Prediction of mountain rainstorms of Uttarakhand Himalaya using Artificial Intelligence on dynamic NWP model data

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Abstract: Complemented with nonlinear dynamic forcing and coupling of convective updrafts, downdrafts and cold pools, mountain rainstorms need most proficient implementation of artificial intelligence. Artificial Neural Networks which are trainable self-adaptive systems to learn to solve complex problems from a set of examples and to generalize the acquired knowledge to solve unforeseen problems are the most accomplished candidate for prediction of complex dynamics of rainstorm. In this paper, experiments has been conducted on artificial neural network (ANN) model to predict severe rainstorms that occurred over Almora May 02, 2018 and over Dehradun on April 23,2017 using twelve potential predictors for rainstorm and validated the model results with observation.

Introduction

The Uttarakhand Himalaya is a seedbed of intense rainstorm activity at times and can be affected by many high impact weather events, especially between the long stretches of April and August. The prediction aspect of rainstorms is as yet exposed to forecaster's insight and understanding of Numerical Weather Prediction (NWP) models. Most of the times the methodology picked by the forecaster is of statistical or probabilistic nature. Vast soft computing programs called Numerical Weather Prediction models helps in deciding,whether the circumstances will be positive for the development of rainstorms or not. The models start with current weather perceptions and endeavour to anticipate future weather, depicting the dynamics and physics of the atmosphere, numerically. Few literatures show successful implementation of predicting convective initiation for forecast of rainstorm using artificial intelligence. In this study, the preliminary results have been obtained in prediction of rainstorm in two locations-Dehradun of Garhwal Himalaya and Almora of Kumaon Himalaya. The data has been taken from Indian Meteorological Department's Gridded Binary (GRIB) archive data. Each GRIB file comprises of a series of GRIB records. One GRIB record grips the gridded data for one parameter at one time and at one level. Matlab 9.3 Toolbox has been used to decode GRIB data. The decoding of GRIB data has helped accessing 234 numbers of parameters. Extraction of the required information from the subsequent data after decoding has been executed to prevent interference of one parameter with another. From the whole 234 parameters, 12 atmospheric parameters such as amount of Precipitable water,Best (4-layer) Lifted Index, relative humidity, U (zonal) component of wind and V (meridional) component of wind, mixing ratio, CAPE, CIN, rate of precipitation, storm relative helicity, vertical wind shear, SWEAT index has been finalised after quantitative analysis.

Methodology

Twelve input parameters are chosen based their core contribution towards the development of rainstorm. Their change in a condition of rainstorm occurrence as contrasted to a normal weather day has been exercised. The associated ascendancies of the parameters are as follows-

1) *Amount of precipitable water*

   The total atmospheric water vapor contained in a vertical column of unit cross-sectional area extending between any two specified levels, commonly expressed as the Precipitable water (measured in milimeter or inches). The Precipitable water value is the depth that would be accomplished if all the water in that column were hastened as precipitation. Data can be viewed on a Lifted-K index. The numbers illustrate milimeters of water as mentioned above for a geographical location.

   In actual rainstorms, amounts of rain may exceed the total precipitable water vapor of the overlying atmosphere. This results from the action of convergence that brings into the rainstorm the water vapor from a surrounding area that is often quite large. Nevertheless, there is general correlation between precipitation amounts in given storms and the precipitable water vapor of the air masses involved in those storms.

2) *Best (4 layer) Lifted index*

   The Lifted Index is the temperature difference between an air parcel lifted adiabatically Tp(p) and the temperature of the environment Te(p) at a given pressure height in the troposphere (lowest layer where mostweather occurs) of the atmosphere, usually 500 hPa (mb). It incorporates moisture and lapse rate (static stability) into a single number, which is less vulnerable to observations at individual pressure levels. However, LI values do depend on the level from which a parcel is lifted, and cannot account for details in the environmental temperature curve above the LCL and below 500 mb. When the value is positive, the atmosphere (at the respective height) is stable and when the value is negative, the atmosphere is unstable.

3) *Relative humidity*

It is defined as the proportion of the partial pressure of water vapour in a gaseous mixture of air and water vapour to the saturated vapour pressure of water at a given temperature. This parameter manifests the amount of moisture in the air relative to the maximum amount it can hold at that temperature.

4) *U-component of wind*
The component of wind flowing in a west to east direction of the horizontal plane of an area is referred to as u component of wind. Strong wind can trigger convection. Thus this parameter is substantial while dealing with a rainstorm.

5) *V-component of wind*
The component of wind flowing in a north to south direction of the horizontal plane of an area is referred to as v component of wind. Strong wind can trigger convection. This component is very important while dealing with a rainstorm.

6) *Mixing ratio*
The mixing ratio is defined as the ratio of the mass of water vapor to the mass of dry air and is expressed in grams per gram or in grams per kilogram. It is numerically very close to specific humidity, but it always has slightly higher value. The mixing ratio has the similar characteristic properties as the specific humidity. It is conservative for atmospheric processes involving a change in temperature. It is non conservative for changes involving a gain or loss of water vapor.

7) *CAPE*
Convective Available Potential Energy (CAPE) is the maximum buoyancy of an undiluted air parcel, associated with the potential updraft strength of rainstorms. On a thermodynamic diagram it depicts the positive area between the air parcel's path and the sounding bounded by the level of free convection to its level of neutral buoyancy.The larger the positive area, the higher the CAPE value and instability, and the greater the potential for strong and perhaps severe convection.

8) *CIN*
The convective inhibition (CIN) is the amount of energy that will prevent an air parcel from rising from the surface to the level of free convection. It is represented by the area on a skew-T diagram enclosed by the environmental temperature profile and the temperature of a parcel lifted from some originating level to the LFC. This area indicates the amount of energy required to lift the parcel to the LFC. CIN is measured in units of joules per kilogram (J/kg).The larger the negative area, the higher the CIN value, and the lower the likelihood of convective storms.

9) *Rate of precipitation*
It is defined as the rate at which water is precipitated to the surface of a field. Usually it is expressed in millimetre per hour.

10) *Storm-Relative Helicity*
Storm-relative (S-R) helicity (Hs-r) is an estimate of a rainstorm's potential to acquire a rotating updraft given an environmental vertical wind shear profile, assuming rainstorms are able to develop. It integrates the effects of S-R winds and the horizontal vorticity (generated by vertical shear of the horizontal wind) within the inflow layer of a storm. A S-R wind is the wind that a rainstorm actually "feels" as the storm moves through the environment. It is different from a true ground-relative (G-R) wind, except for a stationary storm whereby a S-R and G-R wind are equivalent. S-R helicity is proportional to the area "swept out" by the S-R wind vectors between two levels on a hodograph.

11) *Vertical wind shear*
Vertical wind shear is a change in wind speed or direction with a change in altitude. Vertical wind shear that causes turbulence is closely associated with the vertical and horizontal transport of momentum, heat, and water vapour.

12) *SWEAT Index*
The SWEAT Index evaluates the potential for severe weather by examining both kinematic and thermodynamic information into one index. Parameters include low-level moisture (850 mb dewpoint), instability (Total Totals Index), lower and middle-level (850 and 500 mb) wind speeds, and warm air advection (veering between 850 and 500 mb).

Pre-processing of data

NWP data has been decoded and downscaled to the particular area of concern for prediction purpose. Dehradun (latitude 30.3165° N, longitude 78.0322° E) and Almora (latitude 29.5892° N, longitude 79.6467° E) has been considered for this study. Each input node of the neural network comprises an array of different atmospheric parameter values for different time period. A convenient grid of size 5^0 X 5^0 is fixedbased on the area of concern. For every parameter, the two dimensional data is switched over completely to one layered information 1 X 5 by normalization. Likewise all unique ten parameters were extricated and organized to frame a solitary array of size 1 X 60. The NWP data was considered in a time frame of 12 hours over a period of five days. Then, at that point, the size of the information dataset is 12 X 60. Afterwards, each input parameters were standardized to have the qualities between - 1 to 1 to improve the result of the ANN.

Artificial Neural Network design

The Artificial Neural Network design for this study is a supervised, feed-forward perceptron network with two layers- one hidden layer and one output layer trained with back propagation algorithm. This ANN model has been developed trained and tested using MATLAB 9.3.

The input layer of ANN comprises of twelve input nodes (since, 12 hour data for consecutive 5 days were taken). Each input node has an array of 1 X 60 values derived from eight atmospheric parameters. Thus a 12 X 60 dataset is fed as input to the network. For a Multi Layer Perceptron (MLP) with only one hidden layer, Gaussian hills and valleys requires a large number of hidden units to approximate well. Thus the network has been designed for single hidden layer. In the event that there are excesses of hidden units, it might bring about low training error yet at the same time have high generalization error due to over fitting and high variance. A guideline is for the size of hidden layer to be somewhere close to the input layer size and result layer size. The number of hidden layer hubs chose for our study is 13.Sigmoidal activation function has been applied to each layer. The entire design has been illustrated in the figure 1. Since the ANN model requires a complete input set, the screening of the input and target data has been performed once the forecast time and geographical area is selected.

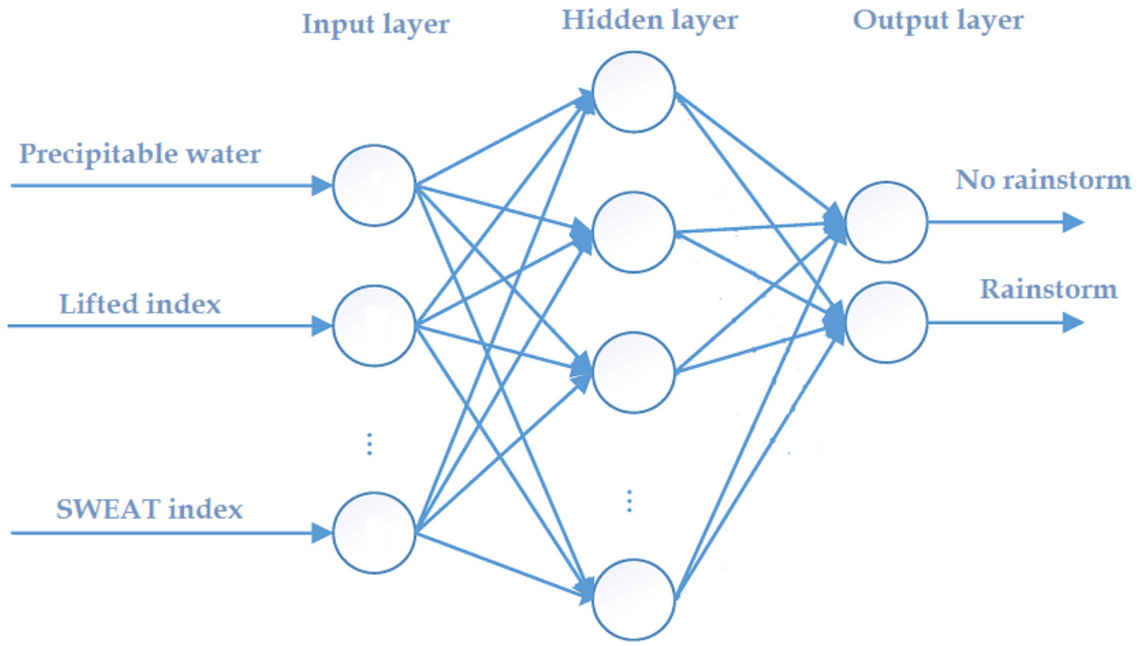

Figure 1. The ANN structure for this study

A critical component of artificial neural network is an iterative learning process wherein data were introduced to the network each in turn, and the weights related with the input values are changed each time. After all eventualities are introduced, the interaction often starts once again. During this learning stage, the network advances by changing the weights, in order to have the option to anticipate the amended class mark of input samples. The necessary result, i.e, rainstorm or no-rainstorm was found out accurately for various real-time meteorological datasets.

Result and discussion

The applied artificial neural network has been executed in accordance with the proposed architecture. It has been tested and trained with different meteorological data. The weights and bias has been rectified with every iteration. It was clearly observed that minimized drastically with the increase in number of iteration as displayed in figure 2. As the iterations approachestowards 40000, the error approaches to 0.005.

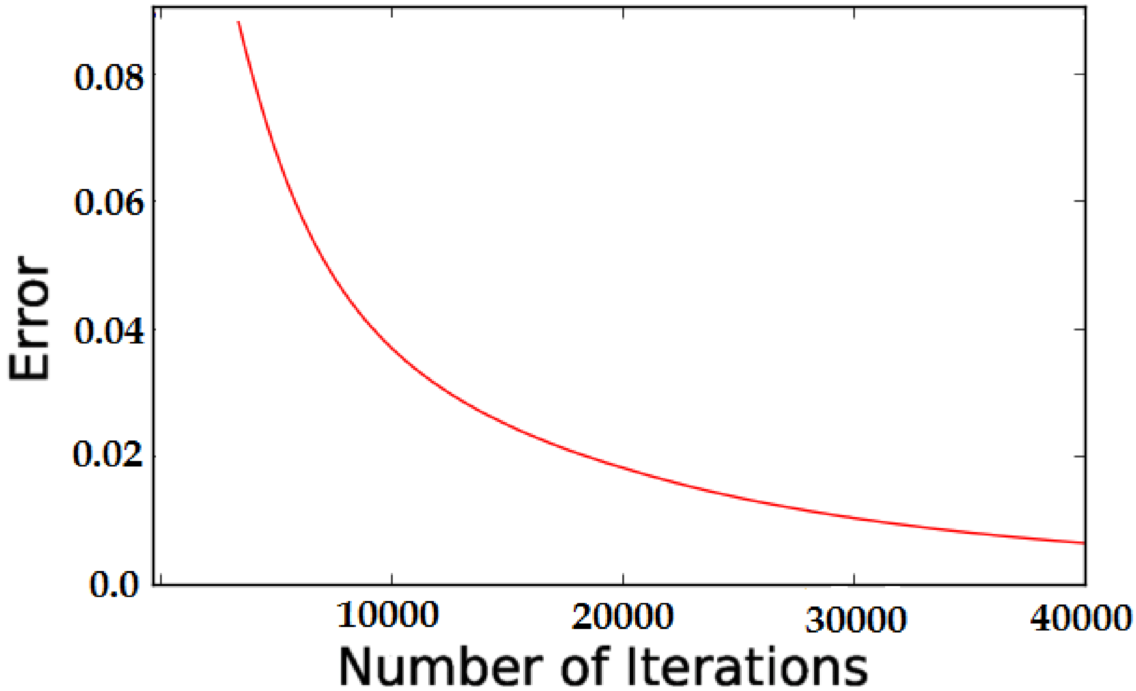

Figure 2. Error Analysis for April 23, 2017, 00 hrs data for Dehradun

After training the ANN with rainstorm and non-rainstorm data, the testing part was carried out. It has been observed that the output nodes gave significant distinct result for rainstorm and non-rainstorm days. Table1 and Table 2 depict the ANN classification for the Dehradun and Almora regions. Table 1 shows the rainstorm occurrence has been accurately predicted on April 23, 2017 in the region of Dehradun and Table 2 shows the correct prediction on May 02, 2018 at Almora.

Table 1: ANN output for Dehradun

Date	Time	Output at node 1	Output at node 2
April 20, 2017	00-12 hour	0.99897	6.36E-06
	12-24 hour	0.99897	6.13E-06
April 21, 2017	00-12 hour	0.99897	5.84E-06
	12-24 hour	0.99897	5.33E-06
April 22, 2017	00-12 hour	0.99897	00.004882
	12-24 hour	0.999683	00.004324
April 23, 2017	**00-12 hour**	**0.007716**	**0.99254**
	12-24 hour	**0.004621**	**0.99018**
April 24, 2017	00-12 hour	0.99932	0.00193
	12-24 hour	0.99894	0.00107

Table 2: ANN output for Almora

Date	Time	Output at node 1	Output at node 2
April 29, 2018	00-12 hour	0.99993	3.12E-06
	12-24 hour	0.99993	3.09E-06
April 30, 2018	00-12 hour	0.99993	3.04E-06
	12-24 hour	0.99993	3.08E-06
May 01, 2018	00-12 hour	0.99979	3.09E-06
	12-24 hour	0.99966	3.09E-06
May 02, 2018	**00-12 hour**	**00.003982**	**0.99319**
	12-24 hour	**00.003717**	**0.99348**
May 03, 2018	00-12 hour	0.99855	0.000165
	12-24 hour	0.99812	0.000113

Conclusion

This work involved the ANN framework with minimum set of input parameters. It is evident from the result that ANN can be effectively deployed for prediction of classification of mountain rainstorm of Uttarakhand Himalaya with appreciable degree of precision.

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