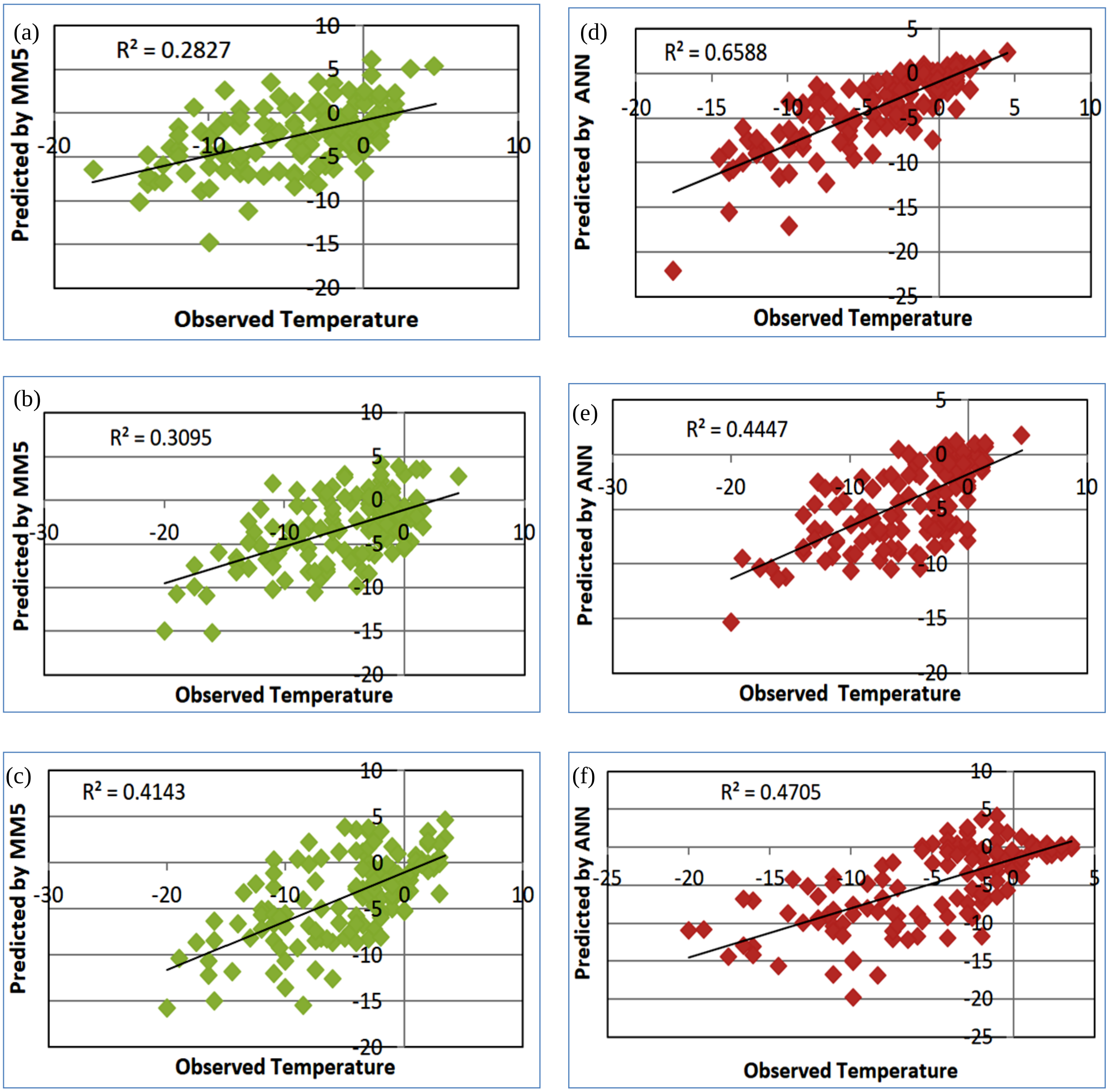


Fig. 4. Observatory network in western Himalaya showing the stations under study

3. Data and methodology

SASE has established a network of snow and meteorological observatories over the western Himalaya. These observatories represent different road axes/sectors, prone to avalanches. There are number of avalanche activities along these axes every winter resulting in huge loss of lives and property. In present study, three observatories Kanzalwan, StageII and Gulmarg (Fig. 4) representing different geographical and climatic conditions of the Jammu and Kashmir (J&K) are considered. These observatories represent the climatic conditions of the region and are also nodal centers for

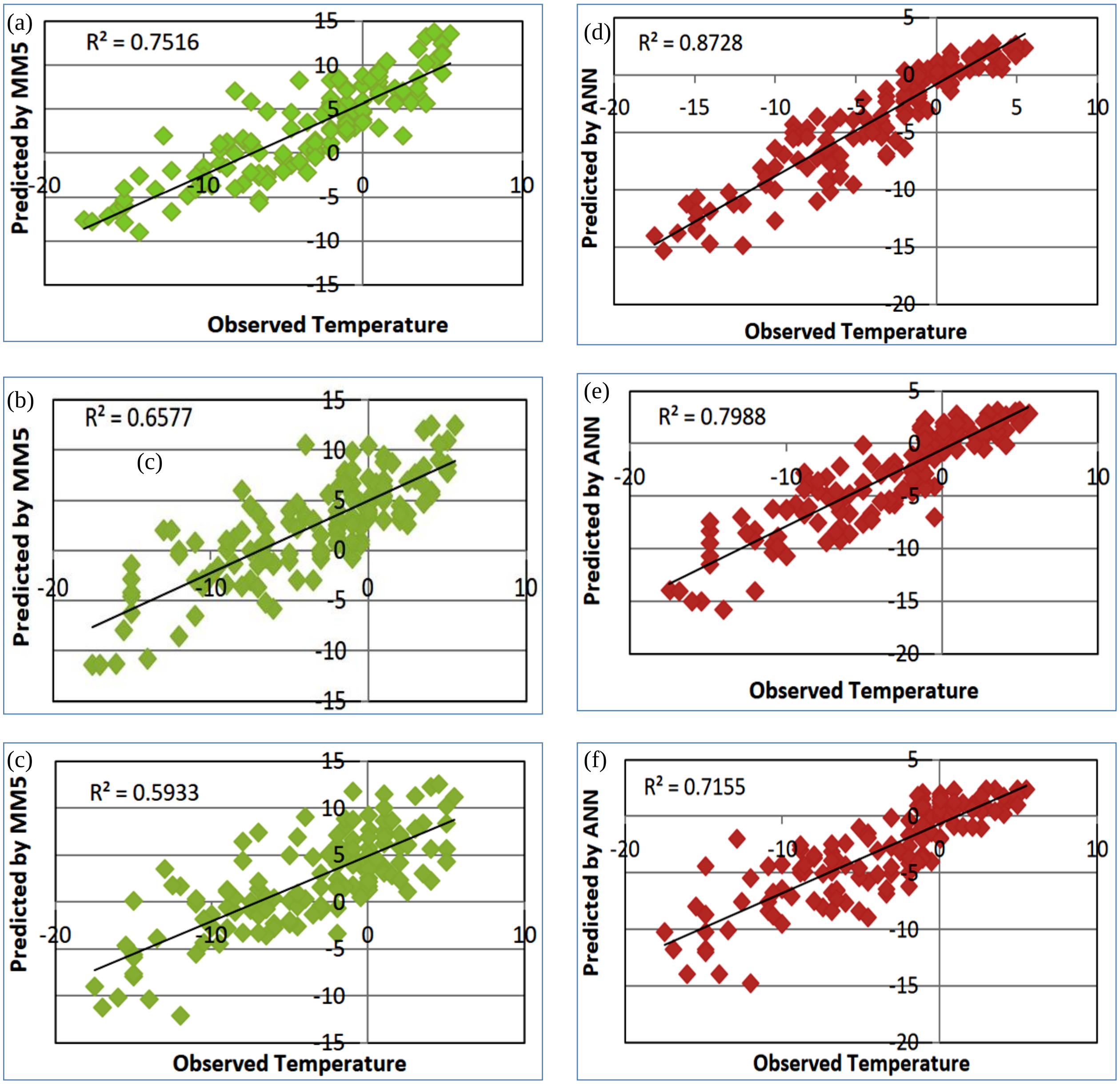


Figs. 5(a-f). (a-c) show MM5 model predicted temperature (°C) Vs Observed temperature (°C) and (d-f) show ANN model predicted temperature (°C) Vs Observed temperature (°C) for validation set corresponding to day 1, day 2 and day 3 over Kanzalwan. The black curve shows the deviation of predicted temperature from the observed one

assessing/disseminating avalanche hazards for the respective areas.

In the present study, six surface weather parameters (Table 2) which include maximum temperature, minimum temperature, dry bulb temperature, average wind speed, pressure change, cloud amount and MM5 output (temperature) have been considered as input parameters. The data set consists of five years winter data (2003-04 to 2008) having total of 435-439 data points. Out of which 300 data points are taken for training the ANN and 135-139 independent test data points, not included in the training set, are considered for validation of the model (Table 3). All the parameters are normalized to values between 0.1 and 0.9 to ensure that the model has similar sensitivity to changes in various parameters. For any variable x with maximum value, x_{max} and minimum value, x_{min} the normalized value x_A is calculated as:

$$x_A = 0.1 + 0.8\,(x - x_{min}) / (x_{max} - x_{min}) \qquad (9)$$



Figs. 6(a-f). Same as Figs. 5(a-f) except for Gulmarg

Corresponding to six surface parameters and MM5 model output (temp.) ANN model is trained for three days temperature forecast and validated on independent data set using back propagation learning algorithm. Time series of temperature is analyzed which shows a large variation in temperature at all locations. Results are analyzed for all stations corresponding to day1, day 2 and day 3 forecasts.

4. Results and discussion

For Kanzalwan, there are total 435 data points, out of these, training set consists of 300 data points and 135 data points are used for validating the results (validation set). The standard deviation corresponding to the training set is 4.97 °C and that of validation set is 4.7 °C. The mean of the observed temperature for the validation set is -4.12 °C while the mean values of the temperature predicted by MM5 model and ANN model are -2.49 °C and -3.75 °C respectively. Thus, the mean of the temperature predicted by ANN model is close to the observed mean value indicating a good prediction by the ANN model. Figs. 5(a-f) depict the comparison of scattered plots between MM5 predicted temperature (left column) and ANN predicted temperature (right column) with the

TABLE 4

Number of days with error in different error range for validation set

Station	Model	Total days	Number of days with error in different ranges for validation set														
			0-1			1-2			2-3			3-4			>4		
			Day1	Day2	Day3	Day1	Day2	Day3	Day1	Day2	Day3	Day1	Day2	Day3	Day1	Day2	Day3
Kanzalwan	MM5	135	23	20	28	24	18	23	22	31	18	19	08	15	47	58	51
	ANN		35	31	14	30	21	24	23	25	25	17	16	24	20	42	48
Gulmarg	MM5	135	02	04	05	03	12	10	07	09	13	19	14	14	104	96	93
	ANN		52	39	36	34	37	26	29	29	28	15	14	23	05	16	22
Stage II	MM5	139	18	23	21	19	21	23	28	27	21	17	15	13	57	52	61
	ANN		47	42	40	39	34	34	23	25	19	20	18	16	09	20	30

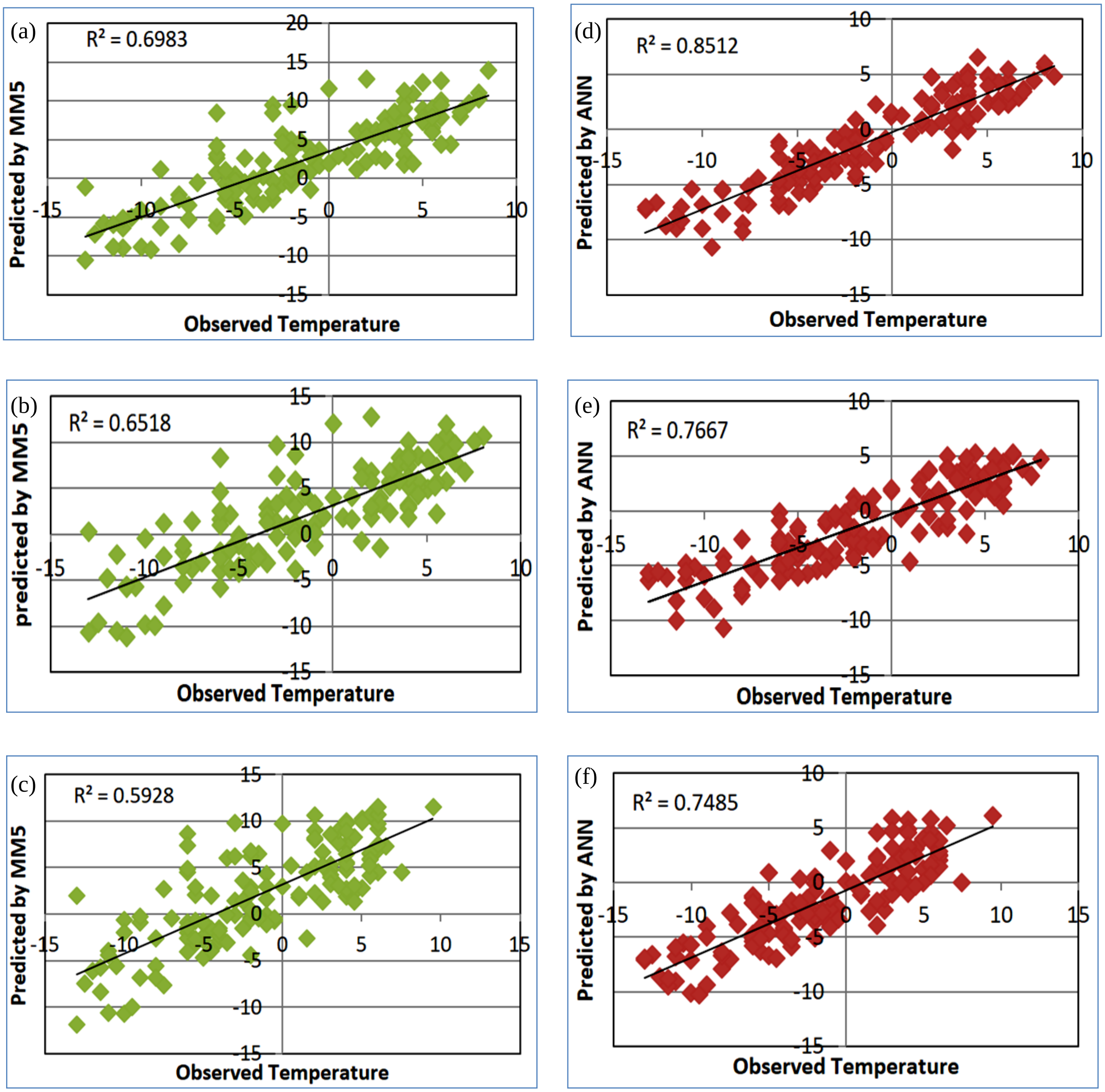
observed temperature for day1, day 2 and day 3 over Kanzalwan. Figure shows coefficients of determination between observed and predicted temperature by MM5 and ANN model are 0.36 and 0.73 for training set while for validation set these values are 0.28 and 0.66 [Figs. 5(a&d)], which shows improvement in forecast skill after downscaling. To check the performance of the model, performance parameter (PP) (ratio of mean square error and the variance of the observed values) is also calculated. For Kanzalwan the value of PP corresponding to MM5 model is 0.81 and 0.88 while corresponding to ANN model the values of PP are 0.27 and 0.35 for training and validation set respectively indicating fairly good prediction of temperature by ANN model.

To explain the results quantitatively, total number of days with error in five different error categories (0-1, 1-2, 2-3, 3-4 and >4 °C) are calculated and provided in Table 4 for validation data set. For Kanzalwan there are 135 data points in the validation set. Within error range of ± 2 °C, MM5 predicts 34.81% and ANN model predicts 48.15% of total days. Only 20 days are predicted with error greater than 4 °C in case of ANN while this figure is 47 for MM5. After downscaling number of data points in the acceptable error range are increased and thus ANN can be used as an effective downscaling technique for operational forecasting purpose.

For day 2 prediction the mean values of the temperature predicted by MM5 model and ANN model are -3.27 °C and -4.24 °C respectively for validation set. The coefficient of determination between observed and predicted temperature by MM5 and ANN model is 0.31 and 0.62 for training set while for validation set these values are 0.31 and 0.44 [Figs. 5(b&e)] indicating fairly good performance of ANN model for day 2 forecast. The values of PP for day 2 corresponding to MM5 model are 0.82 and 0.86 while corresponding to ANN model these values are 0.38 and 0.59 for training and validation set respectively. For day 2, values of PP are higher compared to day 1. This shows deterioration of model forecast skill with increasing time lag. Quantitatively MM5 predicts 28.15% and ANN model predicts 38.52% of total days within error range of ± 2 °C. Number of days predicted with error greater than 4 °C by ANN and MM5 model is 42 and 58 respectively.

Again for day3, the mean values of the temperature predicted by MM5 model and ANN model are -3.61 °C and -4.70 °C respectively. The coefficient of determination between observed and predicted temperature by MM5 and ANN model is 0.20 and 0.52 for training set while for validation set these values are 0.41 and 0.47 [Figs. 5(c&f)]. Though the values are slightly higher for ANN model, the performance of the model is not fairly good for day 3. The values of PP corresponding to MM5 model are 1 and 0.66 while corresponding to ANN model the values are 0.48 and 0.60 for training and validation set respectively. The values are higher even for ANN model for day 3. MM5 predicts 37.38% and ANN model predicts 28.15% of total data points within error range of ± 2 °C. Number of days predicted with error greater than 4 °C by ANN and MM5 model is 48 and 51 respectively. Thus for day 3, corresponding to Kanzalwan, ANN model performance is poor in comparison to day 1 and 2. Thus skill of the model for temperature forecast over Kanzalwan deteriorates for day 3.

Similar analyses have been done for Gulmarg and Stage II. The RMSE is reduced significantly for both the stations. After downscaling the predicted temperatures are



Figs. 7(a-f). Same as Figs. 5(a-f) except for Stage II

closer to the observed one. Figs. [6(a-f) & 7(a-f)] show the scatter plots for MM5 predicted and ANN predicted temperature corresponding to day1, day2 and day3 for Gulmarg and Stage II stations respectively.

Root mean square error (RMSE) is calculated to verify temperature forecast for both training and validation set. For day 1 forecast, RMSE for training set is 4.48 °C (MM5) and 2.58 °C (ANN) and corresponding to validation set is 4.42 °C (MM5) and 2.77 °C (ANN). Thus, using ANN model to downscale the temperature forecast, RMSE is lowered significantly and also quite less than SD, which explains the good performance of the ANN model.

RMSE for training set is 4.27 °C (MM5) and 2.89 °C (ANN) and for validation set is 4.68 °C (MM5) and 3.87 °C (ANN) corresponding to day 2. The lower value of RMSE for ANN model explains fairly good performance of the ANN model for day 2 forecast.

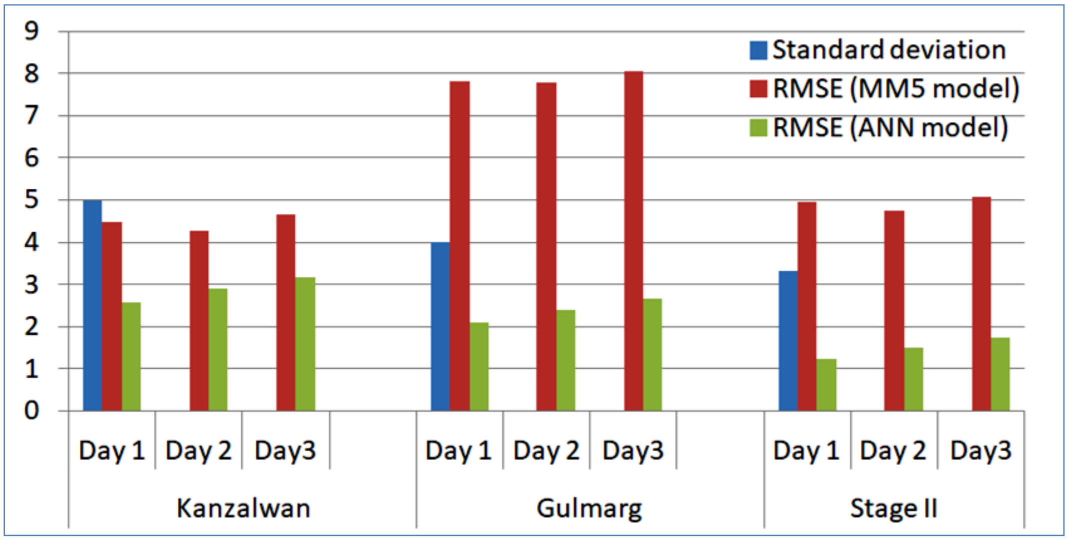


Fig. 8(a). Root mean square error (°C) and standard deviation in *y*-axis for training data set corresponding to temperature forecast for day 1, day 2 and day 3 for all stations under consideration in *x*-axis

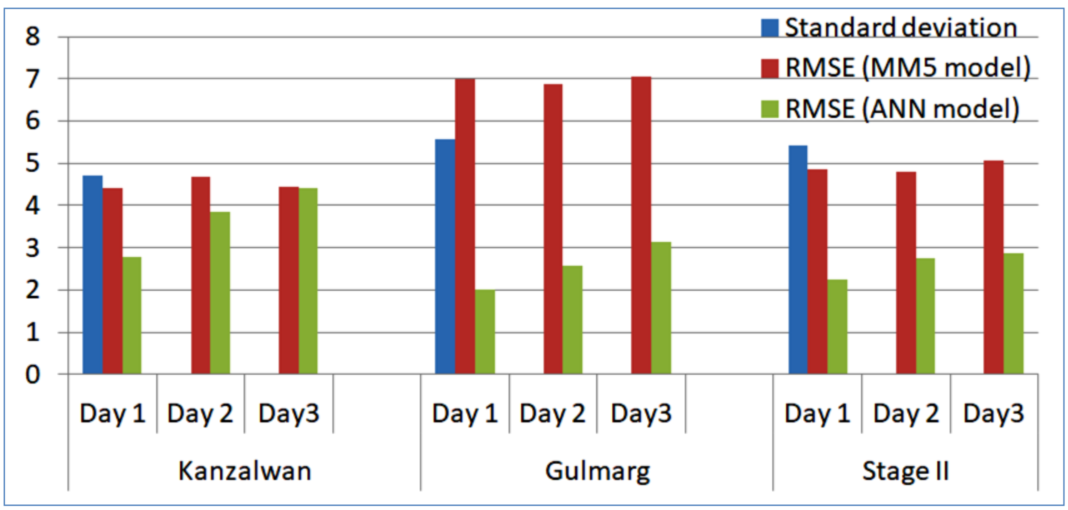


Fig. 8(b). Same as Fig. 8(a) except for validation data set

Corresponding to day 3 RMSE for MM5 model is 4.65 °C and 4.44 °C for training and validation set while for ANN model RMSE is 3.17 °C for training set and 4.20 °C for validation set. RMSE is not reduced significantly in case of day 3, which shows the performance of model to be not good with increasing time lag.

The computed RMSEs of the ANN model, MM5 and observed standard deviation with respect to day 1, day 2 and day 3 forecast of temperature for all the three stations for training data set is given in Fig. 8(a). It is clear that the ANN model shows a reduction in RMSE for all the three days forecast. RMSEs associated with the ANN model are also less than the observed standard deviation, which statistically shows that skill of ANN model is acceptable as a means for improving the temperature forecast at all the three stations of western Himalaya.

In Fig. 8(b), the computed RMSEs of the independent dataset derived from the MM5 are compared with the ANN model results. Even with the independent data set, the ANN model shows a significant reduction in RMSEs for all the stations.

5. Conclusions

Temperature is one of the important parameters for forecasting avalanche in mountainous terrain since it helps in metamorphic processes which trigger avalanches. Forecasting temperature in complex mountain terrain such as Himalaya is a complex job. NWP models provide forecast over a grid covering a large area depending on the resolution of the model. Location specific temperature forecast is vital for future assessment of the avalanche in addition to the other parameters. In present study, an ANN model is developed to downscale three days temperature forecast using MM5 model output at three locations in the western Himalaya. A non-linear differentiable sigmoid transfer function is used in three layer feed forward network. Different forecast verification measures are applied to check the performance of the model. RMSE and skill score are computed for both MM5 and ANN models. RMSE is close to 2 °C in case of ANN model, though there is a large fluctuation in temperatures over the region. Results of the study show that predicted temperatures at particular location, after downscaling of MM5 model output are closer to observed values and thus ANN technique may be very useful for improving the NWP model output at a grid of coarse resolution. Though forecast skill of the model deteriorates with increasing time lag, after downscaling the forecast is improved in all the cases. There are some limitations in this technique as there is no definite rule to decide the number of hidden nodes and value for learning rate and momentum. However ANN can be very effective tool for location specific temperature forecasting which may be very much helpful in assessing likely avalanche danger situation in advance. Studies are going on to develop ANN based model by using outputs of WRF model, which is now being used by several communities in the field of meteorology and is supposed to be a robust model with good Physics and dynamics involved in it.

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